SHRP2 ROUND 5 IAP: INTEGRATING FREIGHT CONSIDERATIONS INTO HIGHWAY CAPACITY PLANNING PROCESS

FINAL REPORT

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16. Abstract

The goal of this SHRP2 round 5 project is to integrate freight considerations into the highway capacity planning process with additional focus on community visioning. Specific Planning Process Bundle product(s) to be addressed include:

1. Integrating Freight Considerations into the Highway Capacity Planning Process (C15)
2. Performance Measures for Highway Capacity Decision Making (C02)
3. Transportation Visioning for Communities (C08)

With the planning process bundle products, the following performance measures/indicators are analyzed and summarized below.

A. Efficient truck parking
B. Freight corridor reliability
C. Freight and land use integration

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EXECUTIVE SUMMARY

The goal of this SHRP2 round 5 project is to integrate freight considerations into the highway capacity planning process with additional focus on community visioning. Specific Planning Process Bundle product(s) to be addressed include:

1. Integrating Freight Considerations into the Highway Capacity Planning Process (C15)

2. Performance Measures for Highway Capacity Decision Making (C02)

3. Transportation Visioning for Communities (C08)

With the planning process bundle products, the following performance measures/indicators are analyzed and summarized below.

A. Efficient truck parking
B. Freight corridor reliability
C. Freight and land use integration

Efficient truck parking: Trucks carry more than 80% of freight tonnage in the United States. A mixture of growing truck traffic, strict delivery schedules and limited driving time bring about increased demand for truck parking at rest areas. Unavailability of sufficient parking spaces during various time periods at rest areas results in illegal and unsafe parking at on/off ramps, and other unauthorized areas which may lead to traffic safety hazards. In this research, the authors attempt to understand truck parking utilization by developing econometric models using truck GPS data for predicting truck parking utilization at rest areas in order to improve truck parking management and ensure proper utilization of the parking spaces. Count models including Poisson and Negative binomial models were developed in addition to generalized ordered response probit (GORP) models that subsume standard count models as special cases to understand the factors that affect the truck parking utilization. Among the different models estimated in this study, the GORP model that subsumes Poisson model as a special case was found to provide the best data fit. This was also confirmed by standard statistical fit measures (e.g., Bayesian Information Criterion) as well as prediction analysis that compared the prediction accuracy of different models. Elasticity effects were also computed to quantify the magnitude of impact of different factors on parking utilization. The model results suggest that several factors positively contribute to the truck parking utilization (example, truck volume on the adjacent roadway, number of lanes etc.) at rest areas whereas factors such as on ramp and off-ramp violation decreases the truck utilization. Also, parking utilization was found to be varying considerably by time-of-day. For instance, high parking rates were observed during the midnight hour (*i.e.,* 12 to 1 AM).

<u>Freight corridor reliability:</u> Reliability is the consistency in the observations of a variable over a period under consistent condition. Recently, reliability of travel time has garnered the attention of most freight agencies as the market is very competitive where goods are moved in tightly scheduled manufacturing and distribution systems. Lot of manufacturing companies nowadays want to know the reliable travel time so that they can manufacture the goods in time, reducing the warehouse and trucks cost. This chapter presents the identification of recurring and non-recurring variables and their impact on travel time in the freight network. This helps the freight companies and drivers pre-plan their travel effectively by increasing the efficiency of transport. Two main types of variation factors exist of which, one is expected delay caused by high volumes at peak period while the other is unexpected delay due to crashes, special events, work zones, and weather condition. The study has been done in Shelby county of Tennessee comprising the major links of freight corridor of United States. Collection of number of affecting variables over a time gives a panel data, which is very helpful to predict their correlation with travel time and its variation. Computation of travel time from truck GPS speed observations in a given origin-destination (O-D) pairs, and use of reliability measures like 95th percentile, Buffer Index (BI), Standard deviation, and Coefficient of Variation (CV) are the base of this research. The major objective of this chapter is to predict the path-based freight reliability considering ideal, recurring, and non-recurring travel conditions between the O-D pairs of the network that assist in transportation planning and decision-making.

<u>Freight and land use integration:</u> Land-use policies govern the types of developments that can be placed on parcels of land thus controlling the locations of the origins and destinations of freight movements. In order to make land use plans for growth, it is necessary to consider current freight flows and project them to a future year and vice

versa. The issue in this regard is connecting the flows of commodities to freight producing and freight attracting facilities. Transportation planning models typically consider amount of freight produced and attracted. Then using trip distribution models, trips produced and attracted used to develop freight origin-destination matrices. However, many planning models use total trip O-D matrices. However, with availability of truck GPS data and land use properties it would be possible to obtain some insights to what commodity is carried by the truck. We use truck trip generation factors to develop commodity specific productions and attractions, and then use truck GPS data to obtain O-D travel time matrix. Using the GPS based travel times it would be possible to use gravity or other trip distribution models to obtain commodity specific O-D truck trip tables. In this study we used the second approach. The case studies on various methods used for freight and land use planning, followed by a tool that was developed to obtain commodity specific O-D matrices for Jackson MPO, has been presented.

The implementation assistance will provide a chance for us to use state-of-the-art tools in this process. With the exception of a few national leaders, we believe that most state DOTs and MPOs are at the same stage where freight planning is either not considered or is an afterthought of the planning process. Our experience with integrating the Planning Process Bundles into our processes will be valuable for these agencies as it will provide case studies and step-by-step implementation of the bundles. Further, the availability of SHRP2 planning process bundle products presents a unique opportunity to obtain a better understanding of three performance measures: i) efficient truck parking, ii) freight land use integration, and iii) freight travel time reliability.

In summary, key outcomes of the C15/C02/C08 SHRP2 IAP project can be integrated with the performance measures of statewide freight planning, programing, and project delivery in TN. To achieve this goal a number of data sources such as truck GPS data, freight establishment data, land use, crash, weather, and other planning and operations data would be helpful. These data sources can be utilized with the processes developed in the SHRP2 project to address portions of “everyday business” needs. In addition to use of data and performance measures, freight stakeholders are recommended to be engaged along with the help of statewide and regional FACs to assist how the outputs of the implementation project will be institutionalized.

Keywords: Truck Parking, Freight and Land use integration, Performance Measures, Freight corridor reliability

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION 18

CHAPTER 2: TRUCK PARKING UTILIZATION 21

2.1 Truck parking: introduction 21

2.2 Truck parking: literature review 23

2.2.1 Truck parking studies in the US 23

2.2.2 Literature gap 40

2.2.3 Statistical and econometric methods for truck parking utilization 41

2.2.4 Use of truck GPS data for truck research 42

2.2.5 Data and methodologies used for truck parking 43

2.3 Truck parking methodology 44

2.3.1 Count modeling framework 44

2.3.2 Generalized Ordered Response Probit (GORP) framework 46

2.4 Data collection 48

2.4.1 Identification of rest areas 48

2.4.2 Identification of parked trucks 50

2.4.3 Collection of additional data 52

2.5 Truck parking results 55

2.5.1 Model estimation results 55

2.5.2 Model selection and statistical fit 60

2.5.3 Elasticity effects 61

2.5.4 Model validation 62

2.6 Truck parking conclusions 63

CHAPTER 3: TRUCK TRAVEL TIME RELIABILITY 65

3.1 Introduction 65

3.2 Relevant: road network reliability literature 66

3.2.1 Travel time reliability and reliability measures 66

3.2.2 Link Travel Time (LTT) focus 76

3.2.3 Trip Travel Time (TTT) focus 83

3.2.4 Miscellaneous 88

3.2.5 Summary 92

3.3 Truck travel time and its reliability from truck GPS data 93

3.3.1 Determination of travel time and its reliability from truck GPS data 93

3.3.2 Panel data approach to model travel time reliability for recurring and non-recurring congestion 94

3.4 Case study 96

3.4.1 Travel time variation vs Volume to Capacity Ratio (VCR) 97

3.4.2 Travel Time Variation (TTV) vs Arterial road composition 98

3.4.3 Travel Time Variation (TTV) vs time of day 98

3.4.4 Travel Time (TT) vs trip length 99

3.5 Conclusion 101

CHAPTER 4: LAND USE AND FREIGHT 103

4.1 Introduction 103

4.2 Methods for freight and land use planning: literature review 104

4.3 Methods for estimating freight flows 108

4.4 Development of GPS tools for freight flows estimation 109

4.5 Results: freight flows by NAICS code and TAZs in Jackson MPO 149

4.6 Conclusion 153

CHAPTER 5: FREIGHT PLANNING AND COMMUNITY VISIONING 155

5.1 Background 155

5.2 Findings 155
5.3 Conclusion: 167
CHAPTER 6: SUMMARY AND CONCLUSION 168
REFERENCES 171
APPENDIX - COMMUNITY VISIONING SURVEY 186

LIST OF TABLES

Table 2-1. Estimated coefficients for truck parking model 28
Table 2-2. Capacity constraint on I-90 (MnDOT Interstate Truck Parking, 2008) 32
Table 2-3. Collected studies: overview 34
Table 2-4. Demand model parameters 40
Table 2-5. Frequency distribution of truck parking utilization 52
Table 2-6. Descriptive statistics of explanatory variables 54
Table 2-7. Frequency distribution of explanatory variables (categorical) 54
Table 2-8. Model results 58
Table 2-9. Elasticity effects of the Generalized Poisson model 61
Table 2-10. Model validations 63
Table 3-1. Path travel time variability (Rakha et al., 2006) 72
Table 3-2. Path based reliability summarized literature review 74
Table 4-1. List of cities with integrated freight and land use plans 105

LIST OF FIGURES

Figure 2-1. Priority facilities with capacity issues 25
Figure 2-2. Accumulation vs time of day 27
Figure 2-3. Average duration vs time of day 28
Figure 2-4. Truck parking problem map for Florida 30
Figure 2-5. Truck parking problem map for Tennessee 31
Figure 2-6. Rest areas in Tennessee. 48
Figure 2-7. Polygon extraction from rest area location. 49

Figure 2-8. Extraction of parked truck data from raw GPS data 52
Figure 3-1. Methodological framework for computing and predicting truck travel time reliability 95
Figure 3-2. Shelby County with its census tracts, FAF network, and truck GPS data for June 10, 2014 96
Figure 3-3. Travel Time Variation (TTV) with Volume to Capacity Ratio (VCR) 97
Figure 3-4. Travel Time Variation (TTV) with composition of Arterial road 98
Figure 3-5. Travel Time Variation (TTV) over time of day with congestion types 99
Figure 3-6. Travel Time (TT) with trip length and crash types 100
Figure 3-7. Travel Time (TT) with trip length and number of vehicles involved in crashes 101
Figure 4-1. Example inputs 110
Figure 4-2. OD-matrix function 111
Figure 4-3. Input GPS data shapefile 111
Figure 4-4. Input Traffic Analysis Zones (TAZ) shapefile 112
Figure 4-5. Select Zone Identifier field 113
Figure 4-6. Estimate OD matrix travel time 113
Figure 4-7. Select Start Hour 114
Figure 4-8. Select End Hour 115
Figure 4-9. Input Output Folder 115
Figure 4-10. Application performed task window 116
Figure 4-11. Displayed processed shapefile 116
Figure 4-12. Example inputs 117
Figure 4-13. LEHD-Census-to-TAZ function 118
Figure 4-14. Input Census Block shapefile 119
Figure 4-15. Select Census Block Unique Identifier 119
Figure 4-16. Input Traffic Analysis Zones (TAZ) shapefile 120
Figure 4-17. Select TAZ Unique Identifier 121
Figure 4-18. Input LEHD dataset 122
Figure 4-19. Select Type of LEHD Area Characteristics Dataset 122
Figure 4-20. Input Output Folder 123

Figure 4-21. Application performed task window 124
Figure 4-22. Displayed processed shapefile 124
Figure 4-23. Example inputs 126
Figure 4-24. Freight Generation function 127
Figure 4-25. Input Establishment feature layer or shapefile 128
Figure 4-26. Select NAICS Field 128
Figure 4-27. Select Employment Field 129
Figure 4-28. Select SIC Field 130
Figure 4-29. Select Metric models 130
Figure 4-30. Select ALL freight modes 131
Figure 4-31. Select Metric Table(s) 132
Figure 4-32. Select Metric Geographic model(s) 132
Figure 4-33. Select to Use CFS models 133
Figure 4-34. Select CFS model(s) 134
Figure 4-35. Select Aggregate check box 134
Figure 4-36. Input Polygon Network 135
Figure 4-37. Input Output Folder 135
Figure 4-38. Application performed task window 136
Figure 4-39. Facility level shapefile with truck trip generation 137
Figure 4-40. Zone level aggregate truck trip generation shapefile 137
Figure 4-41. Example inputs 138
Figure 4-42. Gravity-Model function 139
Figure 4-43. Input Productions and Attractions Network shapefile 140
Figure 4-44. Select Zone Identifier field 140
Figure 4-45. Select Trip Productions attribute field 141
Figure 4-46. Select Trip Attractions attribute field 142
Figure 4-47. Input Travel Time OD Matrix 143
Figure 4-48. Select Power Function 143
Figure 4-49. Select Exponential Function 144
Figure 4-50. Select Combined Function 144
Figure 4-51. Input Exponent in Power or Combined Function 145

Figure 4-52. Input Beta Coefficient 146
Figure 4-53. Input Tolerance 146
Figure 4-54. Input Output Folder 147
Figure 4-55. Application performed task window 148
Figure 4-56. Displayed processed shapefile 149
Figure 4-57. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 31" 150
Figure 4-58. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 33" 151
Figure 4-59. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 44" 152
Figure 4-60. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 72" 153
Figure 5-1. Responses to agency's survey, “What is the type of organization your agency represent?” 157
Figure 5-2. Responses to agency's survey, “Does your agency’s Long Range Transportation Plan (LRTP) have a common, comprehensive set of community visioning and goals?” 157
Figure 5-3. Responses to agency's survey, “If ‘Yes’, are these visions and goals diverse and wide-ranging enough to address a multimodal transportation system?” 158
Figure 5-4. Responses to agency's survey, “How do these reflect previously established vision and goals?” 158
Figure 5-5. Responses to agency's survey, “What issues should the community address in visioning process?” 159
Figure 5-6. Responses to agency's survey, “Has your agency carried out ‘*Freight self-assessment’* for your community?” 159
Figure 5-7. Responses to agency's survey, “Does your agency receive any request from freight users in your community?” 160
Figure 5-8. Responses to agency's survey, “If you answered ‘Yes’ in question 7, what type of freight stakeholders has made a request?” 160

Figure 5-9. Responses to agency's survey, “If you answered ‘Yes’ in question 7, what type of request have you received?” 161
Figure 5-10. Responses to agency's survey, “Does freight movement impact your community’s vision and goals?” 161
Figure 5-11. Responses to agency's survey, “Is truck parking a problem in your community or region?”... 162
Figure 5-12. Responses to agency's survey, “To fully account for the important market-driven behavior and interests of the private-sector freight community, *Highway Capacity Planning* process recommends following key considerations. Please rank them (1—7, 1:Most Important, 7:Least Important) according to your community’s needs and visions” 162
Figure 5-13. Responses to agency's survey, “Who are the participants in your community visioning process besides public?” 163
Figure 5-14. Responses to agency's survey, “How should the agency engage *Freight Stakeholders?*” 163
Figure 5-15. Responses to agency's survey, “Does your agency have a *Citizen Committee* or *Citizens Visioning Task Force* or *Steering Committee?”*....................... 164
Figure 5-16. Responses to agency's survey, “What are the best strategies to encourage the community participation in the transportation planning process?”......................... 164
Figure 5-17. Responses to agency's survey, “Does your agency have a website to display community visioning activities and engagement?” 164
Figure 5-18. Responses to agency's survey, “Does your agency have one of the following?” 165
Figure 5-19. Responses to agency's survey, “Does your agency have a travel demand model for planning and decision making?” 165
Figure 5-20. Responses to agency's survey, “If you answered yes to question 19, does your agency’s travel demand model have a freight component?” 165
Figure 5-21. Responses to agency's survey, “If you answered yes to question 19, which modes are included in freight component of the model?”... 166

Figure 5-22. Responses to agency's survey, “If your agency does not maintain a travel demand model, does your agency use any other travel demand model at all developed by the state DOT or neighboring MPO?” 166
Figure 5-23. Responses to agency's survey, “Does your agency use any freely available or proprietary data or to assist with freight planning?” 167
Figure 5-24. Responses to agency's survey, "Has your agency developed or implemented a Freight Action Plan according to the needs of community?” 167

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CHAPTER 1: INTRODUCTION

State Departments of Transportation (S-DOTs) have moved aggressively in adopting a performance-based approach in their highway capacity planning process philosophy over the past several years. S-DOTs have made great strides in deploying effective planning strategies (such as congestion reduction, enhancing system reliability, efficient freight movement and increasing economic vitality) throughout the state considering the performance measures such as effective parking, consideration of reliability, and land use integration with transportation in the decision-making process. TDOT recently established one of the first offices termed as Office of Community Transportation (OCT) in the United States (U.S.) dedicated to monitoring land use changes and investments that affect the regional transportation network with cooperation from other transportation planning agencies in TN (TDOT OCT, 2013). From a freight planning perspective, TN is in the process of developing its statewide freight plan with help of its Freight Advisory Committee (FAC) members (TDOT Freight Planning, 2018). TN has four regional and one state FAC for freight planning assistance. Each regional FAC meets quarterly and discusses the progress of their respective region. The state FAC meets annually to summarize, evaluate, and make a roadmap for future freight capacity planning process.

TDOT has been in the process of using GPS truck data in support of Tennessee's statewide travel demand model as well as current state freight planning. These initial studies have shown that GPS truck data provide individual truck travels times and location information. TDOT has identified that truck parking in the state of TN is of high priority especially considering the high through truck volume. In the SHRP2 round 5 IAP, we propose further exploration of the utilization of parking areas in key freight corridors in TN. One of the tasks of this project will be to estimate the saturation of available parking along the freight corridors using a ratio of volume and parking locations per roadway segment. This will allow for the identification and reporting of gaps in available parking along the key freight corridors in TN. Additionally, this part of the project will visually demonstrate instances of parking overflow where available and will offer an overview of the impact of the new hours-of-service on truck parking needs and availability. Key questions include: (i) are parking areas under or over-utilized? (ii) how is the utilization of parking areas by time of day (week-days, weekends, and by season)? and (iii) how to develop capacity utilization models for parking areas?

GPS truck data are essential in obtaining corridor/link-based performance measures and O-D travel times for areas where passenger vehicle probe data is not available. In the statewide freight plan, one of the key tasks is to identify and profile truck congestion levels on roadways that connect key freight facilities with the National Highway System (NHS) and major freight corridors within the state of Tennessee. One of the performance measures of these corridors is freight travel time reliability. Since the majority of the freight movement occurs by trucks, it is critical to determine how reliable the freight corridors are during ideal, recurring congestion, and non-recurring congestion times (events of crashes, traffic incidents, and diverse weather conditions). With the availability of truck GPS data, it is possible to analyze travel time reliability during such recurring/non-recurring events for segments and origin-destination (O-D) pairs in the transportation network. Travel time reliability measures can be obtained for various time-of-day, day of the week, and seasons of the year. Key components include: (i) identify key freight corridors based on GPS based data estimated truck flows, (ii) identify reliability of the key freight corridors and O-D pairs during ideal conditions, recurring and non-recurring congestion conditions, (iii) show travel time variations by time-of-day, and (iv) identify variations on urban, sub-urban, and rural freight corridors.

One of the goals in SHRP2 round 5 IAP is to better understand freight and land use integration which can be accomplished using again the GPS truck data. In this project, we focus in obtaining commodity-based origin-destination matrices that can support local area freight planning and modeling by developing associations between individual truck trips and freight establishment characteristics. Typically, in planning models, truck trips are available in the form of productions and attractions (or origins-destinations) at an aggregate level (county level). While such data is helpful for statewide and regional planning purposes, it could have limited application at the local level (e.g. MPO or RPO). With the ever-increasing availability of truck GPS data, it would be possible to obtain commodity-based origins and destinations linked with freight establishment data. Key questions to be answered are: (i) how to obtain truck origin-destination for local planning areas? (ii) how to determine commodity-specific origin-destination for local planning areas? and (iii) how to validate the commodity specific origin-destination such that the models can be used for highway capacity planning purposes? In addition, the project will assess the feasibility of a land use visioning exercise evaluating impacts of rural freight movement on local economies by assessing community composition, undertaking strategies for involving stakeholders through the rural planning organizational structures, and by measuring progress and performance of visions and plans.

In summary, both TDOT and the Jackson MPO are moving forward with a strong highway capacity planning focus in a multimodal transportation systems framework. The implementation assistance will provide a chance for us to use state-of-the-art tools in this process. With the exception of a few national leaders, we believe that most state DOTs and MPOs are at the same stage where freight planning is either not considered or is an afterthought of the planning process. Our experience with integrating the Planning Process Bundles into our processes will be valuable for these agencies as it will provide case studies and step-by-step implementation of the bundles. Further, the availability of SHRP2 planning process bundle products presents a unique opportunity for TDOT and JMPO to obtain a better understanding of three performance measures: i) efficient truck parking, ii) freight travel time reliability, and iii) freight land use integration. Throughout the proposal, the performance measures are envisioned to enhance the highway improvement planning process. However, the term “highway capacity planning process” is used interchangeably and reflects the themes of SHRP2 planning process bundles C15/C02.

The rest of the report is organized as follows. The next chapter presents the first performance measure of the report, truck parking utilization using truck GPS data. Then, the third chapter is about the second performance measure, freight corridor reliability using again the truck GPS data. The fourth chapter is about the last performance measure of the report, freight and land use which is also based on truck GPS data. The fifth chapter presents the brief community visioning survey to understand the current state of practice by public agencies in TN. The last chapter concludes the report highlighting the importance of the performance measures in meeting the goals of SHRP2 Round 5 project and outlining the scope of the future research.

CHAPTER 2: TRUCK PARKING UTILIZATION

2.1 Truck parking: introduction

The freight transportation system in the United States (U.S.) makes one of the most valuable contributions to the nation's economy and growth. In this system, truck traffic is expected to increase by 45% by 2040 (Strocko, Sprung, Nguyen, Rick, & Sedor, 2013). Long term economic growth is expected to result in even greater demand for truck traffic transportation mode. However, there is a huge gap between the demand and supply of truck parking facilities in many states (Dowling, List, Yang, Witzke, & Flannery, 2014). Also, truck traffic does not get access to all roadways because cities and counties regulate truck traffic either by restricting parking, prohibiting trucks from using certain roads, and/or designating specific routes for truck use. This leads truck drivers to search for parking areas for rest and if parking is not available, they tend to park in non-designated areas such as ramps leading to spillover parking that is a significant safety concern to other road users. Moreover, truck parking has been indicated as the most influential factor for route selection decisions (Dowling et al., 2014). Lack of truck parking is also indicated as a characteristic of an unreliable route as the truck drivers do not get the required amount of rest or sleep and this may lead to safety concerns during travel for the truck driver as well as other modes.

The combination of increased truck traffic and tighter delivery schedules is one of the primary reasons for the increased demand for truck parking in the U.S (Fleger et al., 2002). The growing economy demands truck drivers to continue driving for longer hours, even when they are fatigued. This situation has severe consequences for highway safety, and the U.S. Department of Transportation (DOT) has hours of service regulations, which necessitate drivers to pause for rest and sleep after specified hours of continuous driving. According to Federal Motor Carrier Safety Administration (FMCSA), drivers can be on duty for 14 hours, out of which they are allowed to drive for 11 hours. After driving for 11 hours, drivers must have at least 10 hours of rest until they are allowed to drive again. Furthermore, 2013 FMCSA hours of service rule requires truck drivers to take a 30-minute break during the first eight hours of a shift. Although there are facilities for resting and sleeping at public rest areas along major highways, many truck drivers cannot take advantage of these facilities because of unavailability of truck parking especially during peak resting periods. This leads the truck driver to either keep driving without rest which increases the risk of accidents or park at undesignated areas, such as the shoulders along the on- and off-ramps of rest areas and other interchange ramps (Chatterjee & Wegmann, 2000). Chatterjee et al. (Chatterjee & Wegmann, 2000) conducted an extensive survey of truck accumulation and utilization at all public rest areas in Tennessee to understand the usage characteristics of truck parking in public rest areas at night and to assess the nature and magnitude of the problem. In order to understand and ensure proper utilization of the truck parking at the rest areas at specific periods of time, research is needed to understand utilization during different time periods and the factors associated with this utilization.

The primary objective of this chapter is to develop truck parking utilization models using GPS truck data and understand the associated factors that affect truck parking utilization. This study extends the work done by Golias et al. (Golias, Dobbins, Short, & Johnson, 2012) who used truck GPS data to evaluate the performance of roadways in Memphis, TN using truck stop and rest stop demand analysis. All truck stops with duration between eight to twelve hours were considered. The authors provided frequency of truck stops based on the time of the day for major TN rest stop areas. If truck-drivers know the truck parking areas (TPAs) utilization along their route, they can better plan when and where to park (van de Ven, Bakker, Koenders, & van Vugt, 2012). This will lead to less TPA over-crowding and less off-site parking, and thus increase road safety, and in general enable more efficient use of existing TPA capacity (van de Ven et al., 2012). While the study by Golias et al. (Golias et al., 2012) provided a descriptive overview of the problem, a system state prediction model that can forecast TPA utilization was not developed. In this context, the objectives of the proposed research are four-fold: 1) assemble a comprehensive dataset for analyzing TPA utilization in TN; 2) develop econometric models that encompass recent advances in choice modeling literature to estimate the effects of various factors on truck parking utilization; 3) evaluate the developed models using model fit and predictive performance criteria; and 4) compute elasticity effects to quantify the magnitude of impact of different factors on parking utilization.

The rest of the chapter is organized as follows. The next section presents an up-to-date literature review on truck parking utilization using truck GPS data. The third section describes the econometric methodology of models used in this study for predicting the truck parking utilization. The fourth section presents the data collection procedure used to process the GPS truck data and obtain the hourly truck utilization for the 24 hour period for all the rest area locations within the case study area along with a brief description of additional data collected for this research. The fifth section presents the model estimation results along with model fit comparison, elasticity effects, and model validation results. The last section concludes the chapter and proposes future research opportunities.

2.2 Truck parking: literature review

In this section, the relevant literature on application of econometric models to evaluate the truck parking utilization, use of GPS data for truck research, and use of different types of data and methodologies to develop truck parking utilization models is presented.

2.2.1 Truck parking studies in the US

The freight transportation system in USA makes one of the most valuable contributions to the nation's economy and progress. In this system, truck traffic mode makes most contributions and it is expected to increase by 45% by 2040 (Strocko et al., 2013). Long term economic growth shall result in even greater demand for truck traffic transportation mode. Even after such great demand, there is a huge lack of truck parking in many states (Dowling et al., 2014). Also, truck traffic does not get access to all roadways and cities and counties regulate truck traffic by restricting parking, prohibit from certain roads and designate specific routes which leads the truck drivers to search for parking areas for rest and if not available, they tend to park in areas not designated for parking such as ramps and spillover parking which signifies a safety concern for the other forms of traffic. Moreover, truck parking has been indicated as the most influential factor for route selection decisions (Dowling et al., 2014). Lack of truck parking is also indicated as a characteristic of an unreliable route as the truck drivers do not get the required amount of rest or sleep and this may lead to safety concerns during travel for the truck driver as well as other modes.

The review is first categorized by the different states which has concerns regarding truck parking and then on other studies. All the nineteen studies covered in review, are also categorized based on their type covering six major types namely application-based, technology-based, inventory-based, survey-based, methodology-based and review-based. From this review, it can be understood that roughly 42% of the literature mentioned about using truck GPS data for evaluating parking demand, about 33% mentioned different methodologies like surveys to collect truck data and additional data, and about more or less 20% mentioned about technological usage of implementing safe and easier truck parking.

2.2.1.1 Truck parking in Wisconsin

A study of truck parking issues was conducted along the major state highways in Wisconsin (Adams, Srivastava, Wang, & Ogard, 2009). This study determined specific locations in Wisconsin with parking issues and prioritized them based on specific criteria. The methodology that was used included development of a GIS-supported online survey tool to collect information on truck parking issues. Data was collected from total 3 groups of 317 participants: 258 truckers/carriers, 25 highway patrol officers, and 34 public freight planners. The data collected through the survey was exported to ArcGIS for spatial analysis. Other data that were used include shape files of Interstate and state highways networks and related attribute information, taken from the National Transportation Atlas Database (NTAD) 2006 and the Freight Analysis Framework (FAF). One of the outputs from these analyses was determination of priority of interstate and state corridors and cities in the region suffering from truck parking issues. The priority levels were decided based on the responses of the participants. An average severity value was assigned to the facilities which were reported by more than one participant. Therefore, after calculating the average severity value for each cluster or facility, the priority levels were obtained based upon the severity values ranging from 0.45-0.95. Figure 2-1 shows that facilities with different priority levels suffering from capacity issues. The locations of parking facilities were clustered using the Nearest Neighbor Hierarchical (NNH) clustering algorithm in the software tool CrimeStat 3.1. NNH clustering algorithm generates elongated clusters and is useful and applicable only when clusters are spaced very far from each other.

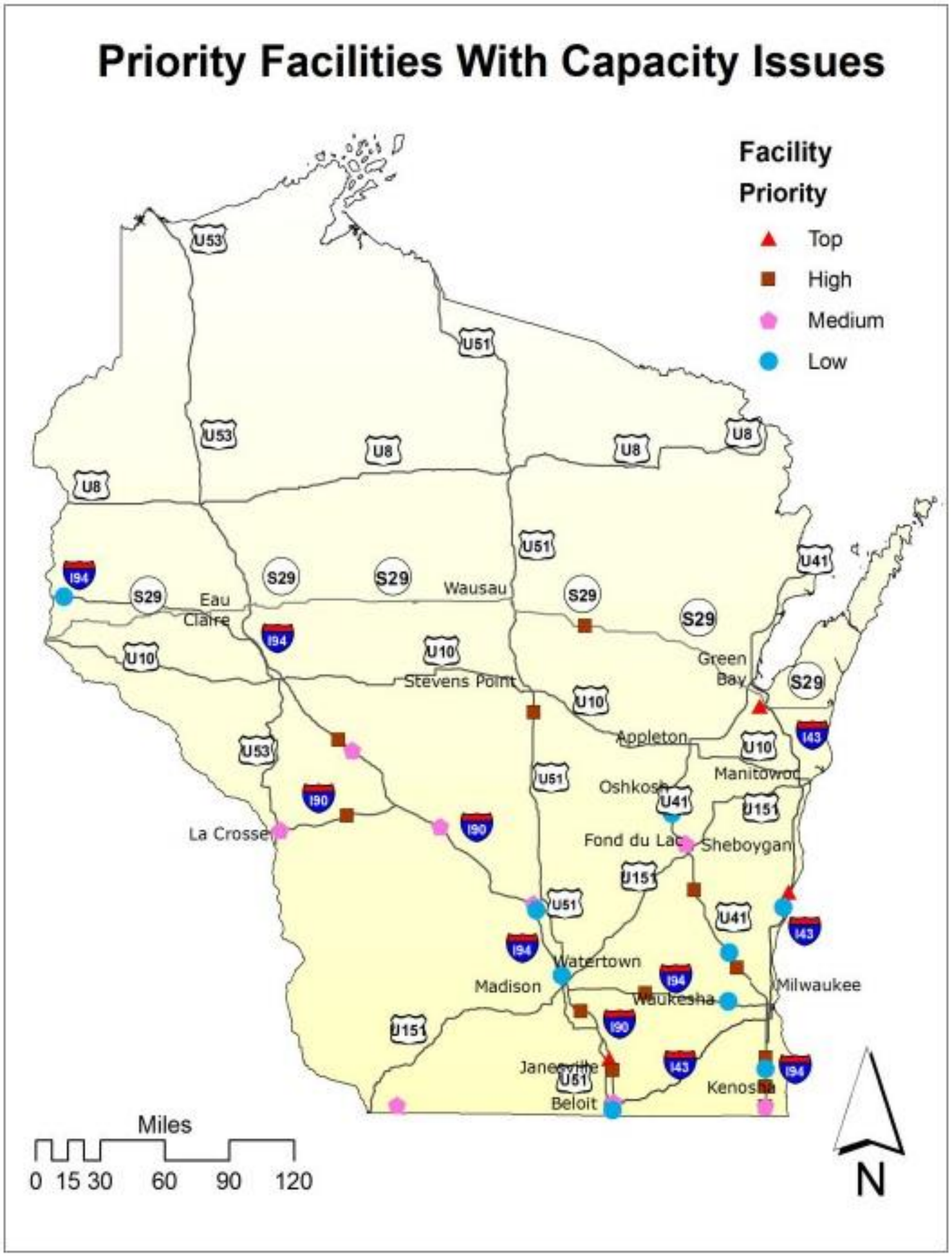


Figure 2-1. Priority facilities with capacity issues

Source: (Adams et al., 2009)

This study found many truck parking problems and the most common parking problem found is related to capacity and ramp parking. There are not enough parking spaces to meet the peak demand during popular hours of use and the overflow trucks park at the ramps. Moreover, parking capacity shortages occur in the early evening or late at night.

2.2.1.2 Truck parking in Washington

Washington State Department of Transportation (WSDOT) performed a study to determine if there is shortage of truck parking at public rest areas (PRAs) and commercial truck stops (CTSs) and identify strategies to increase the amount of truck parking in future (WSDOT Truck Parking, 2005). The study area was I-5, I-90, and I-82. It was found that PRAs are over capacity by 8% and CTSs are underutilized by 13%. Truck parking data was collected by telephone survey for the PRAs and CTSs at the corridor, segment, and facility levels. Truck parking data were also collected at other locations along the study corridors, such as weigh stations, on- and off-ramps, shoulders, and chain-up areas and these were collectively referred to as illegal truck parking in this study. Interestingly, in this study, the highest truck parking demand for both CTSs and PRAs occurred between 6 PM and 6 AM and this was defined as the peak period. Existing truck parking demand was calculated by recording the number of trucks parked at these locations in terms of volume and location. Future truck parking demand was estimated for 2030 by multiplying the existing demand by a growth factor that was developed for the study corridors. The growth factors were estimated based on:

- Washington State annual truck growth rates observed in WSDOT historical traffic volume data,
- The Strategic Freight Transportation Analysis (2003) and Eastern Washington Intermodal Transportation Study (1993) truck volume databases,
- WSDOT’s Weigh-In-Motion recorders for truck traffic volumes,
- Freight forecast estimates for the Port of Seattle and Port of Tacoma,
- The Federal Highway Administration (FHWA) Study of Adequacy of Commercial Truck Parking Facilities (Fleger et al., 2002),
- The draft Freight Report for the 2005 Washington Transportation Plan Update (WSDOT Transportation Plan, 2005).

The study recommended several improvement strategies and options to increase the truck parking capacity at PRAs and CTSs.

2.2.1.3 Truck parking in Virginia

(Garber, Wang, & Charoenphol, 2002) developed a methodology to determine the supply and demand for heavy truck parking. I-81 was used as the study area. Supply was defined as the number of parking spaces available for large truck parking and demand was defined as the sum of the parking accumulation and illegal parking at a given time. Parking duration and accumulation data was obtained for different times along with location, number and types of parking spaces, and availability of other facilities of each truck stop and rest area. Figure 2-2 and Figure 2-3 shows the accumulation and duration of trucks at different time of day.

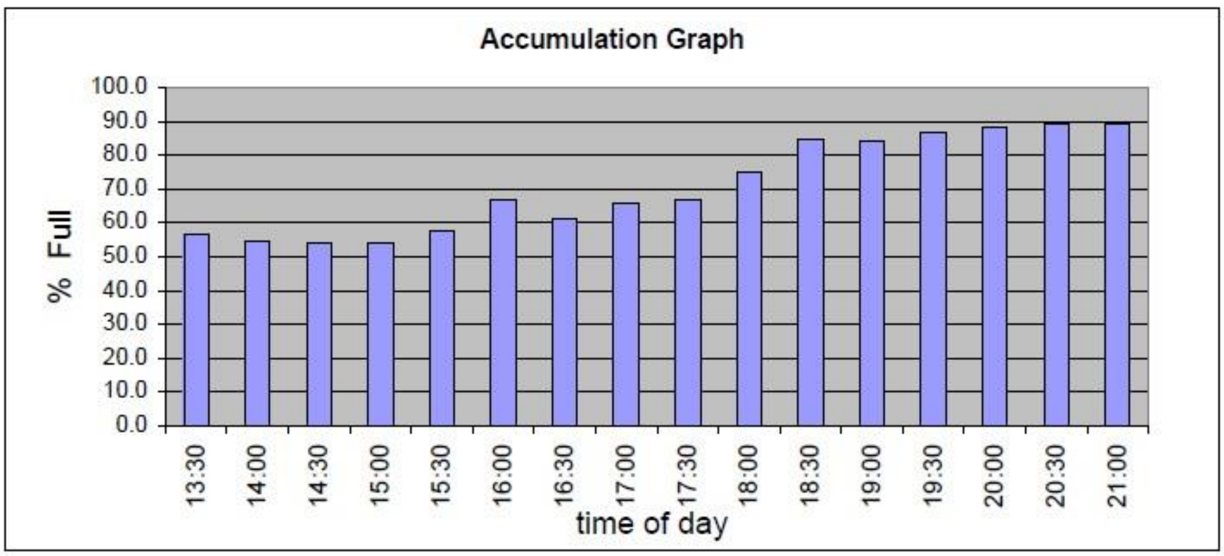


Figure 2-2. Accumulation vs time of day

Source: (Garber et al., 2002)

Survey data was also collected from the truck drivers. Using the dataset, stepwise regression analysis was used to develop demand models. The variables used for the model were:

TotalTruck: Total number of trucks on I-81 near a truck stop in half hour intervals.

PercentTruck: Percentage of trucks in the traffic stream in half-hour intervals.

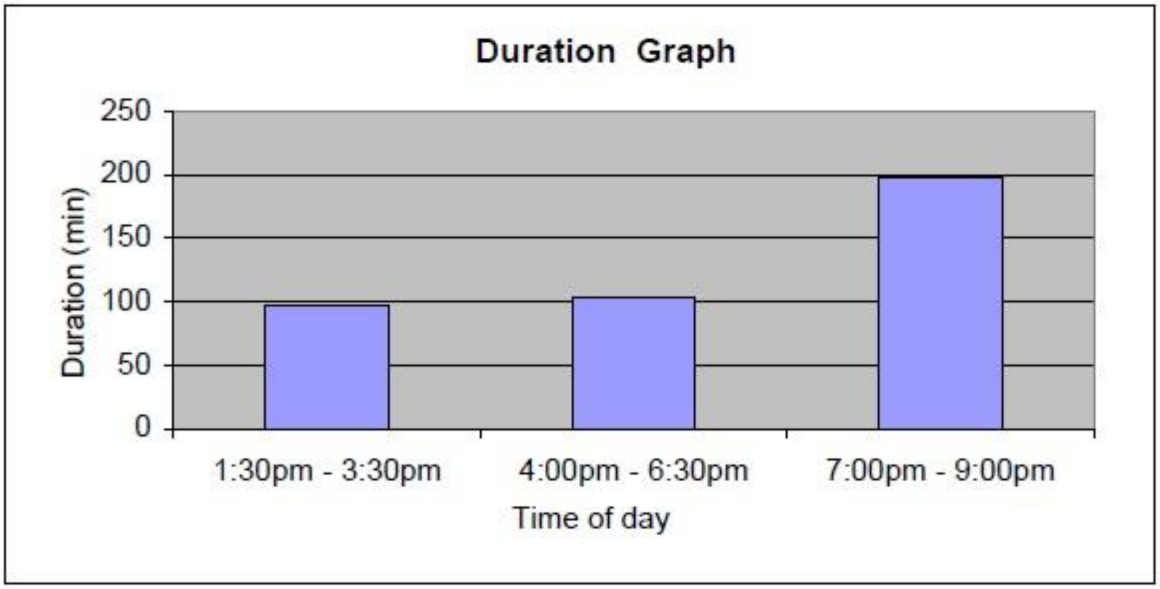


Figure 2-3. Average duration vs time of day

Source: Garber et al., 2002

Duration: Duration at a truck stop in half-hour intervals.

Dist_81: Distance from a truck stop to I-81.

Dist_TS: Distance from a truck stop to the nearest other truck stop.

Dist_RA: Distance from a truck stop to nearest rest area.

SERVICE: Dummy variable for measuring the difference of services between large and small truck stops. (Number of spaces > 60, SERVICE = 1.)

The estimated coefficients for the truck parking model are given in Table 2-1 as follows:

Table 2-1. Estimated coefficients for truck parking model

Independent Variable	Model 1	Model 2	Sign
Intercept	-1586.89	-1475.79	-
Percent of truck	1.41039	1.5478	+
Parking Duration	0.15563	0.13912	+

Total truck volume	0.06955	0.05898	+
Distance to I-81	-123.293	-114.328	-
Distance to Nearest Truck Stop	111.9563	103.7537	+
Distance to Nearest Rest Area	14.22398	13.80663	+
Service Provided	988.9973	919.6157	+

Using the estimated model, demand was forecasted for 10 and 20 years. It was found that there is a deficiency of 309 spaces at present.

2.2.1.4 Truck parking in Florida

(Bayraktar, Arif, Ozen, & Tuxen, 2014) made an attempt to determine the supply and demand characteristics for commercial truck parking in Florida and explored technology that can be used to improve parking management in order to better utilize the truck parking spaces at public rest areas. This research was conducted in two phases. Phase one included collection of rest areas in Florida and observation of truck parking facilities and determine shortfalls in parking supply and determine illegal parking. Phase two consisted of implementation of a smart parking management system for trucks. Smart parking management system was based upon the three tenets: first, accurate and reliable information on number of parking spaces available; second, archiving of historical parking occupancy records and; third, forecasting of space availability on microlevel for upcoming vehicles based upon the past trends and real time information of parking occupancy data. The study area included all of the public rest areas along the I-10, I-75, and I-95 corridors. The data collected was the number of truck parking spaces at each location and total truck parking utilization. Total parking utilization is the percentage of trucks parked both legally in the parking spaces and illegally elsewhere at the facility with respect to the available capacity. The data was analyzed and report was made on each rest area. A sample report is shown in Figure 2-4.

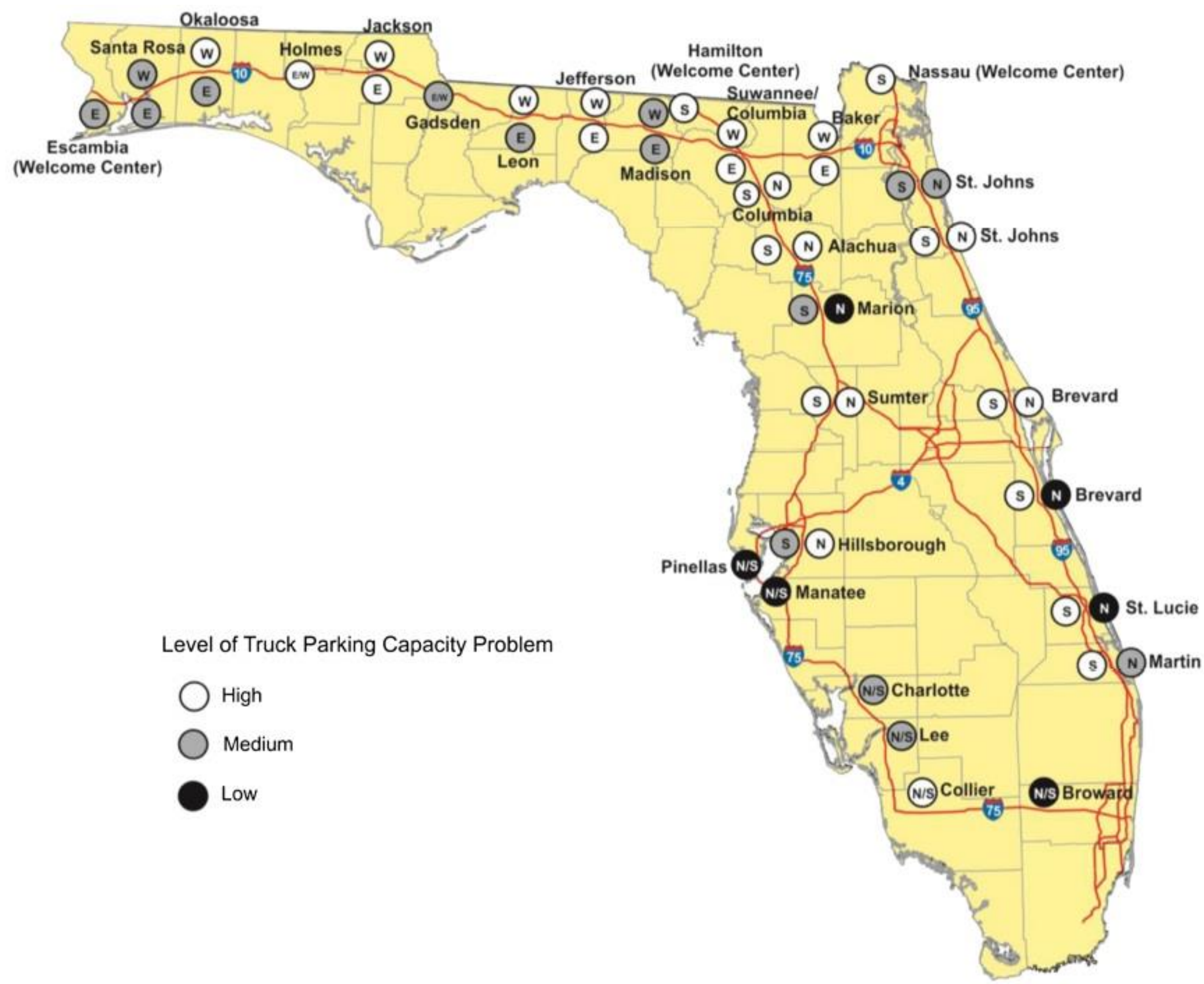


Figure 2-4. Truck parking problem map for Florida

Source: (Bayraktar et al., 2014)

2.2.1.5 Truck parking in Tennessee

(Chatterjee & Wegmann, 2000) presented a survey-based study of truck parking in public rest areas along Tennessee's interstate highways. The study area included all public rest areas in Tennessee. The data was collected in survey form and these were the occupancy of each space from 10 PM to 6 AM along with some identifying information about the trucks, like company name, color, and the configuration of the truck / trailer. The data was analyzed and reported as shown in Figure 2-5. The study found that about 44% of the trucks were parked on the ramps and shoulders indicating unavailability of parking on the rest areas.

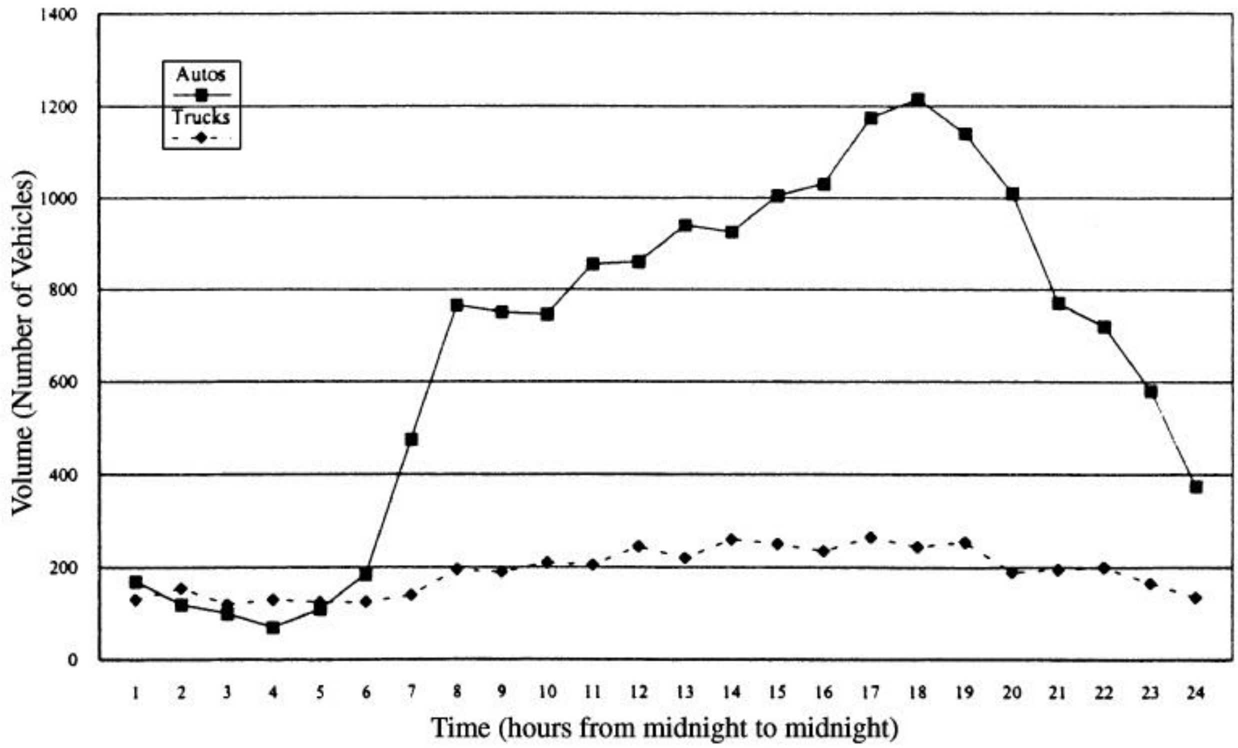


Figure 2-5. Truck parking problem map for Tennessee

Source: (Chatterjee & Wegmann, 2000)

Various findings were reported from the data statistics. It is mentioned that rest areas are more heavily used on Mondays through Thursdays with Monday and Tuesday being the busiest of days. Also, it is mentioned that among the trucks parked inside the rest area, nearly 75% occupy a space for more than 4 hours.

2.2.1.6 Truck parking in Minnesota

Minnesota Interstate truck parking study was done for developing information for supporting future truck parking decisions (MnDOT Interstate Truck Parking, 2008). The study examined the supply and demand of public and private commercial vehicle parking. The study area was Minnesota's three primary interstate corridors, I-90, I-35, and I-94. The study was conducted through 3 phases. Phase one consisted of collection of data regarding truck parking demand by time of day. Aerial photographs, State DOT maps, and google maps were used to obtain the parking supply information and site characteristics. Phase two consisted of truck parking demand analysis. The data collected in phase one were compiled and field records were supplemented with truck parking capacity usage database. This data was summarized and a measure was developed to identify over capacity facilities. Table 2-2 shows an example of capacity constraints on I-90.

Table 2-2. Capacity constraint on I-90 (MnDOT Interstate Truck Parking, 2008)

Interstate 90 Rest Areas	Truck Parking Capacity				Truck Stalls
	Adequate	15%	25%	50%	
Beaver Creek (E.B.) Exit 0	x				16
Adrian (E.B.) Exit 25		x			6
Adrian (W.B.) Exit 26			x		7
Clear Lake (E.B.) Exit 69			x		10
Des Moines River (W.B.) Exit 72	x				9
Blue Earth (E.B.) Exit 118		x			10
Blue Earth (W.B.) Exit 119	x				11
Hayward (E.B.) Exit 161		x			10
Oakland Woods (W.B.) Exit 171			x		10
Highforest (E.B.) Exit 202			x		6
Marion (W.B.) Exit 220				x	20
Enterprise (E.B.) Exit 244	x				11
Dresbach TIC (W.B.) Exit 275	x				5

Phase three consisted of conducting survey on trucking companies within 48 hours of vehicle observation to find out information about the attitude and behavior of drivers. 433 motor carriers were given 89 survey questions to which only 41% responded. All these information was processed and demand and supply maps for the state of Minnesota was created. Based on the demand and supply scenarios, it was found that five rest area facilities are at or over capacity 50% of the time. Several other rest areas are over capacity at least 25% of the time. The authors recommended immediate investment to these rest areas.

Many other studies have been conducted regarding truck parking, summarized in Table 2-3. (Davis, 1997) performed an empirical research at the state and national level to express the concern for additional truck parking space along U.S. interstate highways. Survey was done to measure truck parking supply and demand through peak-period (late night and early morning) at four public rest areas and three private truck stops along a 200 mile segment of I-81. Total number of available parking spaces were counted and legal and illegal space utilization was monitored on an hourly basis. Capacity and facility characteristics were also determined. It was found that large numbers of trucks were parked illegally on shoulders and ramps of rest areas, often before the corridor reached capacity and even when legal parking spaces were available at a rest area.

Table 2-3. Collected studies: overview

Serial No.	Literature	Objective	Type of study	Study Area	Data Used	Tools/Models developed
1	(Adams et al., 2009)	Truck parking issues	Survey based	Interstate 43, U.S. Highways 8, 10, 41, 51, 53 and 151, and State Trunk Highway 29	online and paper-based surveys, in-person and telephone interviews	GIS survey tool
2	(Bayraktar et al., 2014)	Truck parking supply trends	Survey based	public rest areas along the I-10, I-75, and I-95 corridors	Truck parking characteristics, shortfalls in the spaces, illegal parking	Occupancy prediction model
3	(Chatterjee & Wegmann, 2000)	Parking occupancy characteristics	Survey based	Rest areas in TN	Survey data and truck characteristics	N/A
4	(Davis , 1997)	Truck parking space shortfall	Survey based	4 public and 3 private rest area along I-81 corridor	Truck parking space utilization on hourly basis	N/A

Serial No.	Literature	Objective	Type of study	Study Area	Data Used	Tools/Models developed
5	(Garber et al., 2002)	Truck parking supply and demand estimation	Inventory and survey based	Rest areas and truck stops at I-81	Parking duration and accumulation data	Stepwise regression model for demand
6	(WSDOT Truck Parking, 2005)	Find truck parking shortage	Inventory and survey based	I-5, I-82 and I-90	Parking demand data by recordings	Growth factor for future demand forecasting
7	(Fleger et al., 2002)	Investigate adequacy of truck parking facilities	Inventory and survey based	Truck parking facilities serving the National Highway System (NHS)	Interstate America database of commercial truck stops	Simplifies demand model
8	(MnDOT Interstate Truck Parking, 2008)	Examined truck parking supply and demand	Inventory and survey based	I-90, I-35, I-94	Truck parking count data by time of day, site information	N/A
9	(Fallon & Howard, 2011)	Determine truck parking availability using magnetometer	Technology based	Truck stop at US 1 and public rest stop on I-95	Truck counts	Magnetometer device for truck counting

Serial No.	Literature	Objective	Type of study	Study Area	Data Used	Tools/Models developed
10	(Fischer, Hicks, & Cartwright, 2006)	Develop performance measures to evaluate strategies for reducing truck trips	Technology based	Ports of Long Beach and Los Angeles	Port and cargo characteristics	QuickTrip truck trip generation model
11	(Gaber, Gaber, & Khattak, 2005)	Review various literature and methodologies to assess truck parking availability	Review and methodology based	Nebraska Interstate corridors	Survey data from stakeholder focus group	N/A
12	(Nicholson, 2003)	Proposed methodology for improving truck parking information system	Methodology and technology based	I-81	Truck driver survey, truck crash data, truck AADT, traffic facilities	Prototype of truck parking information system

Serial No.	Literature	Objective	Type of study	Study Area	Data Used	Tools/Models developed
13	(Gertler & Murray, 2011)	Field operational test of parking monitoring	Technology based	Charlton Westbound Service Center on I-90	N/A	N/A
14	(Haghani, Farzinfard, Hamedi, Ahdi, & Khandani, 2013)	Improve truck parking safety using technology	Technology based	Truck parking facility at I-95 northbound prior to MD 32	N/A	automated real-time parking information system
15	(Heinitz & Hesse, 2009)	Proposed demand modeling approach for scarce truck parking facility	Application based	Germany	HGV inflow or time-variation curves of road freight transport demand	Car park choice model
16	(Kawamura, Sriraj, Surat, & Menninger, 2014)	Identify factors for truck parking violation	Inventory based	Chicago urban area	parking citations for 12 month period	Simple regression model
17	(Mbiydzenyuy, Persson, &	Developing concept of	Technology based	Sweden	Parking occupancy and vehicle location data	N/A

Serial No.	Literature	Objective	Type of study	Study Area	Data Used	Tools/Models developed
	Davidsson, 2012)	intelligent truck parking				
18	(Pecheux, Chen, Farbry Jr, & Fleger, 2002)	Estimate the distribution of truck parking demand and supply along the NHS	Application based	29 highways segments on I-81	Truck AADT, % of trucks, length of segment, speed limit or average truck speed	N/A
19	(Rodier & Shaheen, 2007)	Explore the truck parking problems and solutions	Review and Survey based	California	Trucker survey data	N/A

(Fleger et al., 2002) investigated the adequacy of commercial truck parking facilities that serves the National Highway System (NHS). The study involved multiple tasks including national survey of truck drivers, develop an inventory of public and private rest areas and developing a truck parking demand model. Nationwide survey of parking spaces at PRAs was done to find the number and characteristics of Government owned spaces for trucks. Also, an inventory of CTSs was created and maintained by Interstate America. Using these data, truck parking demand model was estimated on a highway segment considering the daily truck volume across the segment and other parameters. The simplified demand model is described in the following:

$$D = THT \, . P_{avg} \tag{58}$$

Where, D is the demand along a highway segment

THT is the total truck hours of travel per day

P_{avg} is the average parking time per truck-hour of travel.

THT is calculated by:

$$THT = P_t . AADT . \frac{L}{S} \tag{59}$$

Where P_t is the percentage of trucks in total daily traffic

AADT is the average daily traffic

L is the length of segment

S is the speed limit or average truck speed

Table 2-4 shows the model parameters which were used to adjust the truck volume estimate in equation (59) and P_{avg} in equation (58). Parameters such as seasonal peaking factor was used to adjust truck volume whereas other parameters were used to adjust average parking time for hour-of-the-day.

Table 2-4. Demand model parameters

Parameter	Description	Value
F_S	Seasonal peaking factor	1.15
SH/LH	Short-haul to long-haul ratio	0.36/0.64, 0.07/0.93
D_{ST}	Short-term parking duration per hour traveled	5 min/h
T_{DRVING}	Time driving for long-haul drivers	70 h/8 days
T_{HOME}	Time at home for long-haul drivers	42 h/8 days
$T_{LOAD/UNLOAD}$	Time loading and unloading for long-haul drivers	15 h/8 days
$T_{SHIPPER/RECEIVER}$	Time at shipper/receiver for long-haul drivers	16 h/8 days
P_{RA}, P_{TS}	Portion of demand for public rest areas/commercial truck stops	0.23, 0.77
PPF_{SH}	Peak-parking factor for short-haul trucks	0.02
PPF_{LH}	Peak-parking factor for long-haul trucks	0.09
PR_{LH}	Long-haul parking ratio	0.7833

Seasonal peaking factor is defined as ratio of seasonal peak average daily truck volume to average daily truck volume. Short haul to long haul ratio is the ratio of number of trucks performing short haul trips to number of long haul performing trips. Long haul parking ratio is defined as the ratio of the total parking time to the total driving time for long haul trucks.

Then the parking demand and supply of a highway segment was compared to find if there is a shortage or surplus. The two most important factors that contribute to the demand for truck parking are the need to comply with Federal Hours of Service (HOS) rules and the need for drivers to perform certain non-driving activities like eating, fueling.

2.2.2 Literature gap

A thorough literature review has been done and it has been found that the prediction of parking demand in the rest areas is dependent on several factors and many of them have not been addressed. Moreover, none of the research methodologies insisted on using truck GPS data for estimating demand and supply. Research to estimate the parking demand using truck GPS data should be taken into consideration, and identify factors affecting parking demand for design purposes. Also, identify locations which requires rest areas or truck parking so that the truck drivers get ample rest thus increasing safety and efficiency.

The state of Tennessee acquired few approaches to address the growing demand for truck parking subsequent to the 1996 Study. The University of Tennessee led nighttime observational studies at all public rest areas in Tennessee to learn about the parking space occupancy characteristics of trucks. They examined the availability of space in private truck stops near interchanges. Their results showed that the rest areas were swarming with trucks at night, since a lot of trucks were found parked along the shoulders of highway exit and entrance ramps, as well as on interchange ramps. On the other hand, around 30% of the private truck parking spaces remained vacant (Pecheux et al., 2002). Interview was also held to understand why some truck drivers parked along the highway when there were available private parking spaces.

However, it was a preliminary study and does not explain the demand or shortage during the different time periods like peak and off-peak period. Also, nothing in the literature was found regarding parking supply. In order to get an accurate estimation of the supply, a thorough analysis must be done to minimize the truck parking shortage. This involves analyzing various other factors that may affect the truck parking.

2.2.3 Statistical and econometric methods for truck parking utilization

Simple regression models have been used for estimating large truck parking on interstates (Golias et al., 2012; van de Ven et al., 2012). The main significant factors were percent of large truck, total truck volume, parking duration, distance to I-81, distance to nearest truck stop, distance to nearest rest area, and service provided. The models developed were then used to estimate demand in 10 and 20 years. Any shortfall in supply with respect to the estimated demand was then determined for each truck stop and the entire highway. The results indicated that the existing maximum demand exceeds the supply. This excess demand will keep increasing if the number of parking spaces for large trucks does not increase. Moreover, mathematical models like simplified demand model have been used to develop national commercial vehicle parking demand model which estimates final demand of commercial vehicle parking for the National Highway System (NHS) in order to investigate the adequacy of truck parking facilities (Fleger et al., 2002). The model predicts truck parking demand for a highway segment based on total truck-hours of travel and the time and duration of the stops. Some of the model parameters were seasonal peaking factor, short haul to long haul ratio, short term parking duration, time driving for long haul drivers, time at home for long haul drivers, and long haul parking ratio. Also, Real-time parking data (count the number of arrivals and departure vehicles) along with driver behavior and demographics and AADT have been used to develop truck parking information system for highway corridors using discrete choice and linear regression model (Garber, Teng, & Lu, 2004). Car park utilization/choice model is used to estimate time-dependent demand for truck parking facilities along an interstate highway (Heinitz & Hesse, 2009).

2.2.4 Use of truck GPS data for truck research

Truck GPS data was used to analyze truck parking problems in urban areas (Kawamura et al., 2014) and also to study impact of tolling on truck speed and routing (Wang & Goodchild, 2014). Flaskou et al. (Flaskou, Dulebenets, Golias, Mishra, & Rock, 2015) developed methodology for processing raw GPS data and developed freight performance measures. Thakur et al. (Thakur et al., 2015) developed algorithms to convert large streams of raw GPS data into more useable truck trip databases. GPS data was also used to study trucks travelling between transportation hubs in Toronto and Chicago (Fischer et al., 2006). Several researches have used truck GPS data for evaluating performance measures such as truck trip reduction strategy (Fischer et al., 2006), improvement for growing freight demand (Liao, 2009), improving truck corridors (McCormack & Hallenbeck, 2006), roadway system reliability (McCormack, Ma, Klowcow, Currarei, & Wright, 2010), and in transportation planning applications such as truck travel time estimation in urban networks (Morgul, Ozbay, Iyer, & Holguin-Veras, 2013). Other have used prediction models to determine commercial vehicle demand and supply characteristics using count and survey data (Bayraktar et al., 2014) and also using truck parking inventory data and crash data (Goods Movement, 2018). Moreover, Gaber et al.

(Gaber et al., 2005) discussed various literatures and argued that varying methodologies yield different results in the assessment of commercial vehicle parking. Some have used unique approaches such as step by step segment model (Pecheux et al., 2002) calibrated from field surveys and growth factor (WSDOT Truck Parking, 2005) developed for the study corridors to predict future truck parking demand.

2.2.5 Data and methodologies used for truck parking

In some research, survey of truck drivers and truck stop owners was used along with traffic information and duration data (Garber et al., 2004, 2002). A similar kind of survey was done at 31 rest areas in Tennessee on truck accumulation and utilization to understand the usage characteristics of truck parking at night (Chatterjee & Wegmann, 2000). This survey data was analyzed to generate a variety of statistics useful for the assessment of the nightly truck parking situation in Tennessee. Floating vehicle data (FVD) which are position measurements from a fleet of vehicles equipped with Global Navigation Satellite System (GNSS) enabled smart-phones have also been used for estimating and forecasting parking utilization (van de Ven et al., 2012).

There have been several studies that assessed the use of technology to detect truck parking availability. These technologies are evaluated to identify their capability of collecting data and to determine whether a truck parking facility is full and if not, to indicate the number of parking spaces available. Others have used low-cost strategy and geo-spatial analysis to rank truck parking areas for identifying parking issues in order to increase truck parking (Adams et al., 2009). Some research sought to address a perceived need for additional truck parking space along U.S interstates highway (Davis, 1997).

There have been few different approaches to address the growing demand for truck parking. For example, nighttime observational studies at all public rest areas were done to learn about the parking space utilization characteristics of trucks. The availability of space in private truck stops near interchanges was examined. Results showed that the rest areas were swarming with trucks at night, since a lot of trucks were found parked along the shoulders of highway exit and entrance ramps, as well as on interchange ramps. On the other hand, around 30% of the private truck parking spaces remained vacant

(Pecheux et al., 2002). Interview was also held to understand why some truck drivers parked along the highway when there were available private parking spaces. However, it was a preliminary study and it does not explain the utilization or shortage during the various time periods.

From the review of various literatures, it can be understood that roughly 42% of the literature mentioned about using truck GPS data for evaluating parking utilization/demand, about 33% mentioned different methodologies like surveys, to collect truck data and additional data and about more or less 20% mentioned about technological usage of implementing safe and easier truck parking. It has been found that the prediction of parking utilization in the rest areas that is dependent on several factors has not been addressed. This research intends to estimate the parking utilization, and identify factors affecting parking utilization for design and improvement purposes together with the identification of the locations which require rest areas or truck parking so that the truck drivers get ample rest thus increasing safety and efficiency.

2.3 Truck parking methodology

In this section we present the econometric framework for count data models as a special case of generalized ordered-response models. The generalized ordered response (GOR) model is the generalization of the ordered response (OR) model allowing the threshold values in the OR to vary across the different outcome categories (Eluru, Bhat, & Hensher, 2008).

2.3.1 Count modeling framework

Frequency of trucks parked at a rest area is an example of count data and is typically modeled using count models that assume a parametric distribution for the frequency outcomes. The parameters of the underlying distribution (e.g., mean and variance) are specified as a function of different covariates to capture their influence on the count dependent variable. The two most commonly used count models in the literature are the Poisson and Negative Binomial (NB) models. The Poisson model has the *equi-dispersion* property *i.e.,* the expected mean is equal to the variance. However, this is a restrictive assumption and past literature found evidence for both under-dispersion (although less common) and over-dispersion in certain empirical contexts. The NB model is particularly suited for cases when there is over-dispersion in the count data being modeled. The NB model is a generalization of the Poisson model in which the expected mean parameter is assumed to be gamma distributed (Greene, 2008). Another aspect of considerable importance while modeling count data is over-representation of zeroes beyond the probability mass implied by the standard count models – a property referred to as the *excess zeroes* problem. Several variants of standard models including the zero-inflated count models and hurdle count models were developed in the past to address the excess zeroes problem. However, extending these methods to cases when there can be over or under representation of several count outcomes (not just zero) can result in complex model structures that are difficult to estimate. Recently, Castro *et al.* developed Generalized Ordered Response (GOR) models that subsume standard count models including Poisson and NB models as special cases and can easily handle deviations in probability profile imposed by standard models (Castro, Paleti, & Bhat, 2012). In this study, these different count models in the literature were estimated and compared to identify the best model for analyzing the number of trucks parked. A brief discussion of alternate modeling methods follows.

2.3.1.1 Poisson model

Assuming the truck parking data to be realizations from Poisson distribution, the probability of observing a count outcome *y* conditional on the expected mean parameter λ is given by:

$$P(Y = y) = \frac{e^{-\lambda} \times \lambda^{y}}{y!} \qquad \textbf{Equation 1}$$

As indicated earlier, the Poisson model has the *equi-dispersion* property which implies that the variance of the Poisson distribution is equal to the expected mean parameter λ. So, to ensure that the λ parameter is always greater than 0 during model estimation, it is parameterized as $e^{LOG(\lambda)}$ and $LOG(\lambda)$ is specified as a linear function of different exogenous variables as follows: $LOG(\lambda) = \boldsymbol{\beta}'\boldsymbol{X}$ where $\boldsymbol{X}$ is the vector of exogenous variables and $\boldsymbol{\beta}$ is the corresponding vector of coefficients that were estimated using maximum likelihood inference approach.

2.3.1.2 Negative binomial model

In the NB model, the probability of observing count outcome y conditional on the expected mean parameter λ and dispersion parameter $r > 0$ is given by:

$$P(Y = y) = \left(\frac{r}{r+\lambda}\right)^r \times \frac{\Gamma(r+y)}{\Gamma(y+1)\Gamma(r)} \times \left(\frac{\lambda}{r+\lambda}\right)^y \qquad \textbf{Equation 2}$$

Where Γ is the gamma function defined as follows:

$$\Gamma(t) = \begin{cases} \int_{x=0}^{\infty} x^{t-1} e^{-x} dx \text{ for positive non} - \text{integer } t \\ (t-1)! \text{ for positive integer } t \end{cases} \qquad \textbf{Equation 3}$$

The expected mean of the NB model is λ whereas the variance is $\lambda + \frac{\lambda^2}{r}$ making the model particularly suited for handling over-dispersion. In the NB model, the dispersion parameter *r* must also be estimated in addition to the β parameters in the $LOG(\lambda)$ specification.

2.3.2 Generalized Ordered Response Probit (GORP) framework

In the GORP framework, a latent risk propensity y^* is mapped into observed count outcomes *y* by threshold parameters ψ_k where *k* is the index for all possible count outcomes. Assuming specific functional forms for these threshold parameters will result in the GORP framework replicating standard count models. The latent risk propensity y^* in the standard ordered response framework can be written as:

$$y^* = \boldsymbol{\gamma}'\boldsymbol{Z} + \varepsilon \qquad \textbf{Equation 4}$$

Where $\boldsymbol{Z}$ is a vector of all exogenous variables and $\boldsymbol{\gamma}$ is the corresponding vector of coefficients; ε is the stochastic error term that represents all unobserved factors (not captured in the exogenous variables) that can impact y^* and is assumed to be an independent realization from a standard normal distribution, *i.e.,* $\varepsilon \sim N(0,1)$. In the GORP framework, the probability that the observed outcome is *y* is given by:

$$\begin{aligned} P(Y = y) &= P(\psi_{y-1} < y^* < \psi_y) = P(\psi_{y-1} < \boldsymbol{\gamma}'\boldsymbol{Z} + \varepsilon < \psi_y) \\ &= P(\psi_{y-1} - \boldsymbol{\gamma}'\boldsymbol{Z} < \varepsilon < \psi_y - \boldsymbol{\gamma}'\boldsymbol{Z}) \end{aligned} \qquad \textbf{Equation 5}$$

$$= \Phi(\psi_y - \boldsymbol{\gamma}'\boldsymbol{Z}) - \Phi(\psi_{y-1} - \boldsymbol{\gamma}'\boldsymbol{Z})$$

Where $\Phi(.)$ is the cumulative distribution function of standard normal random variable

Standard count models including the Poisson and NB models can be obtained by imposing certain constraints on the GORP model, *i.e.,* the implied probability expressions for different count outcomes would be identical for the GORP (Equation 5 and standard count models (Equation 3 and Equation 4). To see this, consider the constraints and functional forms imposed on ψ_k parameters below:

2.3.2.1 Generalized Poisson model

$$\psi_k = \Phi^{-1}\left(\sum_{s=0}^{k} \frac{e^{-\lambda} \times \lambda^s}{s!}\right) + \alpha_k \; \forall \; k \geq 0$$ **Equation 6**

If (1) ψ_k is parameterized as shown in Equation 6, (2) all γ parameters in the propensity equation are equal to 0, and (3) all α_k parameters are equal to 0, then the GORP model collapses to the standard Poisson model.

2.3.2.2 Generalized Negative Binomial model

Equation 7

$$\psi_k = \Phi^{-1}\left(\sum_{s=0}^{k} \left(\frac{r}{r+\lambda}\right)^r \times \frac{\Gamma(r+s)}{\Gamma(s+1)\Gamma(r)} \times \left(\frac{\lambda}{r+\lambda}\right)^s\right) + \alpha_k \; \forall \; k \geq 0$$

If (1) ψ_k is parameterized as shown in Equation 6, (2) all γ parameters in the propensity equation are equal to 0, and (3) all α_k parameters are equal to 0, then the GORP model collapses to the standard NB model.

Although theoretically one could estimate one α_k parameter specific to each count outcome *k*, from a practical standpoint, α_k can be fixed as α_K where *K* is a pre-determined count outcome depending on the empirical context, *i.e.,* $\alpha_k = \alpha_K \; \forall \; k \geq K$. Also, the α_k parameters control for any additional probability mass that is not captured by the parameters in the λ and y^* specifications. So, the GORP versions of Poisson and NB models can easily handle over or under-representation of multiple count outcomes without necessitating a hurdle or inflated model set-up.

In the GORP versions of Poisson and NB models, the analyst must also estimate the γ parameters in propensity y^* and the α_k parameters in thresholds ψ_k in addition to the β parameters in $LOG(\lambda)$ specification and dispersion parameter *r* (in case of NB models).

2.4 Data collection

The study area consists of all public rest areas in the state of Tennessee. The rationale for selecting public rest areas is to assess the need for problems of truck parking during peak hours and to assess the need for providing additional parking in the future. This section contains detailed steps of data collection along with attributes of the data. First, we present the steps to identify the truck parking rest areas for the case study area. Second, we explain the procedure for extracting the polygon area of a rest area sample and how to utilize these polygons to extract the truck parking counts. Finally, we explore the additional dataset that was collected for analysis and model development.

2.4.1 Identification of rest areas

The first step is to identify the truck parking areas for the study area. This is done by obtaining the rest area map that features the locations of over 2000 highway rest areas across the U.S. The locations are the coordinates for the entrance to the off ramp for the rest areas. From this shape file, the rest areas that belong to the required study area were obtained. A total of 46 rest areas are found within the case study area shown in Figure 2-6. Once the rest areas were identified, the base map of the U.S. with imagery was

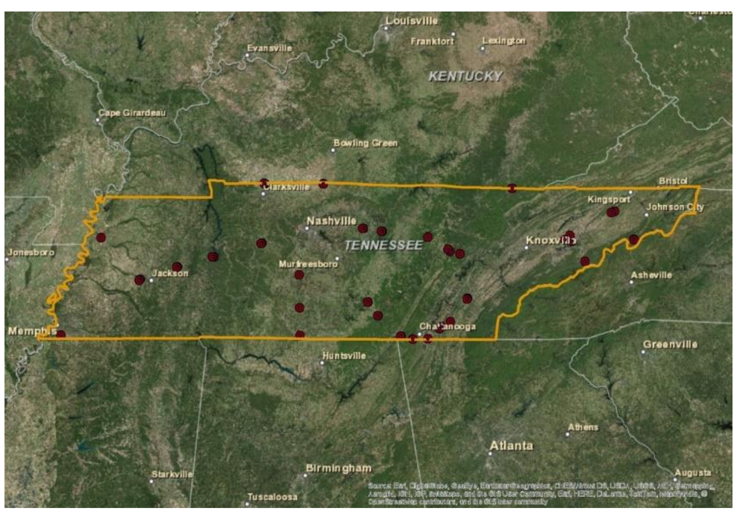


Figure 2-6. Rest areas in Tennessee.

2-7(a) Sample rest area location

2-7(b) Parking area polygon.

2-7(c) Off-ramp polygon.

2-7(d) On-ramp polygon.

Figure 2-7. Polygon extraction from rest area location.

loaded and the rest area locations were identified. Next, three types of polygons were created over the rest area of each location which includes parking area, off-ramp and on-ramp (shown in Figure 2-7. The size of the polygons is approximately scaled to the rest area as revealed by the base map of ArcGIS. Moreover, the locations of the truck GPS points are not 100% accurate and precise. Hence some consideration was given across the capturing of the truck GPS point using the constructed polygon. For example, some of the GPS points were found to be located above the field or tress beside the on and off ramp which did not make sense. This was an error of the GPS point and in order to capture those points, the polygons were extended.

2.4.2 *Identification of parked trucks*

The next step is to determine the number of trucks parked within the three polygons of a rest area (shown in Figure 2-8). The major steps for this procedure are as follows:

Step 1: First, the truck GPS data (shown in Figure 2-8(a)) from ATRI (American Transportation Research Institute) was processed for the study area using Vehicle Probe GPS Data Processing Tool. This tool provides functions to produce refined set of data from a large data set to be used in other modules (Flaskou et al., 2015). Each data point shown in Figure 2-8(a) contains latitude, longitude, speed, heading and a time stamp.

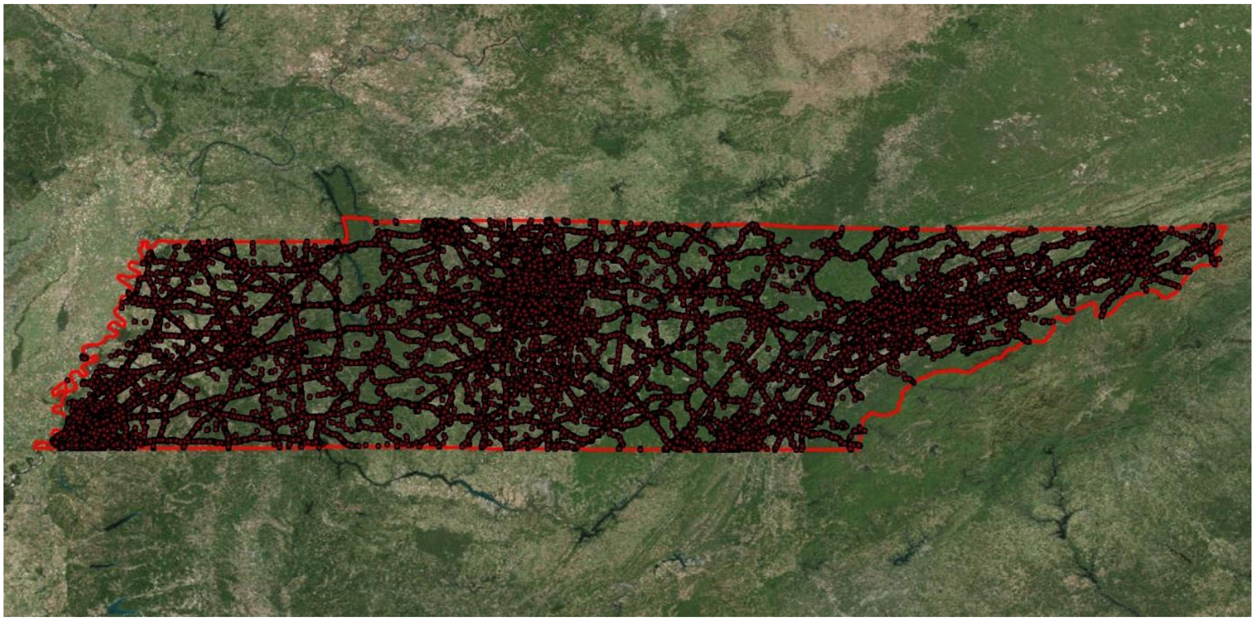
Step 2: The refined truck dataset was loaded in ArcGIS and trucks with the speed being less than or equal to five miles per hour (Flaskou et al., 2015) were identified using SQL tool.

Step 3: The stopped trucks data were exported in Microsoft Excel and then coordinate pairs (latitude and longitude combinations) of those stopped trucks were identified using a common identification number called TRUCKID.

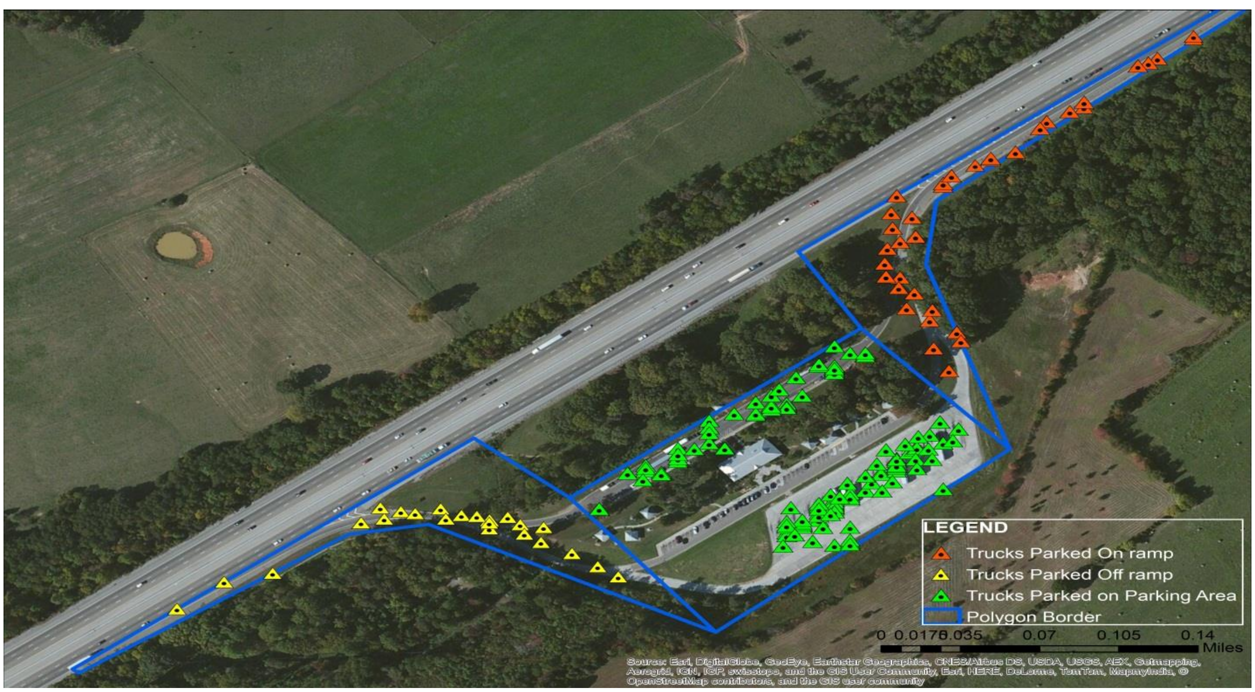
Step 4: Once the unique stopped trucks were identified using the TRUCKID, their coordinates were projected in ArcGIS.

Step 5: Finally, using the rest area polygons, the number of trucks parked in the respective locations was identified and recorded (shown in Figure 2-8(b)).

Since GPS receiver readings can vary slightly, even for stationary objects, the precision of the latitude and longitude fields was rounded down to one decimal place (resulting in 6 decimal places rather than 7). The 7th decimal place of latitude/longitude represents a foot or less of geography precision. The trucks parked on the on ramp and off ramp were needed to find the on/off ramp violation criteria which is used as a categorical variable in the model presented. These are indicator variables that indicated whether the truck was parked on ramp or off-ramp at that particular time period. When the truck drivers see trucks parked off-ramp, in order to avoid congestion and save time, sometimes they choose not to park thinking that the parking space might be full. It is also difficult to maneuver trucks when plenty of them are parked off ramp. On the other hand, when the truck drivers park on ramp, it means either the parking space was full or to save time maneuvering from the parking spot, they park on ramps so that they can exit and hit the road as quickly as possible. Moreover, some of the trucks might have met with crash or collision thus forcing them to park on and off ramp.



2-8(a) Sample truck GPS data.



2-8(b) Parked trucks on rest area location.

Figure 2-8. Extraction of parked truck data from raw GPS data

The ATRI data used in this chapter consists of 3 months (April, July, October) of data for the year 2014. Each month comprises of two weeks of truck data. A total of 46,368 (i.e. 46x42x24) observations were collected, spanning across 46 unique parking locations for 42 days and 24 hours a day. Table 2-5 shows the frequency distribution of the number of trucks parked on all the 46 rest areas which shows the predominance of zero number of trucks parked at the locations (50%). This is because of lower number of samples in the truck GPS data. The truck GPS data used in this study constitutes a subset of the truck population with various penetration rates ranging from 3% to 10% (not evenly distributed) across the state of Tennessee. With increasing sample size and higher penetration rate of truck GPS data, the model results will improve further.

Table 2-5. Frequency distribution of truck parking utilization

No. of Parked Trucks	Count	(%)
0	23,185	50.00%
1	7,666	16.53%
2	7,659	16.52%
>= 3	7,858	16.95%
Total	46,368	100.00%

2.4.3 Collection of additional data

Additional data was collected such as average speed of the truck traffic passing on the adjacent roadway of that particular rest area, the number of lanes of the roadway adjacent to the rest area, and hourly precipitation of the location in concern from the National Climatic Data Center (NCDC). Rest area characteristics such as availability of rest rooms, vending machines, pets' facilities, picnic tables, phone services and handicapped facilities were also collected (Google maps). These variables were used as categorical variables where unavailability of these features indicated 0 and availability was indicated as 1. The reason why average speed is included is because there might be congestion at the road beside the rest area which might affect the truck parking. If the average speed of the trucks passing the rest area is lower, it indicates congestion and hence might affect truck parking. Hence the effect of average speed was included in the model. The hourly precipitation would help identify if precipitation has any significant effect on the truck utilization, that is, if the truck drivers prefer to park at the rest area during rain or continue to drive. Similarly, the rest area characteristics such as size, capacity, and available amenities would also give valuable information as to whether these have any effect on the truck utilization. However, most of these variables were insignificant in the estimated models since there was not enough variation the parking area characteristics across different observations to infer the effect on parking demand.

Table 2-6 and Table 2-7 shows the descriptive statistics and frequency distribution of the response and explanatory variables used in the model. These are, (a) Speed – whether the average speed of the trucks passing the rest area location is 35 miles per hour or greater. 35 miles per hours was chosen because it is the 85th percentile speed. (b) Number of lanes – whether the number of lanes of the roadway adjacent to the rest area in consideration were 2 or more than 2 (c) On ramp – whether there were any trucks parked on the on ramp of the rest area during that time period (d) Off ramp – whether there were any trucks parked on the off ramp of the rest area during that time period (e) Days of the week when the trucks were parked at the rest area. Table 2-7 shows that about 86.3 % of the time, the trucks passing the rest area usually travel at an average speed of 35 miles per hour or less. In addition, it can be seen that the on ramp and off ramp violation are evenly distributed and 82.62% of the observations had trucks parked at the rest area adjacent to the 2-lane roadway. Also, about 71.43% of the trucks were parked during weekdays.

Table 2-6. Descriptive statistics of explanatory variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Number of trucks parked per hour	1.0043	1.1596	0	7.0
Volume (Vph)	32.0887	18.9001	1.0	259.0
Average speed (mph)	23.0612	10.2253	6.0	84.0
On ramp (if parked=1, 0 otherwise)	0.5016	0.5000	0	1.0
Off ramp (if parked=1, 0 otherwise)	0.4991	0.5000	0	1.0

Table 2-7. Frequency distribution of explanatory variables (categorical)

Explanatory Variable	(%)
Speed	
Less than or equal to 35 mph	86.3%
Greater than 35 mph	13.7%
Number of Lanes	
2 Lanes	82.61%
> 2 Lanes	17.39%
On ramp	
No	49.84%
Yes	50.16%
Off ramp	
No	50.09%
Yes	49.91%
Weekday	
Mon-Fri	71.43%
Sat-Sun	28.57%

2.5 Truck parking results

The models' coefficients are estimated using 75% of the dataset and validation is done using the remaining 25% of the data set. In this section, we first discuss the effects of explanatory variables on the number of trucks parked, then the variable effects on the propensity and on the thresholds that affect the translation of propensity to whether or not a truck is parked at any given time. Next, we discuss the model fit comparisons and finally discuss the elasticity effects and model validation.

2.5.1 Model estimation results

The results section presents the statistically significant explanatory variables along with their estimated coefficients and t-statistics (in parenthesis) for each of the developed models as shown in Table 3. Four models are developed: Poisson (Model 1), negative binomial (NB) (Model 2), Poisson with propensity (Model 3), and Poisson with propensity and threshold specific constant (Model 4). Given that there is no a priori reason for the mean and variance in any practical context to be equal, the use of a NB distribution for Model 2 is an important empirical generalization over the Poisson distribution (Model 1). Model 2 is a regular NB model whereas Model 3 and 4 are Poisson models that include threshold parameters which take heterogeneity across observations into account by allowing some of the parameters to vary across observations. Model 4 is similar to Model 3 except it contains threshold specific constants to allow more flexibility and better predictive accuracy.

The model results also show presence of dispersion in the data. By comparing the model results, it can be observed that due to significance of the dispersion parameter, the negative binomial model is more effective in prediction than the Poisson model. However, as the variable *"number of lanes (=2)"* is added to the propensity equation, there is no longer dispersion in the model. Therefore, the negative binomial is collapsing back to Poisson model with Propensity. The dispersion parameter becomes large (implying low dispersion) with the variable *"number of lanes (=2)"* in the propensity. Hence, the model is able to explain variance using explanatory variables without dispersion parameters and therefore Poisson with propensity performs better than the NB model. Hence Model 3 and Model 4 are Poisson with propensity and propensity with threshold respectively.

The variables that have significant effect on truck parking utilization include *truck volume*, *on ramp, off ramp, average speed, number of lanes*, *hour 1*, *hour 3*, *hour 16*, *hour 17, hour 22,* and *Thursday.* It can be noticed that the mean values of parameter estimates are similar in sign in all the four models. The results indicate that higher truck volume is more likely to increase the truck parking utilization at the rest areas. The *on ramp* and *off ramp* variables indicate that with on ramp and off ramp parking violation, the truck parking utilization will likely to decrease. This is intuitive because when truck drivers enter a rest area for parking and when they observe trucks being parked on the ramps, it becomes difficult for them to maneuver the vehicle and they will likely to avoid such rest areas. Moreover, they may also assume that the truck parking might be full and continue driving to find the next location. On the other hand, it can also be instinctive that the parking capacity must be full which lead the drivers to park on the ramps. It is also conceivable that the truck drivers park on the on ramps for easy and quick exit on the roadway. The *speed* indicates that with the average speed of trucks passing the rest area being equal to or lower than 35 mph are more likely to decrease the truck parking utilization on the rest area. The *number of lanes* indicate that the roadway adjacent to the rest area having two lanes have more likelihood to increase the truck parking utilization at the rest area because higher number of lanes is usually accompanied with high traffic flow. The positive coefficient of *hour 1 & hour 3* suggests that truck parking utilization increases during the period 12 AM – 1 AM and 2 AM – 3 AM which is intuitive since the truck drivers at this time tries to find spots for parking and resting. On the other hand, the results show negative coefficients for *hour 16*. This suggests that during the period 3 PM – 4 PM (*hour 16*), truck parking utilization reduces which is also intuitive since the truck drivers prefer to travel during this period. Moreover, positive coefficients for *hour 17* suggest truck drivers tend to stop at a rest area during the period 4 PM – 5 PM due to personal needs like dinner or restroom facility. In addition to this, positive coefficients of *hour 22* suggests that some truck drivers tend to rest early and therefore some of the parking spots are usually filled during this hour. During the period 1 AM – 2 AM (hour 2), truck parking utilization decreases since most of the spots are usually filled at this period and the drivers either park on the ramps or try to move ahead and search for a spot at the next location. During the period 5 AM – 6 AM (hour 6), truck parking utilization decreases since most truck drivers start their trip either early or during this period from the parking spot after having a good night's rest. Similarly, during the period 12 PM – 1 PM (*hour 13*), truck parking utilization reduces because the truck drivers usually stop at a gas station for food and gas since these facilities are usually not available at a rest area. Finally, during the period 5 PM – 6 PM (*hour 18*), the utilization reduces which is also intuitive since the truck drivers like to drive during these periods and do not stop and park at the rest area unless encountered by an emergency like mechanical fault or accidents because they usually like to rest at late night periods mostly after 12 am as indicated by *hour 1*.

2.5.1.1 Threshold parameters

The threshold parameters include the threshold specific constants ($\boldsymbol{\alpha_k}$ values), as well as variables associated with *off ramp* and *Number of lanes (=2)* as part of $\boldsymbol{\gamma}$ vector. The thresholds are responsible for the ''instantaneous'' translation of the truck parking utilization propensity to whether or not the truck driver will park at any given time at any location (that is, they determine the mapping of the latent propensity to the observed count outcome). The threshold specific constants ($\boldsymbol{\alpha_k}$) do not have any substantive interpretations. However, their presence provides flexibility in the count model to accommodate high or low probability masses for specific outcomes. The $\boldsymbol{\alpha_k}$ parameters are identified by specifying $\boldsymbol{\alpha_0} = 0$ and $\boldsymbol{\alpha_k} = \boldsymbol{\alpha_K}\ \forall k \geq K$. We, initially set K=4 and with multiple trials K is reduced based on statistical significance and general data fit.

The elements in the $\boldsymbol{\gamma}$ vector are presented next in Table 2-8. For the other variables, a positive coefficient shifts all the thresholds toward the left of the truck parking utilization propensity scale, which has the effect of reducing the probability of zero trucks parked. The effect of *off ramp* suggests that, given two observations with same truck parking utilization propensity, the segment with off ramp violation is more likely to have a non-zero truck parking utilization occurrence compared to the other. This is an intuitive result since off ramp violation will likely mean truck parking area is full which may not be the case. The effect of *number of lanes (=2)* indicates an increase in non-zero truck parking utilization at rest areas adjacent to two lane roadway, for a given truck parking propensity. That is, the translation of probability into the occurrence of truck parking is elevated for 2 lane roadway adjacent rest areas, most likely because it is easy for truck drivers to enter a rest area adjacent to two lanes where as they may need to change multiple lanes, or maneuver in a different direction before entering a rest area which is difficult and risky.

Table 2-8. Model results

Variables	Poisson (Model 1)	Neg. Bin (Model 2)	Poisson (with γ) (Model 3)	Poisson (with γ & α) (Model 4)
	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)
Constant	-0.0663 (-2.406)	-0.0723 (-2.063)	0.4675 (21.335)	-0.3167 (-2.89)
Log(Volume)	0.0163 (2.286)	0.0166 (1.819)	0.3048 (20.962)	0.0201 (2.365)
On Ramp	-0.016 (-1.493)	-0.0159 (-1.181)	-0.1527 (-3.959)	-0.0196 (-1.531)
Off Ramp			-0.2197 (-5.449)	-0.1047 (-1.796)
Average Speed (<= 35mph)				-0.1931 (-1.822)
Number of Lanes (= 2)	0.0268 (1.878)	0.031 (1.725)	0.3274 (6.095)	0.086 (1.465)
12 am – 1 am (hour 1)	0.0981 (3.741)	0.0997 (2.969)	0.0454 (3.364)	0.1062 (3.382)
1 am – 2 am (hour 2)	-0.0387 (-1.418)	-0.0362 (-1.058)		
2 am – 3 am (hour 3)	0.0441 (1.66)	0.0462 (1.37)	0.0222 (1.641)	0.0525 (1.656)
5 am – 6 am (hour 6)	-0.0494 (-1.782)	-0.0476 (-1.376)	-0.017 (-1.219)	
12 pm – 1 pm (hour 13)	-0.0479 (-1.755)	-0.0455 (-1.334)	-0.0162 (-1.18)	

Variables	Poisson (Model 1)	Neg. Bin (Model 2)	Poisson (with γ) (Model 3)	Poisson (with γ & α) (Model 4)
3 pm – 4 pm (hour 16)	-0.0533	-0.0513	-0.02	-0.0381
	(-1.938)	(-1.496)	(-1.457)	(-1.385)
4 pm – 5 pm (hour 17)	0.0388	0.0416	0.0184	0.0564
	(1.46)	(1.234)	(1.354)	(1.779)
5 pm – 6 pm (hour 18)	-0.0276			
	(-1.002)			
9 pm – 10 pm (hour	0.0527	0.0548	0.0265	0.0601
22)	(1.971)	(1.612)	(1.953)	(1.884)
Thursday	0.033	0.0315	0.0135	0.035
	(2.177)	(1.64)	(1.748)	(1.923)
Dispersion parameter		1.6991		
		(36.366)		
γ Vector				
Log(Volume)			-0.6325	
			(-20.728)	
On Ramp			0.3535	
			(4.182)	
Off Ramp			0.4857	0.0982
			(5.499)	(1.795)
Number of Lanes			0.6648	-0.1054
(= 2)			(6.151)	(-1.466)
Threshold Specific Constants				
α_1				-0.6166
				(-50.13)
α_2				-0.9154
				(-43.799)

Variables	Poisson (Model 1)	Neg. Bin (Model 2)	Poisson (with γ) (Model 3)	Poisson (with γ & α) (Model 4)
α_3				1.3192 (6.724)
Number of Observations	34,776	34,776	34,776	34,776
Number of Parameters Estimated	14	13	17	17
Log-composite likelihood at convergence	-1.419	-1.384	-1.361	-1.244
Log-likelihood	-49,332	-48,113	-47,324	-43,252
BIC	98,810	96,312	94,826	86,682

2.5.2 Model selection and statistical fit

The Generalized Poisson count model with propensity and threshold is superior to the other models, as should be clear from the highest log-likelihood value and presence of several additional statistically significant coefficients in Table 2-8. However, all the models developed in this study were compared formally using the Bayesian Information Criterion (BIC) that penalizes models that attain better fit at the cost of additional parameters. $BIC = ln(n)k-2ln(L)$, where n is the sample size, k is the number of parameters, L is the log-likelihood value at convergence. BIC is a criterion for selecting a model among limited or finite set of models. According to the BIC criterion, a model with lower BIC value is preferred which refers to the less penalty terms. It can be seen from the table that the Generalized Poisson model has the least BIC value of 86,682 among all models suggesting superior data fit. This underscores the importance of using GORP model structures that provide additional flexibility to standard count models for analyzing count outcomes (for instance, parking utilization in the current empirical context).

2.5.3 *Elasticity effects*

The elasticity computed is a measure of the aggregate percentage change in the response variable due to a change in an exogenous variable (Castro et al., 2012). By computing the elasticity effects of the exogenous variables, the magnitude of effects of these variables on the truck parking utilization can be determined. In this chapter, we computed the percentage change in the expected number of trucks that park in a rest area because of a unit change in each exogenous variable. However, since standard elasticity calculations are not applicable to categorical variables, pseudo-elasticity effects were calculated for such variables. The pseudo-elasticity of an indicator variable essentially represents the average percent change in average truck parking utilization when the value of that particular variable is changed from 0 to 1 for all rest areas.

Table 2-9. Elasticity effects of the Generalized Poisson model

Variables	Poisson (with γ & α) (Model 4)
Volume (100% increase)	1.330
On Ramp	-1.921
Off Ramp	-0.109
Average Speed (<= 35mph)	-13.561
Number of Lanes (= 2)	3.338
12 am – 1 am (hour 1)	11.218
1 am – 2 am (hour 3)	5.124
5 am – 6 am (hour 16)	-3.417
12 pm – 1 pm (hour 17)	4.214
8 pm – 9 pm (hour 22)	5.549
Thursday	3.195

For brevity, the elasticity effects are only presented for the best model, *i.e.,* Poisson model with propensity and threshold parameters (model 4) (see Table 2-9). From the Table 2-9, it can be observed that the elasticity effects are consistent with the coefficient estimates. The first entry in the table indicates 100% increase in truck volume is likely to increase truck parking by 1.33% whereas presence of on ramp and off ramp violations decrease truck parking utilization by 1.921% and 0.109%, respectively. One additional lane to an existing two-lane roadway increases parking utilization in adjacent rest areas by 3.338%. Parking areas that are adjacent to roadways with average truck speeds greater than 35 mph have 13.561% lower utilization than parking areas adjacent to roadways with lower truck speeds. Similarly, parking areas have 11.218% more utilization during the hour past midnight compared to other non-peak rest hours Also, interestingly; parking utilization on Thursdays is 3.195% more than on other days of the week. Other numbers in the table can be interpreted similarly.

2.5.4 Model validation

In order to examine the prediction power of the models, a validation exercise was undertaken in which the predicted truck parking counts were compared with the observed count in the data. Then, Absolute Percentage Difference (APD) between predicted and observed counts was calculated. Lastly, Average Absolute Percentage Difference (AAPD) across all truck utilization levels was computed. A model with lower AAPD has better predictive ability than models with higher AAPD values. The results of the prediction analysis are presented in Table 2-10. It can be seen from the table that the Generalized Poisson model with propensity and threshold parameters (model 4) best has the best predictive performance with an AAPD value of 1.50%. The simple Poisson model that ignores dispersion has a very high AAPD value. Even NB model that accounts for dispersion has higher AAPD value than the Generalized Poisson model. So, Poisson model with propensity and threshold parameters is better suited to capture dispersion in count data than NB model in the context of truck parking utilization.

Table 2-10. Model validations

Truck Utilization	Observed Count	Expected Count							
		Poisson (Model 1)		Neg. Bin (Model 2)		Poisson (with γ) (Model 3)		Poisson (with γ & α) (Model 4)	
		Count	APD (%)	Count	APD (%)	Count	APD (%)	Count	APD (%)
0	5838	4193	28.18	6686	14.53	5402	7.47	5776	1.06
1	1896	4222	122.68	2157	13.77	2934	54.75	1891	0.26
2	1907	2268	18.93	1152	39.59	1835	3.78	1944	1.94
3 or more	1951	909	53.41	1597	18.14	1421	27.17	2004	2.72
AAPD (%)			55.80		21.51		23.29		1.50

2.6 Truck parking conclusions

Past studies that analyzed truck parking utilization have been mostly descriptive. The primary objective of this chapter was to develop a set of econometric models that can predict truck parking utilization as a function of geometric and traffic characteristics of adjacent roadways and the rest area characteristics. All the models in this study were estimated using Truck GPS data for rest areas in Tennessee. Given the count nature of parking utilization data, count modeling methods were used in this study. To be specific, standard count models including Poisson and Negative Binomial (NB) models and generalized ordered response probit (GORP) models that subsume standard count models as special cases were estimated. Among the different models estimated in this study, the Generalized Poisson model with propensity and threshold parameters (Model 4) was found to provide the best statistical fit as well as predictive performance. The main contributing factors towards truck parking utilization were found to be truck volume, on ramp and off ramp violations, higher average speeds of the trucks passing the rest area, presence of a two lane roadway adjacent to the rest area. Also, among different hours of the night, the hour past midnight had higher parking demand. Going beyond simple parameter estimates, elasticity effects that indicate percentage change in parking utilization due to unit change in different factors were computed. For instance, a 100% increase in truck volume was found to increase truck parking utilization by 1.33%.

One of the primary drawbacks of this research is lower sample size of the truck GPS data. With private sector competitiveness in an emerging economy and adaptation of GPS units by truck drivers, in the future, it will be possible to obtain large samples of truck GPS data. With availability of more sample GPS data, mixing models that allow random heterogeneity in the impact of different factors on parking utilization and spatial models that control for dependencies in parking utilization rates across proximal rest areas can be developed. This study was performed only on the rest areas of Tennessee and may not represent drivers' decision to park in other states. However, the proposed methodology can be applied for estimating demand of other rest areas of the country; and, it would be interesting to study the transferability of the models developed in this study to other regions.

CHAPTER 3: TRUCK TRAVEL TIME RELIABILITY

3.1 Introduction

In recent years, “Reliability” has become a significant part of transportation planning and operations though the concept is relatively new in the area of transportation. Generally, reliability is defined as the consistency or variability in travel times. Regular congestion delays are often expected by travelers and can be accommodated by early departure, while it is the unexpected delays that bring most frustration to drivers. This has motivated a growing number of studies on the topic of travel time reliability. Several different definitions and measures of reliability have been developed. Turner et al. defined trip time reliability as the range of travel times experienced during a large number of daily trips (Turner, Best, & Schrank, 1996). The 1998 California Transportation Plan defined reliability as the variability between the expected travel time based on the scheduled or average travel time and the actual travel time due to the effects of non-recurring congestion. Federal Highway Administration (FHWA) defines reliability as the consistency or dependability in travel times, which can be measured from day to day and/or across different times of the day. Performance measures of travel time reliability include 95th percentile travel time, buffer index, planning index, frequency of congestion, etc. Although the definitions and measures of travel time reliability vary in different contexts, they are all closely related to the variation of travel time. Lomax et al. identified that while reliability and variability are interchangeable in many contexts, they are different in their focuses (Lomax, Schrank, Turner, & Margiotta, 2003). More precisely, variability represents the amount of inconsistency and can be used to measure the degree of unreliability.

FHWA identified seven major sources of travel time variation: incidents, work zones, weather, fluctuations in demand, special events, traffic control devices, and inadequate capacity. Travel time reliability can be estimated at segment/link level, path level and also for the entire network. In this study, path-based travel-time reliability is defined as the dispersion in travel time distribution between an origin-destination pair. The key parameters in O-D based travel time reliability estimation includes the mean path travel time and path travel time variance. The fundamental idea is that small variation suggests high reliability and vice versa.

Reliability is also an important performance measure of the transportation system (Gaver Jr, 1968). Travel time reliability, in the form of distribution of travel times, is a critical indication of the operating conditions of any facility. Considering its importance, transportation planners have included reliability as a key component in congestion management. Although, majority of the past research analyzed link based reliability and for passenger cars, there is still significant gap in literatures regarding determination of path-based reliability of freight origin-destinations. The uncertainties in transportation system such as congestion lead to freight operators facing uncertainties in goods delivery. Travel time reliability is becoming increasingly critical to businesses, especially the manufacturing sector as many manufacturers are positioning to adopt “just-in-time” manufacturing processes and other schedule dependent inventory, assembly and distribution logistics (Systematics, 2012). Further reliability estimation and model development becomes complex as the network condition changes in the event of crashes, inclement weather conditions or any other non-recurring congestion. The objective of this research is to model path-based reliability using truck GPS data considering *ideal*, *recurring* and *non-recurring* travel conditions to assist short-term transportation planning and operations decision-making. The contributions of this study is to (1) measure travel time reliability for freight O-D pairs, (2) assessment of reliability variation in the event of non-recurring congestion, and (3) prediction of travel time given the condition of network.

3.2 Relevant: road network reliability literature

3.2.1 Travel time reliability and reliability measures

In this section, we present different methodologies used in estimating path-based travel time reliability along with different performance measures used. To investigate the use of travel time reliability in transportation planning, Lyman and Bertini (Lyman & Bertini, 2008) analyzed twenty Regional Transportation Plans (RTPs) of Metropolitan Planning Organizations (MPOs) in the U.S. None of the RTPs used reliability in a comprehensive way, though a few mentioned goals of improving regional travel time reliability. Even though many studies have tried to measure behavioral response to reliability, their application in a transportation-planning context is limited. Studies were conducted to understand the reliability of specific routes (Chen, Skabardonis, & Varaiya, 2003; Levinson, Harder, Bloomfield, & Winiarczyk, 2004; Liu, Recker, & Chen, 2004; Tilahun & Levinson, 2010). Specifically, reliability measures are studied for freeway corridors through empirical analysis and simulation approaches were also applied (Chen, Tatineni, Lee, & Yang, 2000; Levinson et al., 2004; Rakha, El-Shawarby, Arafeh, & Dion, 2006; Sumalee & Watling, 2008; Zhang, 2012). However, freeway corridors only encompass a portion of a real-life multimodal transportation network. A planning agency trying to evaluate the effect of various policies (other than freeways) may not be able to fully utilize such information to estimate the value of travel-time reliability savings on an overall network level. In the planning stage, agencies often are not ready to collect new data, but would like to utilize available resources to estimate travel time reliability using existing tools. Hence, a framework to measure path-based reliability to calculate network-wide reliability using available data will be very useful and is currently lacking in the literature.

In several studies, the procedure for estimating path travel-time reliability assumes that travel times follow a normal distribution and requires a measure of trip travel-time variance. Past study (Rakha et al., 2006) shows that the assumption of normality is, from a theoretical standpoint, inconsistent with field travel-time observations and that a lognormal distribution is more representative of roadway travel times through goodness-of-fit tests. However, visual inspection of the data demonstrates that the normality assumption may be sufficient from a practical standpoint due to its computational simplicity. A method for synthesizing a distribution of consistent path-dependent O-D travel times from the known distribution of link counts is suggested in the SHRP 2 C04 report (Vovsha et al., 2012). This method generates of origin– destination (O-D) travel time distribution for the base year, which is needed for calculating travel time reliability measures. These reliability measures are used in travel demand models to explain travel choices along with the average travel time and cost. The method is designed to produce a distribution of travel times for a full regional O-D matrix for a certain time of day, period or hour. SHRP L35B report (Sadabadi, Jacobs, Erdogan, Ducca, & Zhang, 2014) uses an instantaneous travel time aggregation method to estimate path travel times based on link travel times. Travel time data used as input in this study are provided by INRIX. In this study, data archived during calendar year 2011 are used at 1-minute resolution on all segments considered. The study shows that as trip length becomes longer, the risk impact of any newly added segment, while still positive, becomes marginal compared with the rest of the path. This phenomenon is reflected by the concavity of reliability ratio (RR) curves. Other elaborate path based travel time estimation methods (e.g., trajectory construction based models) will result in more accurate travel time estimates for long distance trips.

3.2.1.1 Travel time reliability performance measures

Travel-time reliability can be considered a generalization of connectivity reliability where the probability of travel time exceeding a threshold value (representing disconnectedness) is calculated. This definition provides a measure of travel time stability (Bell & Iida, 1997). While connectivity reliability was developed to study severe events, travel-time reliability was developed to study more frequent disruptions by less severe (supply or demand) variations that may occur on a daily basis (Sumalee & Watling, 2008).

If we consider a path *s* with *a* links and assume statistical independence of past link flow observations link travel time distribution (usually a normal) can be developed. The mean path travel time *T* (as the summation of normal distributions means) is normally distributed with a mean μ_α and a variance σ_α^2 shown in equation 36 (Bell & Iida, 1997):

$$T \sim N\left(\sum_{\alpha \in P(s)} \mu_\alpha, \sum_{\alpha \in P(s)} \sigma_\alpha^2\right) \qquad (1)$$

By normalization we can define the probability that travel time along a path is less than some threshold value *t* (Iida, 1999):

$$Pr\{T \leq t\} = \Phi\left(\left(t - \sum_{\alpha \in P(s)} \mu_\alpha\right) \Big/ \sqrt{\sum_{\alpha \in P(s)} \sigma_\alpha^2}\right) \qquad (2)$$

where: *t* is a threshold travel time value.

Travel time reliability can then be determined for individual paths and path-based performance measures can be developed.

Travel time reliability performance measures may be grouped into three broad categories (Lomax et al., 2003): i) statistical range, ii) buffer time, and iii) tardy trip indicators. Statistical range measures typically use standard deviation statistics to form representative estimates of traffic conditions (in terms of travel time). They are typically presented with an average value plus or minus a deviation value. Buffer time measures indicate the amount of additional time needed to allow on-time arrival at a destination for the majority of trips. These measures may represent average trip times or additional time to average trip times to select a departure time that ensures on-time arrival to a destination with a specific confidence level. Tardy trip indicators provide a measure of unaccepted lateness (i.e., frequency of late arrivals) where a threshold value is used to identify acceptable late arrivals. Numerous studies exist on travel-time reliability performance measures (Lomax et al., 2003; Lyman & Bertini, 2008; Pu, 2011; Rakha et al., 2006).

3.2.1.2 Path-based travel time reliability

The uncertainties in transportation system such as congestion lead to freight operators facing uncertainties in goods delivery. Travel time reliability is becoming increasing critical to businesses, especially the manufacturing sector as many manufacturers are positioning to adopt “just-in-time” manufacturing processes and other schedule dependent inventory, assembly and distribution logistics (Systematics, 2012).

Once segment roadway travel times have been estimated, the next step is to estimate path or trip travel times. Path travel-time reliability is estimated as the probability that the travel time between an origin-destination pair is within a specified range. The key parameters in estimating path travel-time reliability include estimating the path mean travel time and path travel-time variance.

3.2.1.2.1 Different approaches

Two approaches have been used in past studies to define reliability for valuation studies: Mean-variance and Schedule Delay. The former approach uses statistical measures to separate out the value of typical/usual travel time (mean or a measure of central tendency) and measures for the dispersion of the travel time distribution, such as the standard deviation whereas the latter approach focuses on the magnitude of the time during early and late arrivals in relation to a pre-determined schedule.

Mean-variance approach is easy to implement in existing analysis frameworks. However, there is concern that the mean value may include a portion of the reliability component, leading to double counting of benefits when analyzing an improvement. Several researchers have indicated their preference for the schedule delay approach on conceptual grounds, but it is difficult to implement for the highway mode where travelers' schedules are not known and would vary widely if they were.

In schedule delay approach travelers define their own schedule and adjust their departure times, routes, and modes accordingly. In the scheduling delay approach, early arrivals can be valued differently than late arrivals. Reliability and scheduling are related concepts. The former refers to the disutility of the inconvenience and possible penalties attributed to the unreliability of travel times. The latter refers to the disutility of arriving either too early or too late, when the traveler has time restrictions in terms of flexibility of schedules.

One of the initial studies (Small, 1982) established that scheduling costs play a major role in choice of departure times by defining a variable to measure how early or late the commuter is with respect to the official work start time. Let tw be the official work start time. If a commuter leaves home at time th and the travel time is T, then commuter arrives early if $t_h + T < t_w$. Two components of Schedule delay concept are Schedule Delay Early (SDE), defined as $t_w - (t_h + T)$ and Schedule delay late (SDL) is $(t_h + T) - t_w$. The scheduling cost function is as follows:

$$C_s = \alpha T + \beta(SDE) + \gamma(SDL) + \theta D_L \tag{3}$$

where, α is the cost of travel time β and γ are the costs/min of arriving early and late respectively and θ is an additional discrete lateness penalty. D_L is 1 when SDL>0 and 0 otherwise.

The scheduling cost function (Noland & Small, 1995) to allow for decomposition of morning commute which are the expected cost of schedule delay, lateness and travel time. The modified model is:

$$EC_s = \alpha E(T) + \beta E(SDE) + \gamma E(SDL) + \theta P_L \quad (4)$$

where, PL = E(DL) is the lateness probability.

3.2.1.2.2 Past studies using different approaches

A recent study (Lyman & Bertini, 2008) used the standard travel time reliability measures for corridor analysis: 95th percentile TT, Travel Time Index, Buffer Index, Planning time index (PTI), congestion frequency. The study corridor was I-5N, 23.5 miles in length, a freeway in Portland, Oregon. The analysis was carried out using PORTAL's monthly report system which is a collection of all measured corridor travel times, extracted at 5 minute intervals for all of 2005.

The procedure for estimating path travel-time reliability assumes that travel times follow a normal distribution and requires a measure of trip travel-time variance. Past study by (Rakha et al., 2006), shows that the assumption of normality is, from a theoretical standpoint, inconsistent with field travel-time observations and that a lognormal distribution is more representative of roadway travel times through goodness-of-fit tests that. However, visual inspection of the data demonstrates that the normality assumption may be sufficient from a practical standpoint due to its computational simplicity. This study also proposes five methods for the estimation of path travel-time variance from its component link travel-time variances as shown in Table 3-1.

The mean-variance approach allows the estimation of two widely used reliability metrics: value of travel time reliability (VTTR) and Reliability Ratio (RR). VTTR represents the user's monetary weight for improving reliability and RR is defined as ratio of VTTR to VOT. An established RR along with knowledge of the VOT simplifies the task of VTTR estimation. In recent studies (Asensio & Matas, 2008; Brownstone & Small, 2005; Tilahun & Levinson, 2010) VTTR and RR are determined to capture the travel time reliability.

Table 3-1. Path travel time variability (Rakha et al., 2006)

Method	Equation
1	$\bar{\sigma}_{1t}^2 = \frac{\sum_{i \in V(s)} \left(\sum_{j \in L(s)} t_{ij}^2 \right)}{n} - \sum_{j \in L(s)} \bar{t}_j^2$
2	$\hat{\sigma}_{2t}^2 = \frac{\bar{t}_t^2}{\sum_{j \in L(s)} \bar{t}_j^2} \cdot \left\{ \frac{\sum_{i \in V(s)} \left(\sum_{j \in L(s)} t_{ij}^2 \right)}{n} - \sum_{j \in L(s)} \bar{t}_j^2 \right\}$
3	$\hat{\sigma}_{3t}^2 = \frac{\bar{t}_t^2}{m^2} \left(\sum_{j \in L(s)} \frac{\sigma_j}{\bar{t}_j} \right)^2$
4	$\hat{\sigma}_{4t}^2 = \left\{ \bar{t}_t \cdot \mathrm{Med}_j \left(CV_j \right) \right\}^2$
5	$\hat{\sigma}_{5t}^2 = \frac{\bar{t}_t^2}{4} \left(CV_{\max} - CV_{\min} \right)$

A method for synthesizing a distribution of consistent path-dependent O-D travel times from the known distribution of link counts is suggested in the SHRP 2 C04 report (Brinckerhoff, 2013). This method generates of origin–destination (O-D) travel time distribution for the base year, which is needed for calculating travel time reliability measures. These reliability measures are used in travel demand models to explain travel choices along with the average travel time and cost. The method is designed to produce a distribution of travel times for a full regional O-D matrix for a certain time of day, period or hour.

SHRP2 L35B report (Zhang, 2012) uses an instantaneous travel time aggregation method to estimate path travel times based on link travel times. Travel time data used as input in this study are provided by INRIX. In this study, data archived during calendar year 2011 are used at 1-minute resolution on all segments considered. The study shows that as trip length becomes longer, the risk impact of any newly added segment, while still positive, becomes marginal compared with the rest of the path. This phenomenon is reflected by the concavity of reliability ratio (RR) curves. Other elaborate path travel time estimation methods (e.g., trajectory construction based models), will result in more accurate travel time estimates for long distance trips.

SHRP2 L35B (Zhang, 2012) study uses “Real Options Theory” which was first used by the SHRP 2 L11 project (Kittelson & Associates, 2013) for determining the value Background of travel time reliability by using speed and volume data as input (Sadabadi et al., 2014). The options-theoretic approach introduced by the SHRP 2 L11 uses an analogy where premiums are set for an insurance policy on guaranteed speed levels. Specifically, the method calculates the dollar value of reliability by multiplying the certainty-equivalent penalty (measured in minutes/mile and obtained by applying the closed form Black-Scholes equation) by the value of time, thus it requires an estimation or adoption of VOTT as input. The SHRP 2 L11 study takes into account heterogeneity of the road users and different trip purposes by applying a separate value of time that corresponds to each user group. All these studies have been summarized in Table 3-2.

3.2.1.2.3 Freight travel time reliability

Past studies on the valuation of freight travel time reliability are limited compared to passenger travel. Most of the studies (Bergkvist & Westin, 2001; Bolis & Maggi, 1999; Danielis, Marcucci, & Rotaris, 2005; Wigan, Rockliffe, Thoresen, & Tsolakis, 2000) indicate that the freight value of reliability varies by commodity, with bulk commodities having the lowest value. However, there is little consensus on what the values of VORs or Reliability Ratios should be. If the Reliability Ratios for freight are equivalent to passenger travel, i.e., around 1.0, then VOR for freight will be higher (Systematics, 2012).

3.2.1.2.4 Path based dynamic travel time

In most of the past studies, it is generally assumed that path travel time is the aggregation of the travel times on its consisting links. However, for a probe-based data collection system in which the number of reports is rather limited, this link-based estimation/prediction might not be reliable (Chen & Chien, 2001), evaluate the performance of dynamic travel time prediction models with real-time data (travel time) collected by probe vehicles on path and its consisting link. In this study, “Kalman filtering method” is chosen because it enables the prediction of the state variable (travel time) to be continually updated as new observation becomes available. This approach has been used in the forecasting of traffic volume and real-time demand diversion as well as the estimation of trip-distribution and traffic density. Here, this technique is used to perform travel time prediction based on real-time information provided by probe vehicles.

Specifically, the average travel time of probe vehicles at each time period is used as the real-time observation to predict the travel time in the next (or future) time period.

3.2.1.2.5 Preliminary methodology

Step 1: Collect Link Travel time data (GPS, probe, or any other source) at discretized time step (We have that for each link)

Step 2: Define regional O-D

Step 3: Create/build k-shortest paths (with predefined impedance function)

Step 4: Obtain path travel time by aggregating the TT of the links

Step 5: Obtain path travel time reliability measures

Table 3-2. Path based reliability summarized literature review

Literature	Reliability Measure	Notes
(Bergkvist & Westin, 2001)*	VTTR	Data was collected through computer based SP survey.
(Bolis & Maggi, 1999)*	VTTR (dependent on type of operation such as Just In Time production)	Based on the Leeds Adaptive SP (LASP) survey which provides choice of alternative ways for the freight operators.
(Danielis et al., 2005)*	VTTR	Also determined VOT.
(Wigan et al., 2000)*	VTTR (dependent on segment type)	Data was collected on three market segments: Inter-capital FTL, Metropolitan FTL and metropolitan multidrop
(Brownstone & Small, 2005)	90^{th} -50^{th} percentile and Reliability Ratio= VTTR/VOT	

(Asensio & Matas, 2008)	Standard deviation using Scheduling approach and Reliability Ratio	
(Tilahun & Levinson, 2010)	Difference between actual late arrival and usual travel time and Reliability Ratio	
(Brinckerhoff, 2013)	Standard Deviation per unit distance	Used a distribution of path dependent Origin– Destination travel times
(Sadabadi et al., 2014)	95% TT, TTI, PTI, BI, VTTR, RR	Uses Real Options Theory to improve travel time reliability
(Lyman & Bertini, 2008)	95% TT, TTI, PTI, BI,	Also provides segment, corridor and network analysis
(Rakha et al., 2006)	Path Travel time variability	

Note: * For Freight; metropolitan multidrop- a very common urban freight movement involving a rigid truck or light commercial vehicle with many deliveries

3.2.1.3 Use of truck GPS data for freight performance measure

The evaluation of corridors' performance is essential in identifying bottlenecks and determining network sections that need to be improved. Past practices include travel diaries and traffic counts but these practices tend to be time consuming and with low accuracy. Since every truck in the U.S. is equipped with a GPS device researchers have explored possibilities of using information from these devices not only to calculate FPMs but also to define travel patterns and make prediction models. The performance measure used mainly in studies is travel time (TT), hence this part of the literature review is classified in three categories based on how TT is computed: i) link TT (LTT), where travel time is computed for a link; ii) trip TT (TTT), where travel time is calculated for a trip or tour; iii) miscellaneous – different from i and ii.

3.2.2 Link Travel Time (LTT) focus

Quiroga & Bullock (Quiroga & Bullock, 1998) proposed a methodology to perform studies for estimating TT of roadway segments using GPS and Geographic Information System (GIS) technologies. GPS data were collected from three metropolitan areas in Louisiana, LA (i.e., Baton Rouge, Shreveport, and New Orleans). Average TT and travel speed (TS) values were computed for all highway segments. A length of segment comprised 0.2-0.5 miles. GIS was utilized to process queries, produce reports and colored-theme maps, depicting TT by link. Results showed that shorter GPS sampling periods (1 to 2 seconds) decreased errors in TS estimation. The authors underlined that median speed was a more accurate measure of the central tendency than mean speed as the latter was affected by incidents occurred during peak hours. Quiroga (Quiroga, 2000) conducted a similar study for the LA transportation network (Baton Rouge). Highways were separated into segments, and LTT was calculated for each segment. The author also provided a procedure for estimating several other performance measures (acceptable TT, segment TS, travel rate, delay, total delay, delay rate, and relative delay rate) that could be used for quantifying congestion.

Storey & Holtom (Storey & Holtom, 2003) used GPS data to compute link TS (LTS) and LTT at West Midlands highways in the UK. The GPS device provided information every 60 seconds, while a vehicle ignition was being on. Around 20% of the data were discarded, as they provided coordinates (latitude and longitude) that didn’t belong to the road network. Links of the considered highways were separated into 50 m segments, and the average TS was calculated for each segment. It was assumed that segments between two GPS data points had the same average speeds. The journey times at the link level, estimated using GPS data, were calibrated, and results demonstrated an acceptable accuracy of the proposed approach. The analysis of journey speeds indicated the existence of congestion issues at major junctions of links, leading to the city center.

Jones et al. (Jones, Murray, & Short, 2005) presented a methodology that could be applied to measure performance of busy freight corridors. The procedure was separated in 4 steps: 1) identification of freight corridors, 2) review of data collection technologies, 3) System Alpha Test, and 4) System Beta Test. Top ten US cities with the highest truck volumes were identified using American Transportation Research Institute (ATRI) satellite position reports. The busiest freight corridors were determined for each of those cities based on the data, provided by Cambridge Systematics. Different methods of data collection were described: satellite-based systems, terrestrial wireless systems, hybrid systems, on-board systems, and fixed site systems. GPS was found to be efficient for the analysis. The Alpha Test was performed to associate a vehicle ID with a highway segment geo-position, to calculate the average vehicle TS, and to remove outliers that could affect the accuracy of speed estimation. The main purpose of the Beta Test was to process TT and TS at each segment and to transfer the data to the visualization tool. As a result of the conducted study, the authors created a map, depicting the average TS at the busiest US corridors.

Ando & Taniguchi (Ando & Taniguchi, 2006) developed a model for the vehicle routing problem with time windows (VRPTW), minimizing the total cost of LTT uncertainty and penalties due to early arrival/delayed arrival to customers, requesting a particular time window. The information on LTT was collected using sensors, radio beacons, and GPS devices. Truck arrival times were assumed to follow a normal distribution. Statistical TT distributions were obtained for each link and were approximated to triangular distributions. An additional linear regression analysis was performed to quantify relationship between LTT and link distance. The traffic flow simulation was used to estimate TT distribution for each route and determine the optimal visiting order of customers. Results indicated that the proposed approach reduced the total cost by 4.1%, the total cost standard deviation by 75.1%, and mitigated environmental impacts, caused by trucks.

Schofield & Harrison (Schofield & Harrison, 2007) underlined the importance of FPMs for the US Department of Transportation (DOT), State DOTs, and various transportation agencies. Practices for assessing performance of freight corridors, employed in different states, were described in the report. The study focused on developing appropriate FPMs in the Texas (TX) area. The busiest state highways were identified. GPS records were provided by ATRI for the entire year of 2005. The authors indicated that the location error for each observation could reach up to ¼ mile. The segment length comprised 50 miles. TT, TS, and TT index (TTI) were estimated for each segment. Changes in travel pattern were noticed when the Hurricane Rita notification was announced. The report provided distribution of hourly truck traffic. Future research directions included comparison of the actual speed with the free-flow speed for each segment, estimating FPMs for highway corridors in case of non-recurring congestion, calculating of truck wait time at boarders, consideration of other FPMs, etc.

Liao (Liao, 2008) compared two ATRI FPM database systems: the GIS – based system and the Structured Query Language (SQL) – based system. The second system was able to process truck GPS data without the GIS software. The GIS-based system allowed separation of a highway into segments with minimum size of 10 miles. The minimum segment size for the SQL-based system was 3-miles. It was found that smaller segments improved accuracy of average speed estimation. The author underlined the importance of trip filtering parameters and projection algorithms. The GIS-based system employed a ¼ mile radius search method, while the SQL-based system used more complex snapping algorithm. Several deficiencies of the SQL-based system were mentioned (e.g., duplication of data in tables). According to the report, the ideal FPM system should include the SQL-server, capable to process data from external applications and visualize performance measures using a GIS - based software.

Liao (Liao, 2009) evaluated performance of I-94/I-90 freight corridor between St. Paul, Minnesota (MN), and Chicago, Illinois (IL). GPS data for 12 months (May 2008-April 2009) were provided by ATRI. The raw data were processed in ArcGIS software, GPS points were snapped to the nearest route, and then the average TS was computed for each 3-mile segment. The analysis was performed for the key corridor locations (i.e., St. Paul, O'Hare Airport, I-90 toll highway), including truck speed, volume, TT reliability, truck stops, truck stop duration, etc. Results indicated that average speeds declined in areas approaching Chicago from 55 mph to 40 mph and lower. The westbound traffic between St. Paul and Madison had higher speed standard deviation than the eastbound traffic. A significant speed standard deviation and the average speed drop were observed on I-90 toll highway, leading to Chicago.

McCormack (McCormack, 2009) described how GPS data were used to improve performance of the Washington State (WA) freight network. LTT and its reliability were chosen as performance measures. The data were collected from various vendors. GPS records were received with frequencies, varying from vendor to vendor (every 30 seconds, every half-mile, every 15 min, etc.). ATRI and FWHA developed a program, focusing on performance of interstate corridors. A specific algorithm was developed to define origin and destination of each trip, using stop time, travel distance, GPS signal quality, and location of travel. It was highlighted that some GPS points were removed as they provided erroneous data. In some cases truck information was known only every 15 min. The author concluded that truck GPS data could be very useful for public agencies to evaluate conditions of busy freight corridors and to identify bottlenecks.

The Washington Department of Transportation (WSDOT) outlined the main features of the Truck Performance Measure Program at the Washington State Transportation Commission (WSDOT Freight Performance, 2009). The WSDOT initiated this program in 2007. GPS data process and analysis are similar to the ones, described by McCormack (McCormack, 2009). LTT and its reliability were selected as performance measures. The main objective of the program was to identify and rank bottlenecks at the WA State highways. Four criteria were developed for prioritizing highway segments for further improvements: 1) Truck speed below the congestion threshold (60% of posted speed limit); 2) Average speed; 3) Speed distribution; 4) Truck volume. The authors underlined that the program was efficient, and its future success would be highly dependent on the access to the data, owned by trucking companies. McCormack et al. (McCormack, Scharnhorst, Zhao, & Tabat, 2011) and McCormack & Zhao (McCormack, Zhao, & Tabat, 2011) conducted a similar study, using the same FPMs as (McCormack, 2009). The authors described the process of bottleneck identification and prioritization in WA. The overall procedure was subdivided into 5 parts: a) Segment the roadway; b) Add attribute information to the segments; c) Geo-locate the truck; d) Locate the bottlenecks; e) Rank the bottlenecks.

Chien (Chien, 2011) estimated link and path TT, variability of TT by departure time of the day and days of the week for 18 New Jersey highway corridors. The data were collected from GPS enabled devices, installed into different vehicles, traveling along considered highways between October 8, 2007 and April 21, 2008 from 6.15 am to 8.15 am during weekdays. The buffer index (BI) and 95th TT percentile were calculated for each route. Results indicated that TT on the most of roads followed a shifted log-normal distribution. The lowest mean TS was found for a segment NJ 208 & NJ 4 (28.3 mph), while the highest one was determined for a segment NJ 24 & I-78 (59.9 mph). The highest TT coefficient of variation (TTCV) was calculated for a segment US 46 & NJ 3 during A.M. peak hour (TTCV=0.4). The lowest TTCV was estimated for US 1 (TTCV=0.09). The scope of research didn't include assessment of incident impacts on link/path TT due to data limitations.

Cortes et al. (Cortés, Gibson, Gschwender, Munizaga, & Zúñiga, 2011) used GPS data to evaluate performance of a bus transportation system in Santiago, Chile. Data were collected for 6,178 buses operating over a one week. The authors applied a path rectification procedure to determine paths for each route. The path rectification identified line segments that were located close to GPS points with an acceptable error. Rectified paths were separated for grid elements. An average bus TS was calculated for each grid element. The report presented speed diagrams illustrating bus speeds for each route segment during a given time of day. The proposed methodology was found to be efficient for problem identification in bus operations (e.g., low speeds at certain segments, congestion issues, improper traffic light times, etc.).

The Federal Highway Administration (FHWA) Office of Freight Management and Operations (FHWA, 2011) developed a Freight Performance Measures (FPM) web Tool to evaluate performance of the US freight corridors using truck GPS data. The FPMweb Tool estimates the operating speed of a given segment by averaging over the total number of speed observations. The segment length was assumed to be 3 miles. The tool can process data by time and date for 25 interstate corridors. Several drawbacks of the tool were mentioned: 1) it doesn't provide commodity and origin-destination data; 2) it is not capable to forecast future truck volumes and speeds; 3) it is useful for analysis of average and not individual truck TS.

Sarkar et al. (Sarkar, Figliozzi, Wheeler, & Rice, 2011) developed an algorithm for assessing TT reliability of the I-5 interstate in Oregon (OR). GPS data were provided by ATRI. The corridor was separated into particular segments. Traffic flows were estimated for every mile and direction of each segment. Smoothing was performed by averaging counts for 20-miles segments. Volumes were also determined for different seasons of the year. Segments were analyzed based on two factors: a) time of the year and corresponding weather conditions, and b) truck density pattern along the segment. The designed algorithm was able to estimate 95%, 80%, and 50% percentile TT for each segment (if traffic counts were sufficient at considered segment) using GPS data. Minimum and maximum TS limits (10 mph and 80 mph) were set to remove outliers. Results indicated that differences between three types of TT (i.e., 95%, 80%, and 50% percentile TT) were significant for urban areas and relatively small for rural areas. TT costs per mile were calculated and presented in the chapter.

Wheeler & Figliozzi (Wheeler & Figliozzi, 2011) assessed effects of recurring and non-recurring congestion on freight movement characteristics (LTS, LTT, and TT reliability) at the Oregon I-5 Interstate (the same freeway as studied by (Sarkar et al., 2011)). Along with GPS data, the authors used corridor TT loop data and incident data (provided by the Oregon DOT). A specific methodology was developed to identify through trucks (that don't make any stops and provide at least two GPS readings in the beginning and in the end of the corridor). Results of a recurring congestion analysis indicated that the highest TT and TTCV were observed during evening peak. As for non-recurring congestion, it was found that incidents significantly affected truck TS in the incident area throughout the day. Congestion cost estimates indicated that daily delay costs for freight vehicles were 19% higher that free-flow costs without variability consideration (and 22%-31% higher with variability consideration). GPS data were found to be more accurate in estimating TT than the loop sensor data.

Blazquez (Blazquez, 2012) addressed the problem of snapping GPS points to roadways segments. Various techniques, resolving spatial ambiguities, were listed (e.g., semi-deterministic map-matching, probabilistic map-matching, fuzzy logic map-matching, Kalman filter approach, etc.). The author developed a topological map-matching algorithm for snapping GPS points. The algorithm was able to identify a feasibility of the path between two snapped points (by comparing a speed along the path and the average vehicle speed). Numerical experiments were conducted using the data, collected by winter maintenance vehicles in Wisconsin (WI) and Iowa (IA). Preliminary calculations were performed to determine the buffer size. Results demonstrated the efficiency of the presented methodology. It was found that the GPS spatial error decreased the percentage of solved cases on average by 30%. Frequent sampling intervals provided more accurate results. An increasing number of consecutive GPS points improved performance of the algorithm.

Liao (Liao, 2014) used GPS data, provided from ATRI for twelve months in 2012, to estimate FPMs, such as truck mobility, delay, and reliability index, and to identify bottlenecks for 38 key freight corridors in the Twin Cities metropolitan area (TCMA). To validate the methodology the computed average truck speeds and hourly volume percentage at certain locations were compared with the data from weight-in-motion (WIM) sensors and automatic traffic recorders (ATR). Truck bottlenecks were identified and ranked based on hours of delay and number of hours with TS less than the target speeds, set by Minnesota DOT during A.M. and P.M. peak hours. Also, the truck congestion cost was estimated for TCMA to be \$212 and \$286 million annually based on ATRI's truck operation cost and Texas Transportation Institute's (TTI) truck congestion cost respectively. As another part of the study, one month data from FHWA's National Performance Management Research Data Set (NPMRDS) was used to compute freight mobility and speed variations along Minnesota's National Highway System.

Wang et al. (Wang et al., 2014) suggested naïve and mapping methods to estimate LTT using GPS data. The naïve method computed the average TS and its variability on each link individually. The variability was measured by a standard deviation. The authors presented a mathematical formulation for a mapping method with an objective, minimizing the total difference between the recorded trip times and the estimated trip times for all trips. Both methodologies were tested on the San Antonio corridor (TX) and the Milwaukee highway corridor (WI). The mapping method was found to be more efficient, since it was able to analyze truck trips with large road intervals covering multiple links.

Gong et al. (Gong, Adams, & Wang, 2015) used truck GPS data to estimate link travel times a highway corridor in Wisconsin using a regularized regression model that maximizes the likelihood of obtaining the observed trip travel time while penalizing changes in speeds on adjacent links. Trip travel time is the duration between two successive timestamps and trip length is obtained as the roadway length traversed. Basic assumption of the model is that travel speed of a trip is constant along a link while a trip traverses several partial/full links. The proposed method results were found to outperformed results obtained from a simple OLS regression and a benchmark method. Namely, one hour traffic data collected from double loop detectors was used for validation and it was found that regularized regression method improves the travel time allocation results from the benchmark method, trip travel time allocation errors decrease as link speeds grow and travel time allocation error increases as variation of speed within link grows.

Mishra et al. (Mishra, Golias, Dulebnets, & Flaskou, 2016) used truck GPS data provided by ATRI to calculate link based FPMs on Tennessee freight network. The study provides a guideline on how GPS data should be preprocessed and pinpoints possible problems researchers may face with this type of data. Besides estimating link FPMs the GPS data was used to develop turn times regression models for different types of freight facilities, calculate occupancy and entry/exit volumes. The researchers also developed two algorithms to analyze truck trips. The first one identifies intercity truck trips having as input the TN TAZs while the second one detects inter and intracity trips and their characteristics (dwell times, traffic light stops etc).

3.2.3 Trip Travel Time (TTT) focus

McCormack & Hallenbeck (McCormack & Hallenbeck, 2005) suggested two data collection methodologies to evaluate truck movements along particular roadway corridors in WA and to measure performance of freight mobility improvement projects against benchmarks. The first approach was based on implementation of Commercial Vehicle Information System and Networks (CVISN) electronic truck transponders, which were installed on the windshields of approximately 20,000 trucks. A specific program was designed to estimate TTT using the data, provided by transponders. Another technology employed GPS devices that transmitted truck movement records every 5 seconds. The information, collected using CVISN and GPS, was processed to identify congested segments, TTT, and TT reliability. It was highlighted that both techniques might be efficient for analysis of truck trip patterns. However, selection of a methodology should depend on the data required for a particular benchmark project.

Greaves & Figliozzi (Greaves & Figliozzi, 2008) processed passive GPS data from 30 trucks to identify characteristics of freight movements in the Greater Melbourne region, Australia. The authors underlined difficulties of getting GPS data from trucking companies. The GPS device was installed into each truck and provided second-by-second information. The trip identification algorithm was developed to determine trip ends. Around 5% of records were inaccurate due to loss of satellite signal and were excluded. The final output of the processed data included a summary for all truck trips and tours. The average number of stops per tour was found to be 12.2 stops. The lowest average TS were observed for morning and evening peak hours. A trip length distribution was presented in the chapter. It was mentioned that GPS data didn't provide additional information about driver behavioral features (respond to weather, empty/loaded vehicle, type of commodity, etc.) that might be useful for the analysis.

National Cooperative Freight Research Program (NCFRP) Report 008 (NCFRP, 2010) highlighted the importance of truck GPS data for evaluation of freight corridors performance. The study was conducted for the following metropolitan areas: Los Angeles (California CA), Chicago (IL), Phoenix (Arizona AZ), and Baltimore (Maryland MD). GPS records were used to identify the number of stops during the trip, distance between stops, stop purpose, stop location, TT between stops, etc. It was found that likelihood of making trip in the tour depended both on the truck trip purpose in the current and subsequent stops. Besides, the information about trip origin, origin land use, and trip destination could be used to predict the destination land use. The highest percent of stops in industrial land use (27%) was observed in Chicago. Retail and commercial land use stops were more common in Los Angeles (31%). The most of residential land use stops occurred in Phoenix (31%).

Bassok et al. (Bassok, McCormack, Outwater, & Ta, 2011) demonstrated how truck GPS data, collected from the device vendors, could be used for the analysis of freight movements in the WA area. The authors developed an algorithm for identifying trip ends. Truck stops for refueling, rest and delivery were filtered out (dwell time threshold comprised 180 sec, which is a common standard in WA). A threshold speed limit of 5 mph was set to determine trip ends. The analysis was performed for 91 days in the Puget Sound region (WA), when 2,400 trucks made 22,000 tours and 215,000 individual trips. Results indicated that each truck made on average 9 tours and 10 trips per tour. Besides, around 2 truck trips at each tour were made to grocery stores. Areas with higher population density produced more truck trips.

Golias et al. (Golias et al., 2012) used truck GPS data to analyze freight movements within the Greater Memphis area in TN. Available data provided information about truck trips from September 1, 2011 to October 30, 2011. The highest truck volumes on I-40 were observed during evening peak hour between 4 pm and 5 pm. Trip durations were increasing for a period since 10 pm until 8 am. This was explained by the fact that most of truck drivers stopped for rest during that time interval. Truck turn times were considered for 4 types of facilities: public warehouses, private warehouses, distribution centers, and intermodal facilities. The authors developed regression models predicting facility turn times depending on the truck volume per time interval and facility type. The overall fit of proposed models was found to be low due to small sample size. Intermodal facilities and private warehouses demonstrated the best fit. The scope of research included truck stop and rest stop demand analysis. All truck stops with duration from eight to twelve hours were considered. The authors provided frequency of truck stops based on the time of the day for major TN rest stop areas.

Pinjari et al. (Pinjari et al., 2013; Pinjari, Short, Pierce, et al., 2012; Pinjari, Short, & Tabatabaee, 2012) investigated how GPS data, provided by ATRI, could be used for assessing performance of freight corridors and transportation planning in Florida (FL). The study was directed to identify FPMs for state highways, build a truck-trip database to understand truck travel patterns, and derive truck trip O-D tables for the Florida Statewide Model. Several FPMs were suggested, such as average trip TS (TTS), reliability measures (TTI and Planning Time Index PTI), analysis of chokepoints, truck flow analysis, etc. Truck flows were estimated by month of the year and by day of the week. It was found that seasonal variations of truck speeds were not significant. However, travel patterns during weekdays were different as compared to weekend travel patterns. Trip

Origin Destination Identification algorithm was designed to define O-Ds. The procedure was validated based on comparison with Google Earth and discussions with ATRI and FDOT. Trip length and trip duration distributions were provided in the report.

You (You, 2012) studied tour-based models for drayage trucks at San Pedro Bay Ports in Southern California area. The main objective was to develop a methodology, which could help to alleviate congestion of trucks at the gates, reduce truck turn times at the ports, and mitigate environmental impacts. A tour-based approach was found to be more efficient for modeling behavior of drayage trucks than a single trip-based approach. GPS data for 545 drayage trucks was provided by the ports of Los Angeles and Long Beach. The collected data were processed to identify closed and open tours. It was observed that each truck made on average 1.7 tours and 6.2 stops per day. A typical tour TT lied between 3 and 9 hours. The author suggested two approaches to analyze trip-chaining behavior of drayage truck movements: 1) A disaggregate level tour-based model based on Sequential Selective Vehicle Routing Problem (SSVRP); 2) An aggregate level tour-based model based on Entropy Maximization Algorithm (EMA). It was underlined that the SSVRP was more realistic approach for modeling drayage truck tours.

Bierlaire et al. (Bierlaire, Chen, & Newman, 2013) used GPS data, generated by smartphone Nokia N95, for route choice modeling in the Lausanne area, Switzerland. The authors listed advantages (short warm-up time, full track of trips) and disadvantages (weak signals, not accurate data points in some cases, high energy consumption) of GPS capable phones. A probabilistic map matching method was developed to estimate the likelihood of choosing a particular path based on the smartphone GPS data. A path with a higher log-likelihood was more preferable among all alternative paths. Speed distributions were generated from the observed speed data. Data points with speeds less than 8 km/h were filtered out. Results obtained by the suggested approach were close to the ones, provided by the Mobility Meter (dedicated GPS device, carried by the person along with smartphone).

Carrion & Levinson (Carrion & Levinson, 2013) assessed the effect of converting I-394 (between Minneapolis and St. Paul, MN) High Occupancy Vehicle (HOV) lanes to High Occupancy Toll (HOT) lanes. The main objective was to determine a traveler’s respond to increasing TT reliability on HOT lanes. The GPS devices were installed in 54 vehicles to collect the detailed trip information. A 20-meter buffer was used for all roads. GPS points, located outside the buffer area were excluded. The authors developed an algorithm to identify the commute trips (from origin to home location, from destination to work location and vice versa). The preference of travelers for choosing tolled or non-tolled routes was analyzed using discrete choice models. The utility function included TT measures, travel cost, and socio-demographic factors. TT reliability was measured by standard deviation, shortened right range, and interquartile range. Results of study indicated that the desire of travelers to pay tolls for reliable routes was dependent on how they perceived reliability savings.

Golias & Mishra (Golias & Mishra, 2013) used truck GPS data, provided by ATRI for the months of September and October 2011, to evaluate the impact of the new Hours of Service (HOS) rule for Commercial Motor Vehicles (CMV) drivers on traffic conditions using as case study a part of I-40 network between Memphis and Nashville, TN. Existing truck TTT and volume by time of day on a daily and weekly basis were computed by statistically analyzing the provided data, while future conditions were estimated for the shifted truck trips which had to be identified based on the new working hours. The Level of Service (LOS) for both cases was calculated based on the methodology suggested in Highway Capacity Manual with some adjustments because of the low percentage of data used. By comparing LOS in both cases it was found that the new HOS would worsen LOS, as truck volumes would increase at certain routes after each rest period, which might cause delays.

Kuppam et al. (Kuppam et al., 2014) demonstrated how truck GPS data could be used for Tour-Based Truck Travel Demand Modeling. The study was conducted based on GPS data for 22,657 trucks and 58,637 tours, purchased from ATRI. The number of tours for each truck was determined using the information about truck coordinates, changes in TT and TS. The accuracy of vehicle stops was checked using highway maps and Google Earth. The following Tour-Based Truck Models were developed for the Phoenix region (AZ): tour generation, stop generation, tour completion, stop purpose, stop location, stop time of day choice. It was found that construction tours had lower tendency to making stops, while government-related tours were dedicated to making more stops. An increasing number of stops caused incompletion of tours for the majority of trucks. The purpose of the previous stop influenced duration of the next stop.

3.2.4 Miscellaneous

Fisher et al. (Fischer, Outwater, Cheng, Ahanotu, & Calix, 2005) proposed a modeling framework to evaluate the Los-Angeles County (CA) freight transportation network performance. The framework combined characteristics of logistics chain and tour-based models. Logistics chain models were found to be useful for cases, when particular types of goods were transported from the production points to the assigned destinations. Those models combined information from three layers: economic, logistics, and transport. Tour-based models were efficient to determine vehicle tours and trips without focusing on commodity type. Those models provided the following information: generation of tours by zone, number of stops during the tour, stop purpose, stop time, stop location, number of trips during the tour, etc. The suggested integrated framework was found to be promising for analysis of freight movements.

Cambridge Systematics (Systematics, 2007) indicated that GPS devices could be effectively employed along with travel diary surveys for data collection and understanding truck traveling patterns in urban areas. Several disadvantages of using diaries were mentioned: 1) process of data depends on willingness of drivers to complete the form, 2) lack of the contact information, 3) some vehicles may not be registered in the study area, 4) low response rates due to confidentiality issues, etc. GPS devices, installed into trucks, might be utilized to validate the data, collected from driver diaries (e.g., trip origin, trip destination, routing, speeds at particular road segments). However, GPS data don't provide any information regarding commodity hauled, size of shipment, and type of carrier operation (e.g., truckload, LTL, private). Besides, high cost of GPS devices was found as a major implementation issue.

NCHRP Report 618 (NCHRP, 2008) suggested a set of performance measures that can be used to evaluate highway conditions. Performance measures were classified into two categories: individual measures (related to an individual traveler) and area measures (related to the area, region or corridor). Delay per traveler, TT, TTI, BI, and PTI were referred to individual measures. Area measures included total delay, congested travel, percentage of congested travel, congested roadway, and accessibility. The report also distinguished between the performance measures as primary and secondary depending on the analysis area.

Dong & Mahmassani (Dong & Mahmassani, 2009) developed a methodology for estimating TT reliability. TT reliability was associated with traffic flow breakdowns and delays. A probability distribution function for pre-breakdown flow rate was calibrated using field data, from I-405 Irvine freeway in CA. The normal distribution was the most suitable for the Jeffrey section of the freeway, while the Weibull distribution provided the best fit for the Red Hill section. The authors assumed a linear relationship between breakdown and pre-breakdown flow rates. The delay was estimated based on TTI and flow rate values. Numerical experiments were performed for I-405, and results indicated that the proposed concept was efficient for relieving congestion and TT delays.

The Memphis Urban Area MPO (Memphis MPO, 2013) conducted a Freight Peer to Peer Program meeting to exchange the best practices between regional freight industry stakeholders from public and private sectors, and also various transportation agencies. Establishment of performance measures for freight transport was found to be a very important aspect in prioritizing highway improvement projects. It was underlined that performance measures should be set at state level with assistance of regional agencies if necessary. Performance measures should take into consideration interests of both private and public sectors.

Pinjari et al (Pinjari et al., 2014) used GPS data provided by the American Transportation Research Institute (ATRI) to compute FPMs and develop algorithms that estimate truck trips and Origin-Destination (OD) matrices. Data consists of trucks traveled across Florida in a 4 month period. Based on truck id, GPS data for these trucks was also extracted from ATRI database for the rest of North America in order to track flows in and out of the state. GPS records information provide x, y coordinates, time and date, truck id and distance to the closest interstate, while a subset of the trucks had also spot speed information. A GIS polygon shape file with major truck stops (rest areas, weight stations etc.) was also used in this study. The developed algorithm identified potential stops (origin or destination) based on spatial movement, time gap and speed between consecutive observations for the same truck and eliminated possible stops less than dwell-time buffer, combined small trips (less than 1 mile) and discarded incomplete trips or trips with large time gap between observations. Then, it eliminated trip ends in major truck stops and breaks circuitous trips (ratio between air distance and cumulative geodetic distance from origin to destination less than a predefined value) into multiple ones. In the results trips were categorized in 3 types: all trips (including trips outside Florida), FL-link trips (at least one end in Florida), and FL-only trips (both origin and destination in Florida).

Besides truck trip characteristics, OD matrices for a part of the 6000 Florida TAZs were calculated and compared to travel times used in the Florida Statewide Model (FLSWM) and google maps. It has been found that factors that may affect the calculated travel distance and travel time are route choice, GPS data ping rate (time gap between two consecutive GPS records), TAZ size, time of day and number of trips between ODs. Based on the results travel distances from ATRI data were smaller compared to FLSWM and google maps mainly because of the straight line distance approximation between two GPS points. The computed travel times were found to be higher when compared to google maps results but smaller compared to those extracted from FLSWM.

Another part of this study was to examine the extent to which these trips capture observed traffic flows in Florida. Focus of the study was the truck type composition, the proportion of truck traffic flows captured by the GPS data and geographical differences in the data. Trucks that did not make at least one trip of 100 miles and trucks with more than 5 trips per day were classified as medium trucks and removed from the database. To determine the proportion of heavy truck traffic flows captured in ATRI data in Florida they were compared with observed truck traffic volumes from Telemetered Traffic Monitoring (TTM) sites in Florida. It was found that this coverage is 10% for heavy trucks, information used later to compute the seed matrix in the origin-destination matrix estimation (ODME) model. Other input to the model was a highway network of the study area, observed traffic flows on various links and OD matrices for travel volumes other than freight truck extracted from the FLSWM. Also, cells with zero flows in the seed matrix that was expected to have flows were corrected after aggregating from TAZs to county level. The

ODME was evaluated for different assumptions (upper/lower bounds on trip number) and the results for one set of assumptions are presented in this study with acceptable validation results.

Lee and Ross (Lee & Ross, 2015) studied how truck GPS data can be utilized for freight demand forecast at the state and regional levels. ATRI GPS data for Atlanta and Birmingham was collected for eight weeks and used to develop a tour-based freight demand model at the state/regional level in conjunction with existing data sources, employment data and transport network. The model was divided in 7 sections. First, the Tour Generation Model produces truck tours in each TAZ based on zonal characteristics. This output was used to scale GPS data. Next, the Tour Main Destination Model calculates the probability of each zone being a primary destination for tours originating from all other zones and the Intermediate Stop Model calculates how many intermediate stops there are for each tour, if any, using a multinomial logit model and identifies destination zones for each intermediate zone. The Time of Day model splits tours into different time periods and the Trip Accumulator breaks tours into truck trips that are used as inputs to the Traffic Assignment model. Link volumes from the developed model were compared to Atlanta Regional Commission (ARC's) trip based model and it was found that the new model assignment was closer to the reported traffic counts for the examined period.

Bernardin et al. (Bernardin Jr, Trevino, & Short, 2015) used ATRI's truck GPS data in Iowa and Tennessee to identify possible biases and calculate ODMEs. Data used consists of 8 week truck observations for each quarter in 2012 and are already processed giving information for begin and end TAZs between two consecutive observations, distance, time, speed and status (moving/stopped). Further process of the data was needed to identify ODs for each sequence of moving records and discard bad data (GPS positional errors, partial trips, intrazonal trips greater than 30 miles). ODME algorithms applied use truck counts on the network and scaled raw ATRI trip table to represent the proper amount of VMT extracted from iTRAM. The results were analyze to evaluate if there were any biases on geographic regions or trip length. It was found that for Iowa there were no geographic biases but there was evidence of bias towards longer haul trips.

Also, it was found that ATRI's ODME trip table had a smaller RMSE when compared to iTRAM results which indicated that this data can be used to produce a better model than the existed.

3.2.5 Summary

The following FPMs were identified as a result of conducted literature review:

a) Link/path/trip/tour TT (min, hrs.)
b) Link/path/trip/tour TS (km/hr., mi/hr.)
c) Tour characteristics: tour generation, stop generation, stop duration, tour duration, tour completion, stop purpose, stop location, stop time of day choice, number of stops during the tour, number of trips during the tour
d) TT reliability/variability

1. 90th and 95th percentile travel time ($tp_{90\%}$ and $tp_{95\%}$)
2. Buffer index $BI = \frac{tp_{95\%} - \bar{x}}{\bar{x}}$

where $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ - mean travel time; x_i - travel time for the observation *i*; N – number of observations

3. Buffer travel time $BTT = tp_{95\%} - \bar{x}$ (minutes, hours)
4. Planning travel time $PTT = tp_{95\%}$ (minutes, hours)
5. Planning travel time index $PTTI = \frac{tp_{95\%}}{x_{FFS}}$

where x_{FFS} – free flow speed travel time

6. Travel time index $TTI = \frac{x}{x_{FFS}}$
7. Travel time standard deviation $\sigma = \sqrt{\frac{(\sum_{i=1}^{N} x_i - \bar{x})^2}{N-1}}$
8. Travel time coefficient of variation $CV = \frac{\sigma}{\bar{x}}$
9. Travel time range $Range = x_{max} - x_{min}$
10. Ratio of mean travel time to median travel time $r = \frac{\bar{x}}{\hat{x}}$

where $\hat{x}$ - median travel time

e) Total segment delay $TSD = (tp_{95\%} - x_{FFS}) \times V$ (vehicles-minutes)

where V – volume of vehicles at the segment

f) Congested travel $CT = \sum ConLength \times V$ (vehicles-miles)

where $ConLength$ – congested segment length

g) Congested roadway $CR = \sum ConLength$ (miles)

A few studies computed the average travel cost along with FPMs for considered highway corridors. Ando & Taniguchi (Ando & Taniguchi, 2006) estimated the total cost of link TT uncertainty and penalties due to early arrival/delayed arrival to customers, requesting a particular time window. Wheeler & Figliozzi (Wheeler & Figliozzi, 2011) and Sarkar et al. (Sarkar et al., 2011) included TT, cost of traveling, and TT variability into the cost function. Several researches also assessed environmental impacts and emissions, produced by vehicles. Emissions were estimated based on the vehicle travel distance and the vehicle TS (Ando & Taniguchi, 2006; Wheeler & Figliozzi, 2011).

3.3 Truck travel time and its reliability from truck GPS data

In this section, the determination of observed travel time and travel time reliability from truck GPS data is presented.

3.3.1 Determination of travel time and its reliability from truck GPS data

The methodological framework for computing and predicting path-based truck travel time reliability is shown in Figure 3-1. The first task is to collect GPS data for multiple days for the study area. Typical truck GPS data consists of latitude, longitude of the truck, time stamp, speed, and heading (direction). The next task is to attach the GPS data to the network. Following the attachment of GPS data to the network, the succeeding work is to determine the shortest path for each O-D pair and corresponding links associated with the shortest path. O-D represents travel from a specific origin centroid node of the network to a destination centroid node. Shortest path represents the least cost path out of all available paths between an O-D. The shortest path is calculated using free flow travel time. Since the GPS data includes speed of the truck, travel times for each link can be computed. The path travel time is obtained by aggregating the link travel time over the links used in traversing the shortest path. Since travel times will be affected by recurring and non-recurring congestion, travel times need to be separated by each type. Travel time reliability measures for each path can be determined by replicating the procedure and collecting data for multiple days. Reliability measures including but not limited to 95th percentile travel time, standard deviation, and coefficient of variation can be determined for each path. Path based reliability can be helpful in number of ways such as incorporating travel time reliability in travel demand models and short-term travel time predictions.

In this study, travel time reliability is compared for three different travel conditions: ideal, recurring, and non-recurring congestion. Ideal travel conditions consider the free flow travel time and when compared with other conditions help to identify the variations in travel time. Recurring congestion refers to primarily the travel condition mostly associated with roadway network operating at over-capacity. This type of congestion is not affected by external factors such as inclement weather, crash etc. Non-recurring congestion occurs due to construction, severe weather, crashes, and special events. In this study, we only considered crashes as the external factor behind non-recurring congestion. Comparing three different travel conditions will allow us to capture the variability in travel time and identify the O-D pairs, which are mostly affected. Distinction between recurring and non-recurring congestion was made by attaching crash, weather, and special event data from TDOT.

3.3.2 Panel data approach to model travel time reliability for recurring and non-recurring congestion

The development of prediction model for path based travel time reliability demands a collection of travel time data to observe its distribution over a period. As the approach is path based, the identification of origin destination pairs and the shortest path is the first step. Then the multiple observations of travel time across different links in a path provides an opportunity to study the reliability. For this, the proposed methodology is applied in Shelby County, Tennessee.

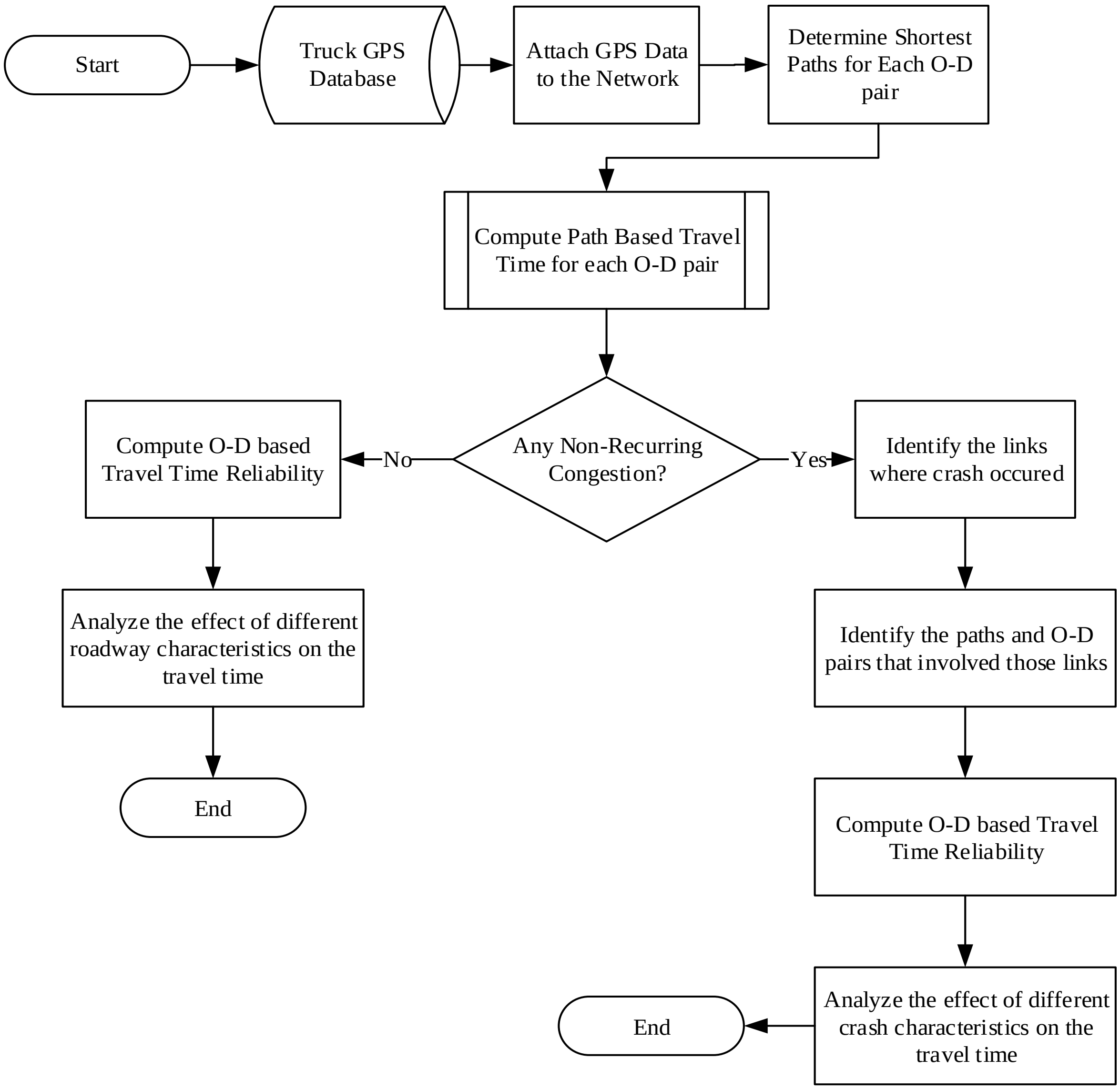


Figure 3-1. Methodological framework for computing and predicting truck travel time reliability

The centroid of each census tracts, in Shelby County, snapped to the nearest point in FAF network gave us 53,361 (221 x 221) O-D pairs. The observations of truck GPS data are attached to the FAF network and the travel time of each link is computed from speed measurement. The shortest path for each O-D pair is found using the code explained above in methodology section. Different data like crash, freeway traffic, and roadway network data has been obtained from different organization and system. The reliability measure, standard deviation, is computed from the observed datasets for multiple days over a same path. After collection of travel time distribution of multiple paths, the modelling can be done to compute the travel time reliability in ideal, recurring, and non-recurring scenarios.

3.4 Case study

Figure 3-2 shows the zones, FAF network, and truck GPS data for one day. Shelby is the most dense and populous county in TN and encompass five class I railroad terminals, and FedEx world headquarters. It also consists of one of the major freight travelled corridor (Lamar Corridor, US 72) in the country.

- Crash data: Four years (2011-2014) of crash data, from the Tennessee Roadway Information Management System (TRIMS), a total of 89,705 crashes. It also provides roadway and traffic characteristics.
- Freeway Traffic Data: Lane specific traffic data.
- Roadway Network: A detailed transportation network of Shelby County containing 282 miles of freeways was available from TDOT.

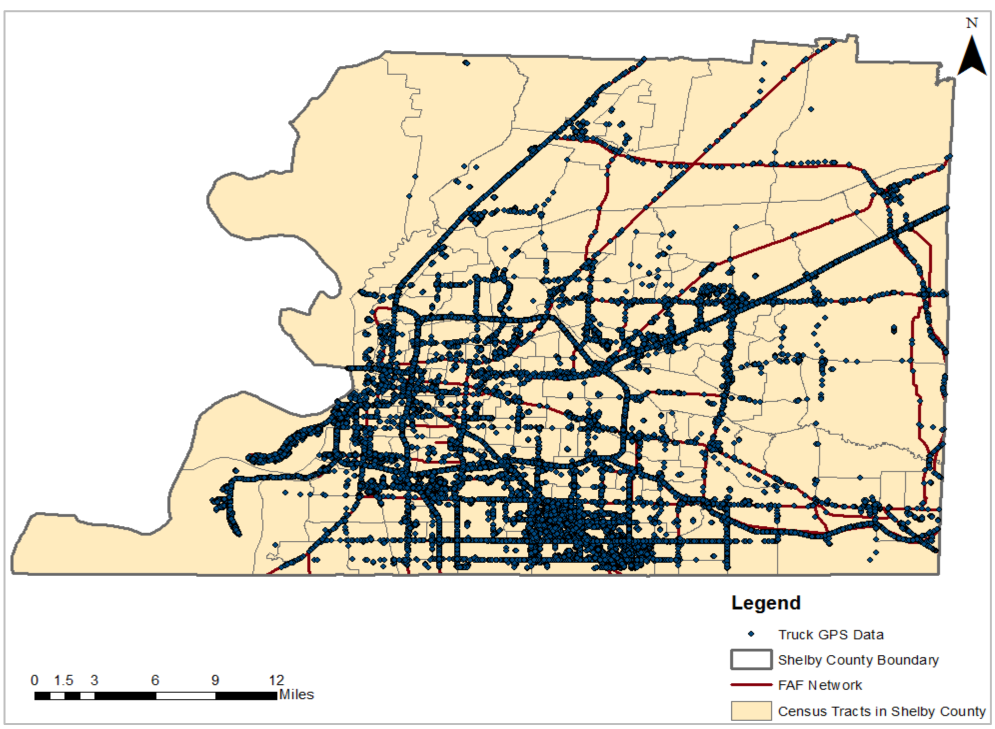


Figure 3-2. Shelby County with its census tracts, FAF network, and truck GPS data for June 10, 2014

3.4.1 Travel time variation vs Volume to Capacity Ratio (VCR)

Figure 3-3 explains the effect of volume, for a given road, in the travel time variation. The variation is shown for four different time periods which are AM peak (6-10 am), PM peak (4-8 pm), off peak hours (rest of time) and overall day. The average travel time for a trip increases proportionally with increment in VCR and so is the case for travel time variation and VCR. For the same volume to capacity ratio (VCR), the variation of TT is maximum in PM peak hours while minimum in off peak hours due to congestion. Hence, from the case study, it has been observed that the delay in PM peak hours is more than AM peak hours for recurring congestion. The overall TT variation lies between AM and off-peak hours' TT variation. The interesting fact is that the overall and PM peak travel time variation suddenly increases at 75% VCR and slightly decreases until 78% before increasing smoothly afterwards. The reason behind this may be the congestion state of path is critical at 0.75 VCR and travel time varies highly at this point, mostly in PM peak period.

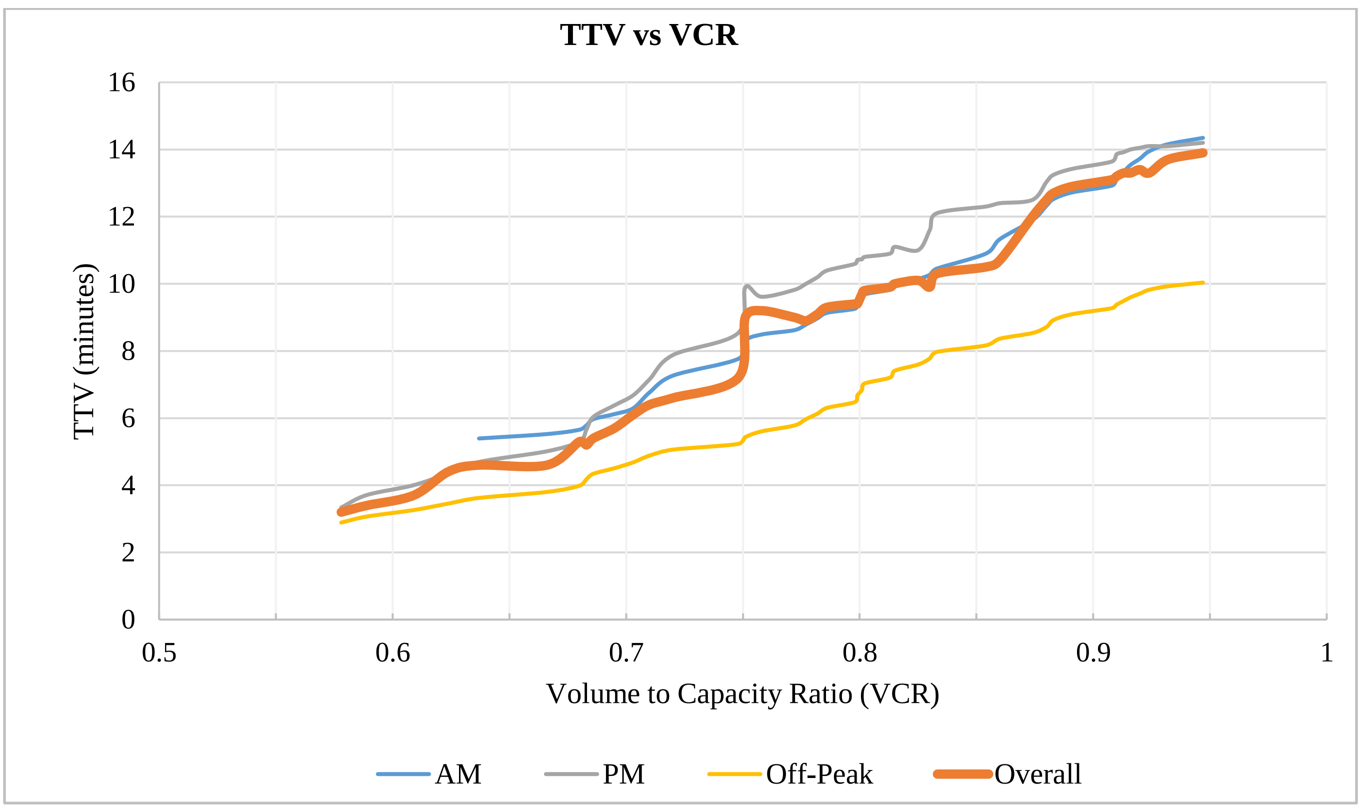


Figure 3-3. Travel Time Variation (TTV) with Volume to Capacity Ratio (VCR)

3.4.2 *Travel Time Variation (TTV) vs Arterial road composition*

In Figure 3-4, the solid curve depicts the actual variation in TT while the dotted line is the fitted line, which increases exponentially with the increment in composition of arterials. The increment in the slope of the curve is more in later half of the plot. The higher slope exponential curve justifies the result of model explaining the higher correlation between the TT variation and composition of arterials in the path. As the arterial segments are high capacity urban roads with higher traffic, the delay in TT increases with the increment in composition of arterials in the path between O-D pairs.

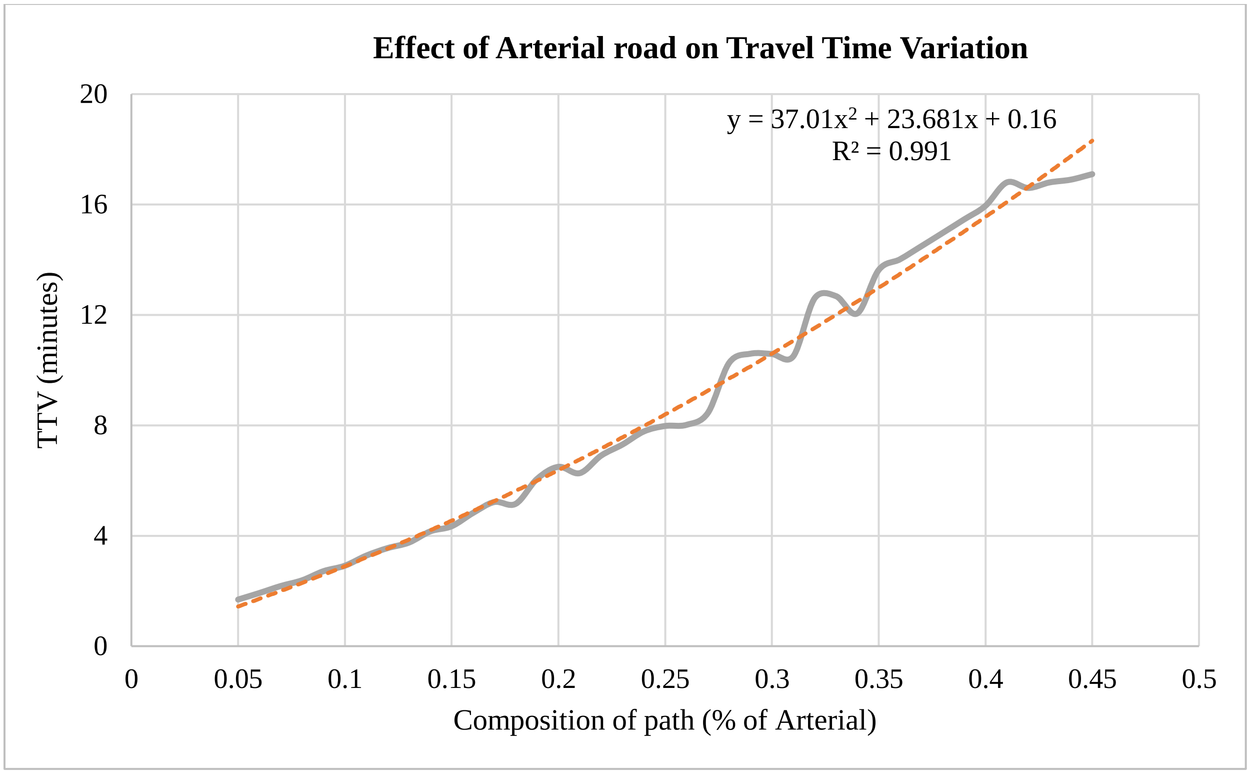


Figure 3-4. Travel Time Variation (TTV) with composition of Arterial road

3.4.3 *Travel Time Variation (TTV) vs time of day*

In Figure 3-5, the blue solid and red curves represent the variation in travel time with time of day for non-recurring and recurring congestion respectively. The recurring congestion, mainly due to capacity & behavioral issues, and non-recurring, mainly incidents causing unexpected congestion, both differs with time of day. While they are almost similar at morning off-peak hours (2-6 am), variation in TT due to non-recurring congestion is higher at all remaining periods. Both the curves have two unequal peaks, coming almost at the same time, the higher one at am peak (10 am) while the lower at pm peak (6 pm). This may be due to the heavy commuters and school travel time falling all in same time frame in AM while giving more time frame for return at PM. Hence, the reliability is lesser in AM peak hours for both RC and NRC.

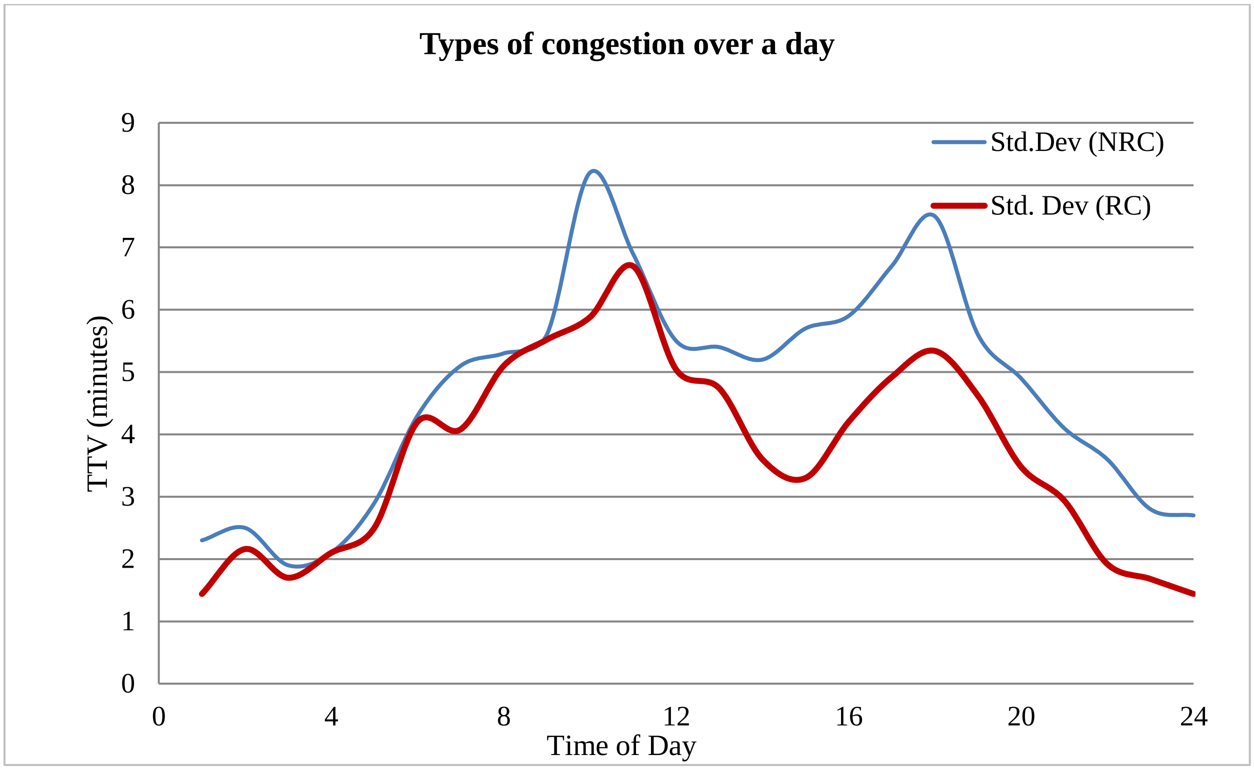


Figure 3-5. Travel Time Variation (TTV) over time of day with congestion types

3.4.4 Travel Time (TT) vs trip length

Figure 3-6 presents the scenario of severity of crash on non-recurring congestion. Each point on the graph represents average path travel times. Among 103 crashes occurring on FAF network in Shelby County, 82 were property damage only (PDO), 19 resulted in some injury while only two crashes were of severe injury with no fatal crashes. If a segment is included in multiple O-D pairs, a single crash in that segment affects all the paths. In the graph, it can be observed that the severe injury crash has significant effect on travel time as compared to injury crash and so does the injury as compared to PDO for same trip length. It is found that, 63% of the time a crash involving injury would increase the travel time significantly compared to PDO. Together with the effect of severity of crash, number of vehicles involved, incident type, clearance time etc. also affect the travel time, which is clear from the graph as the travel time is different for same trip length and same injury type. The succeeding graph of Figure 3-7 explains the relation of travel time with trip length for different number of vehicles involved in the crash. For the crash involving two or more vehicles, the linear relationship between travel time and trip length can be figured out but there exists a random relationship for crash with one vehicle. Unlike the graph with crash severity, the specific inference cannot be made from this graph.

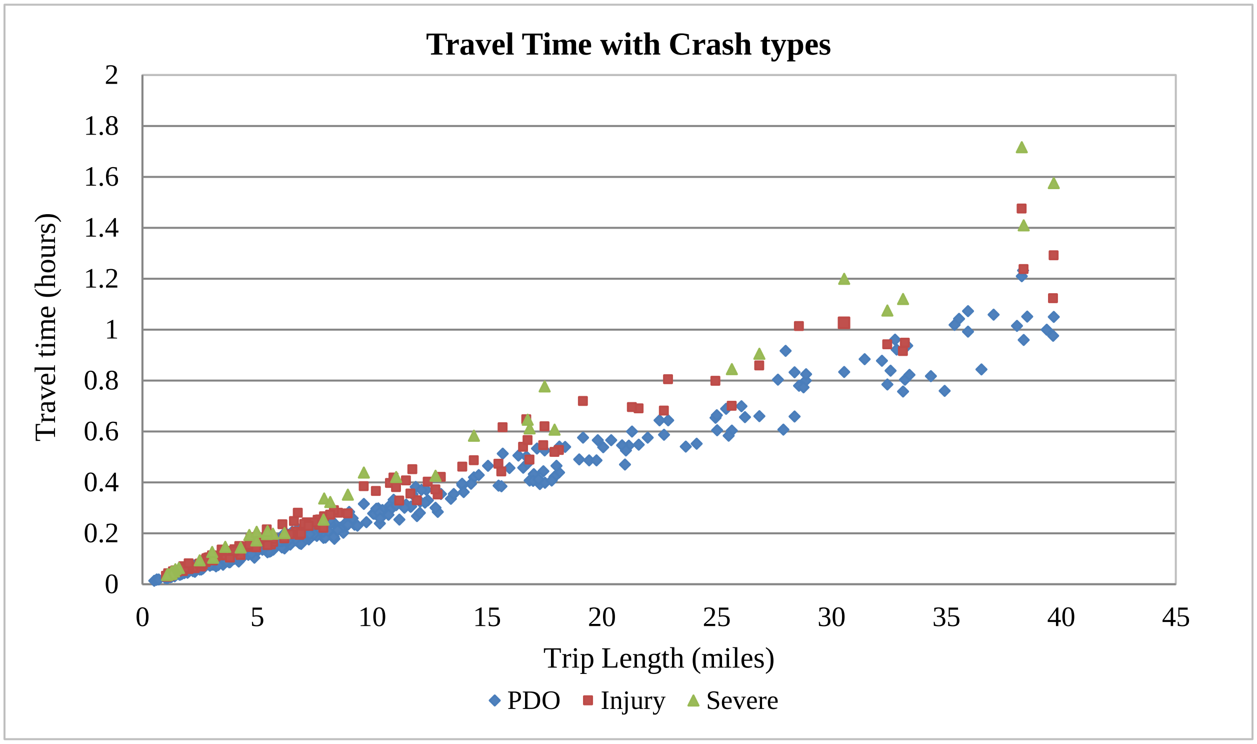


Figure 3-6. Travel Time (TT) with trip length and crash types

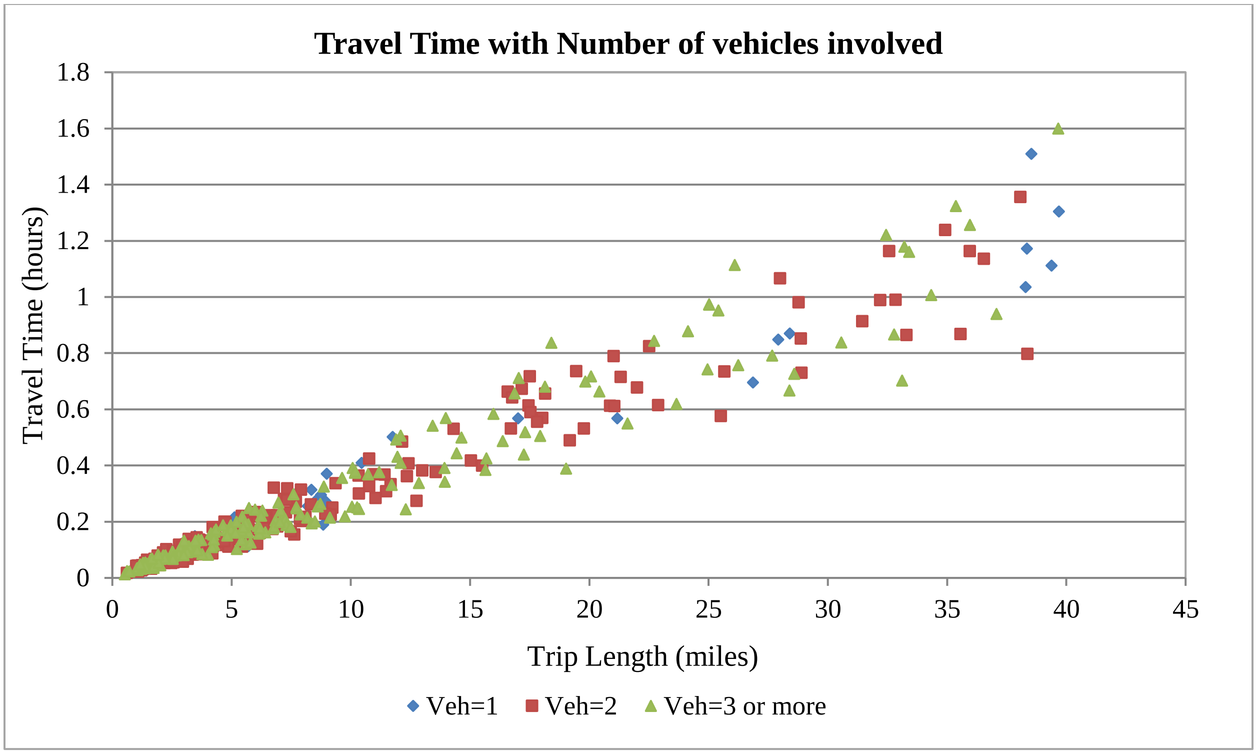


Figure 3-7. Travel Time (TT) with trip length and number of vehicles involved in crashes

3.5 Conclusion

This chapter presents the correlation of travel time and its reliability (inverse of standard deviation of travel time) with different factors. The use of truck GPS data has yielded a lot of information about the travel time reliability in freight network. The reliability of travel time is inversely proportional to volume to capacity ratio (VCR) i.e. travel time is less reliable for higher VCR and vice versa. Also travel time is less reliable in pm peak than am peak period for same VCR which highlights the fact of increment in freight economy if peak periods especially the pm peak can be escaped. The exclusion of arterials in the freight network together with increment in broader and rural roads increases the freight reliability. The travel time variation (TTV) across the hours of day (Figure 3-5) shows two peaks indicating the more variation of travel time (less reliability) during am and pm peak hours with off peak hours being the most reliable. Also, the variation pattern is similar for both recurring and non-recurring congestion with higher index in case of non-recurring congestion thereby highlighting the importance of unexpected congestion compared to regular congestion. We can expect the similar figure for travel time as it is reflected in case of travel time variation. More than the roadway characteristics, the crash characteristics (non-recurring congestion) plays a significant role in travel time reliability.

The observation of travel time distribution with the length of the path for a given crash severity (Figure 3-6) show a direct relationship of travel time with increasing severity of the crashes. However such kind of trend was not observed in case of number of vehicles involved in the crash highlighting that the severity and type of crash (angle, side swipe, etc.) are more important and decide the travel time of the path rather than the number of vehicles (Figure 3-7). For example, a fatal crash with only one vehicle may increase the travel time more than a PDO crash with two vehicles involved, for a same path.

Although the case study is done in Shelby County, the result can be implemented in other area with similar freight characteristics. Since there is very less research in travel time reliability using panel data, future research can be done by incorporating this data for the development of various static and dynamic prediction models. As human behavior is an important parameter in transportation model, development of model including behavioral attributes of human (drivers) would be more realistic. In addition, recurring congestion is something we know more about, research in travel time reliability for non-recurring congestion with work zone and severe weather condition can also be a direction for future work.

CHAPTER 4: LAND USE AND FREIGHT

4.1 Introduction

Land-use policies govern the types of developments that can be placed on parcels of land thus controlling the locations of the origins and destinations of freight movements. Freight facilities are in many cases very disruptive in terms of noise and impact on infrastructure therefore it is important to consider the land use of the areas surrounding freight facilities (Hartshorn & Lamm, 2012). In order to make land use plans for growth, it is necessary to consider current freight flows and project them to a future year. The issue in this regard is connecting the flows of commodities to freight producing and freight attracting facilities.

Transportation planning models typically consider amount of freight produced and attracted. Then using trip distribution models, trips produced and attracted used to develop freight origin-destination matrices. However, many planning models use total trip O-D matrices. However, with availability of truck GPS data and land use properties it would be possible to obtain some insights to what commodity is carried by the truck. There are two approaches when the goal is to obtain commodity-based O-D matrices. The *first* approach is use the truck GPS data and associate it with the land uses to find what commodity the truck is carrying and then based on the truck trajectory it will be possible to find commodity-based O-D matrices. However, there are manifold disadvantages of this approach. Typically, GPS data represents a small sample of total truck travel. Conversion of sample to population requires expansion factors. Developing such expansion requires multiple assumptions. Even though a truck is travelling a specific land use location it may carry a different commodity for pick-up and delivery. The *second* approach is to use truck trip generation factors to develop commodity specific productions and attractions, and then use truck GPS data to obtain O-D travel time matrix. Using the GPS based travel times it would be possible to use gravity or other trip distribution models to obtain commodity specific O-D truck trip tables. In this study we used the second approach. The next section discusses case studies on various methods used for freight and land use planning, followed by a tool that was developed to obtain commodity specific O-D matrices for Jackson MPO.

4.2 Methods for freight and land use planning: literature review

Freight generation can bring increased employment, increased tax revenue, and increased economic output to communities, but freight requires transportation which is why many localities are creating land-use plans that consider the transportation needs of freight generating land-uses (Hartshorn & Lamm, 2012). Facilities that generate freight need access to the transportation network which has multiple implications ranging from ramps to intersections with adequate clearance for truck turning radii. Equally important is that freight facilities need the ability to expand and grow with the increased freight demand of the community. Failure to protect the area around freight facilities can lead to the sites being land-locked by urbanization and incapable of keeping in tune with growing demand as is the case for the Radnor railyard near Nashville TN (Farmer, 2016). The impacts of freight facilities and growing freight demand extend beyond the areas near the facilities because the roadways must have adequate capacity to handle the truck traffic. Failure to consider that freight facilities will generate more truck traffic will lead to passenger cars and trucks competing for use of the roadways thus creating congestion (Hartshorn & Lamm, 2012). A secondary effect will be that the region will be unattractive to developers because of the transportation issues.

A study on Urban Freight Transport by the European Commission (Allen, Thorne, & Browne, 2007) reviewed the practices of urban transport planning and found four key measures: (1) zoning of retail and logistics activities, (2) develop off-street loading, (3) safeguarding rail and water accessible sites, and (4) require large distribution sites to be rail and water accessible. Zoning of retail and logistics activities for critical mass minimizes the need for transport as the goods are located at critical mass. Developing off-street loading and unloading is very beneficial for removing congestion in urban areas. Safeguarding rail and water accessible sites is beneficial for future growth. Requiring large distribution sites to be rail and water accessible is an easy way to promote freight diversion. Table 4-1 shows a list of cities that have adopted freight and land use plans to alleviate issues using many of the same measures as the study by the European Commission (Allen et al., 2007) and the FHWA Handbook (Hartshorn & Lamm, 2012).

Table 4-1. List of cities with integrated freight and land use plans

Locality and Program Name	Description of Issues	Recommendations/Solutions
Chicago Industrial Corridor and Planned Manufacturing District (City of Chicago, 2016)	• Conversion of industrial buildings into residential created patchwork zoning	• Designated industrial corridors • Used zoning as a tool to preserve industrial land use • Establish truck routes
Atlanta Regional Freight Mobility Plan (Atlanta Freight, 2008)	• Freight activities are sprawled	• Develop distribution facilities in transportation corridors • Seek coexistence of freight and non-freight land uses
City of Seattle Urban Mobility Plan (Switalski et al., 2009)	• Need to ensure economic vitality • Need to ensure accessibility	• Incentivizes properties in goods movement through tax relief • Unattended delivery systems • Retail delivery stations • Off-street truck loading areas • Reserve some on-street parking for commercial vehicles
Morris County Freight Infrastructure and Land Use Analysis (MCDOT, 2011)	• Projected substantial growth in truck traffic • Limited land supply for industrial use	• Develop truck route system • Enhance truck access • Promote development around rail

Locality and Program Name	Description of Issues	Recommendations/Solutions
Frederick County Freight Dependent Land Use Plan (Systematics, 2011)	• Quickly growing population • Continued growth would place more demand on congested transportation system	• Promote industrial corridors and zoning • Explore rail-access funding for adjacent properties
Alameda County (Systematics, 2014)	• Limited supply of land in Bay Area • Pressure to convert industrial land to other uses • Aged infrastructure for goods movement	• Implement land use policies to protect industrial use • Minimize off-site impacts in areas surrounding industrial use • Ensure new sites have adequate access
Michigan Department of Transportation Land Use Technical Report (MDOT, 2006)	• Economic activity hindered by land use patterns	• Co-locate supply chain partners in an industrial region • Brownfield redevelopment of industrial areas • Locate service establishments in commercial districts
Monarto South Intermodal and Land Use Study (City of Monarto, 2008)	• Need to assess viability of intermodal transportation hub and airport	• Locate intermodal facilities adjacent to existing rail and protect land use

Locality and Program Name	Description of Issues	Recommendations/Solutions
		• Reserve land in strategic areas for industrial use
Greater Shepparton Freight and Land Use Study (Greater Shepparton Council, 2013)	• Central business district located on major gateways into Shepparton • Industrial facilities are located along major gateways	• Identify routes suitable for trucks • Advocate inland rail route • Provide incentives for freight generators to relocate

4.3 Methods for estimating freight flows

The methods for estimating freight flows focus on synthesizing origin-destination matrices from different sources of data. The four major sources of data are: (1) surveys, (2) truck GPS, (3) waybills, and (4) facility demographics. Most of the methods rely heavily upon observed truck counts in order to properly calibrate or scale the resulting truck trips.

Surveys are typically used to collect a sample of the freight trips via roadside interviews which are then scaled to represent the population of freight trips. Park and Smith (Park & Smith Jr, 1997) used truck origin-destination survey data along with link counts to better inform a gravity model in the estimation of truck trips.

Truck GPS data is used in a similar fashion as surveys where data is collected on a sample of trucks and then scaled. Zanjani et al. (Zanjani et al., 2015) used truck GPS data from the American Transportation Research Institute (ATRI) along with observed truck flows to estimate truck trips for the state of Florida. The procedure estimates the penetration rate of the truck GPS sample and uses the rate to scale the trips from the GPS sample.

Waybills differ from the other sources of data in that the focus is on the movement of individual commodities. Waybills detail the volume of a commodity that is transported from an origin to a destination, but they do not indicate number of trucks used in the transportation of the commodity. Zargari and Hamedani (Zargari & Hamedani, 2006) proposed a method to generate truck origin-destination matrices using waybill data and link counts. The method estimates the average weight of loaded trucks and the percentage of empty trucks to convert the commodity flows to truck flows.

Facility demographics represent the size, employment and industry sector of freight facilities. Iding et al. (Iding, Meester, & Tavasszy, 2002) proposed a method to use facility demographics to estimate truck trip productions and attractions by facility based upon employment. Lawson et al. (Lawson et al., 2012) analyzed the effects of land use and business size (quantified as number of employees) on freight trip generation in 2012. They implemented standard trip generation rates, ordinary least squares, and multiple classification analysis to a New York City data set specifically Manhattan and Brooklyn by use of three land use classification codes: the City of New York zoning resolution (NYCZR) which was developed in 1916 and is updated regularly, the Land Based Classification Standards (LBCS) which was developed by FHWA in partnership with the American Planning Association, and the Institute of Transportation Engineers (ITE) manual. These systems provide the basis to analyze the effects of land use on FTG (Freight Trip Generation) (Lawson et al., 2012).

The authors developed models for NYCZR and function and activity of LBCS and used the ITE manual's trip rates. Root mean square error analysis was used to compare the performance of these models. It was found that models for NYCZR and LBCS land use classification codes provide better alternatives to ITE trip rates because they give more accurate estimates of freight trip attraction, cover a wider range of land use classifications, and are exclusively for freight trip attraction (Lawson et al., 2012). Primarily this section uses data from three sources: (1) truck GPS data for estimating travel time between zones, (2) LEHD data for employment, and (3) NCFRP 37 report for trip rates for various industry classifications.

4.4 Development of GPS tools for freight flows estimation

NCFRP Research Report 37 based on Commodity Flow Survey is used to develop various GPS tools in order to estimate the generation of freight and freight trips. Four major tools developed for this task are ODM-Estimation, LEHD-Census-to-TAZ Tool, Freight Generation Tool, and Gravity-Model Tool. Each tool is described in detail as follows:

OD-matrix estimation tool

This section presents a step-by-step example of how to use the developed ArcGIS application.

EXAMPLE INPUTS

Following shapefiles were used in executing freight generation example (see Figure 4-1):

- **Example_GPS_Data.shp** – Shapefile containing vehicle GPS data points of vehicle.
- **Example_Network.shp** – Shapefile containing polygon shapes with unique zone identifier field.

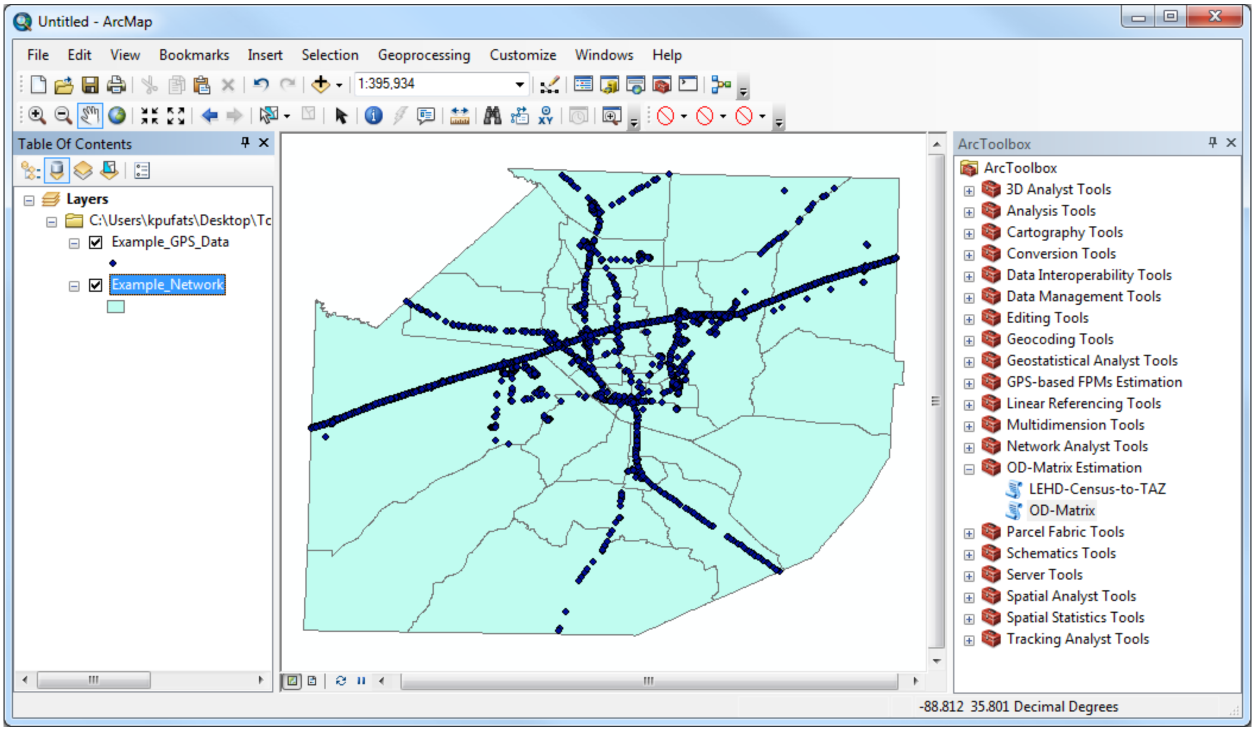


Figure 4-1. Example inputs

STEP 1

Open newly added OD-Matrix Estimation toolbox and lunch OD-Matrix function (see Figure 4-2).

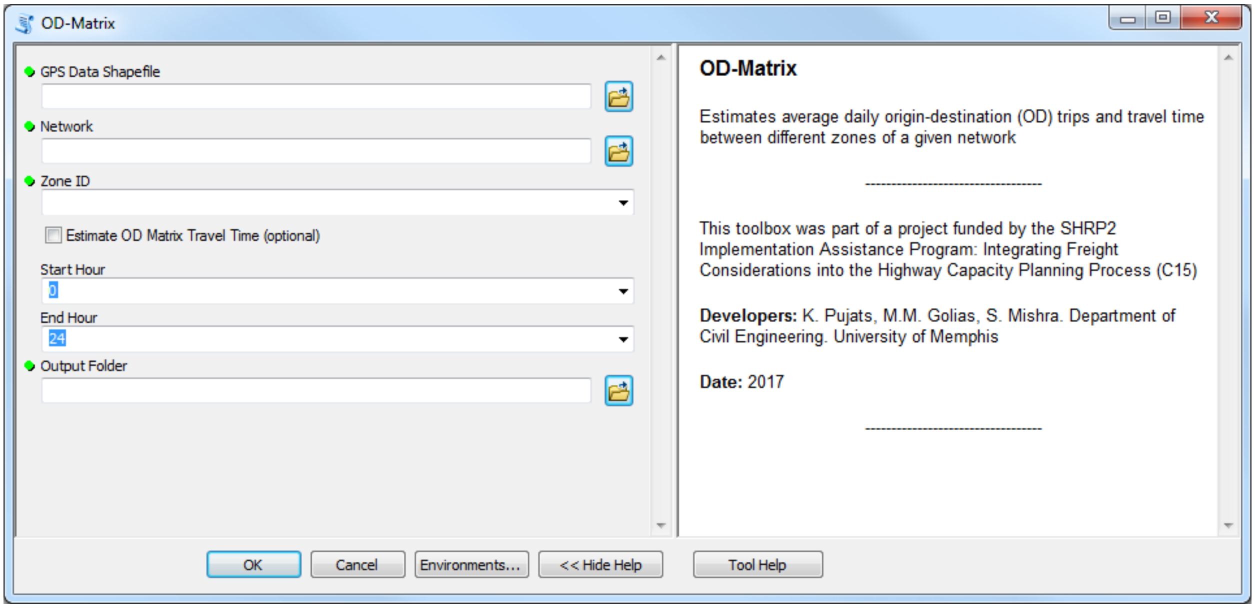


Figure 4-2. OD-matrix function

STEP 2

Input path to GPS data shapefile into OD-Matrix first input parameter GPS Data Shapefile (see Figure 4-3).

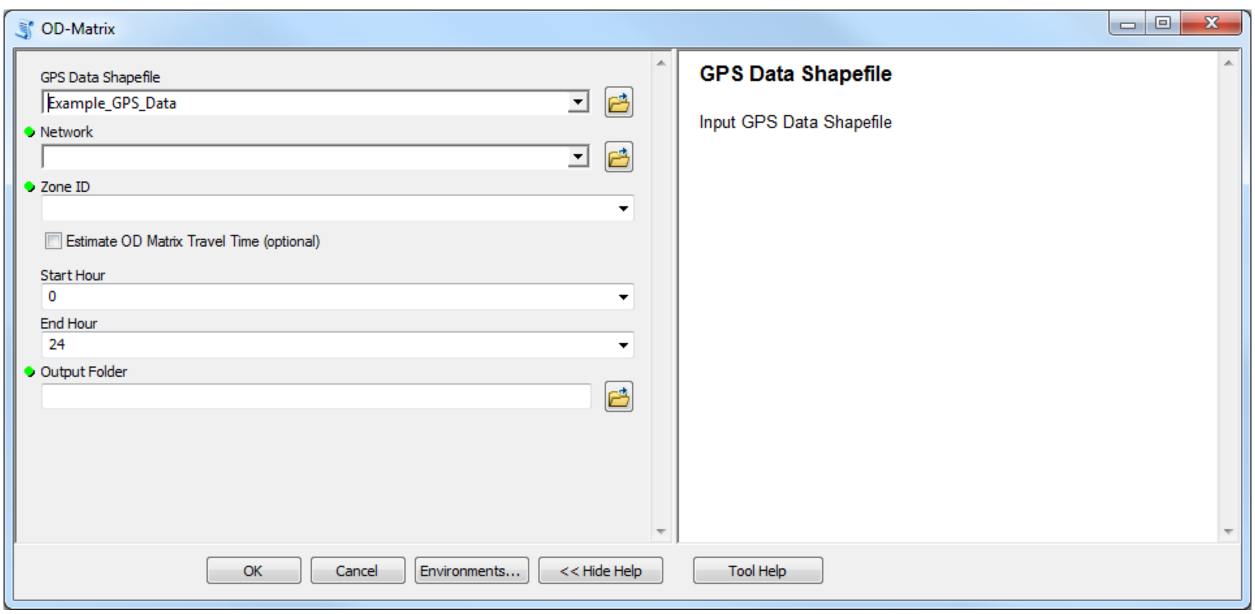


Figure 4-3. Input GPS data shapefile

STEP 3

Input path to Network of Traffic Analysis Zones (TAZ) shapefile into OD-Matrix second input parameter Network (see Figure 4-4).

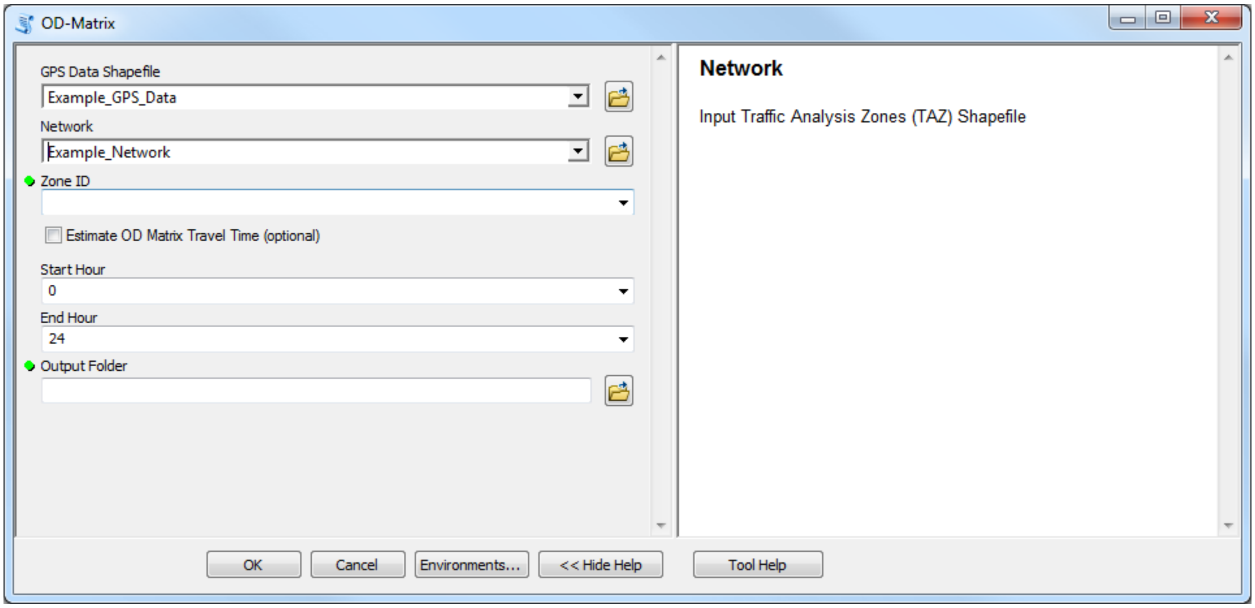


Figure 4-4. Input Traffic Analysis Zones (TAZ) shapefile

STEP 4

Select unique zone identifier field from input parameter Zone ID (see Figure 4-5).

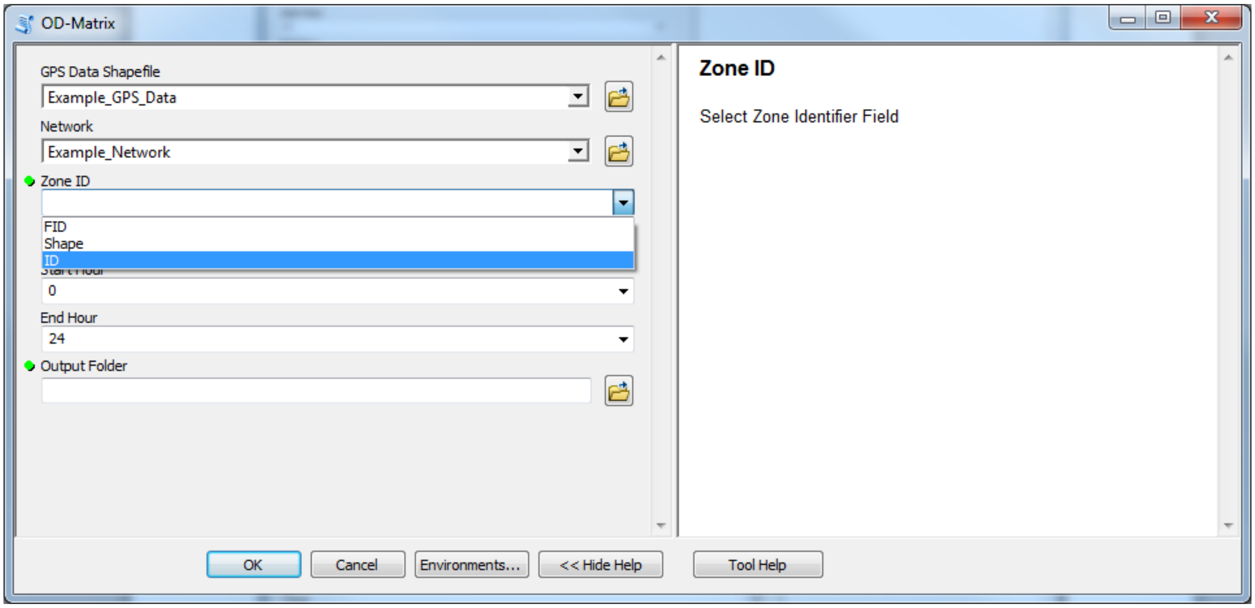


Figure 4-5. Select Zone Identifier field

STEP 5 (optional)

Select option Estimate OD Matrix Travel Time if user wishes to estimate OD Matrix by average travel time between TAZs (see Figure 4-6).

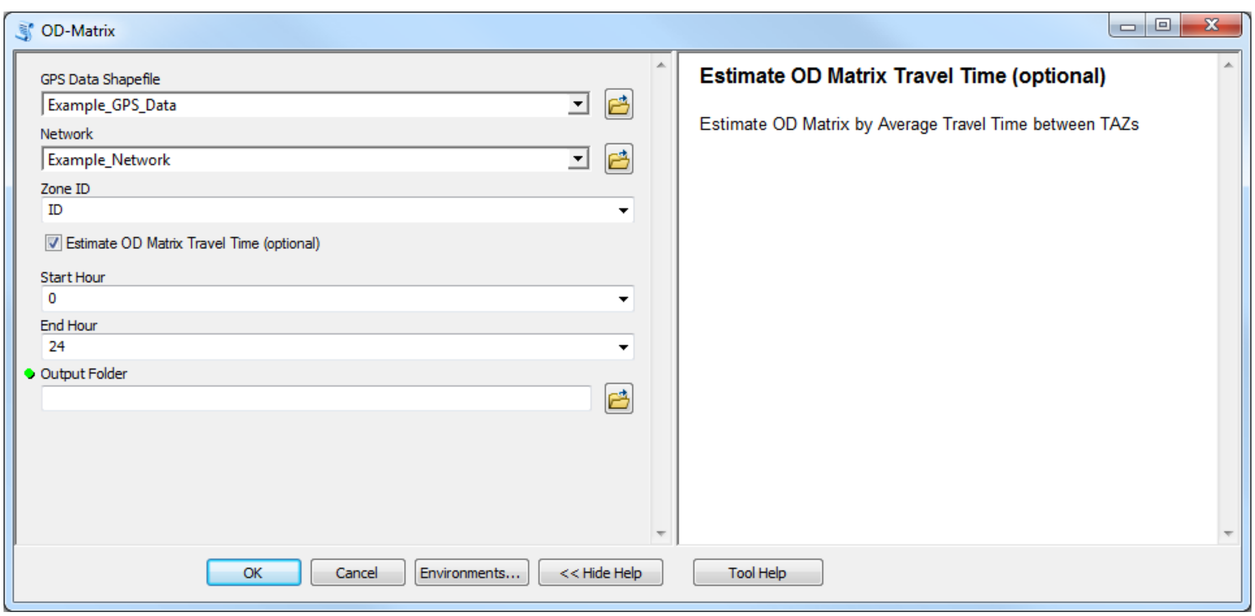


Figure 4-6. Estimate OD matrix travel time

STEP 6

Select start hour value to be analyzed, ranging from 0 to 24 in toolbox third input parameters Start Hour from drop down list (see Figure 4-7). *(A default value 0 will be set as input parameter.)*

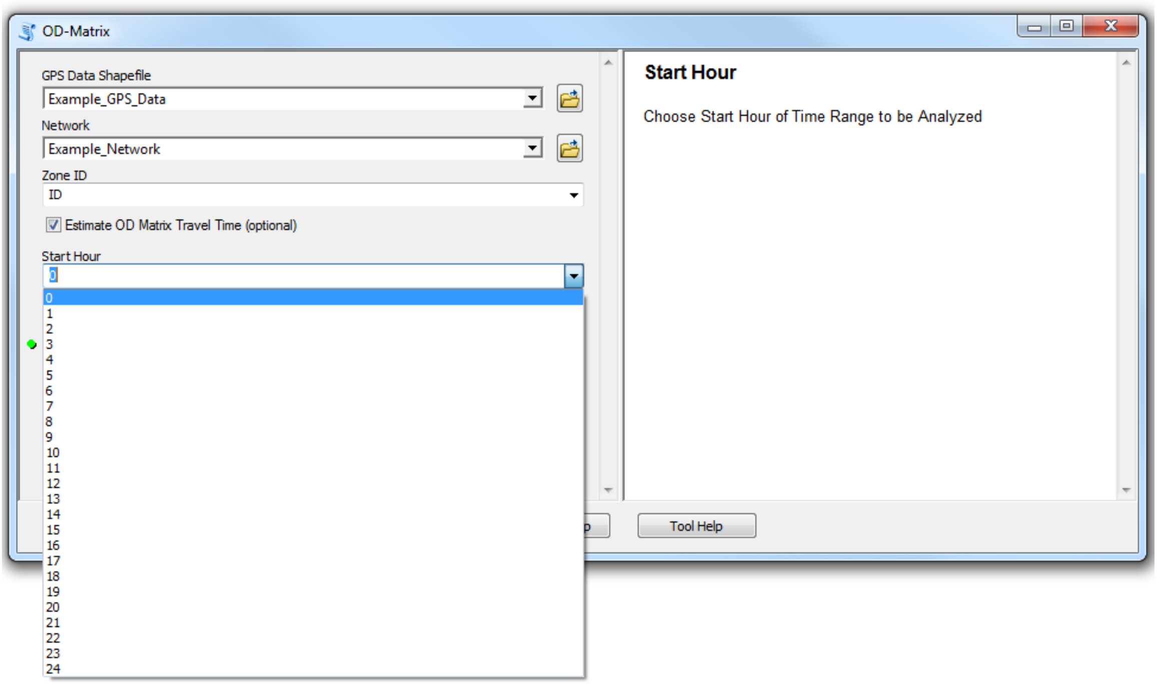


Figure 4-7. Select Start Hour

STEP 7

Select end hour value to be analyzed, ranging from 0 to 24 in toolbox input parameters End Hour drop down list (see Figure 4-8). *(A default value of 24 will be set as input parameter.)*

(Parameters End Hour input value has to be greater than Start Hour value. If a range of hours are given that does not exist in GPS point data file, closest existing hour value will be chosen to analyze the data.)

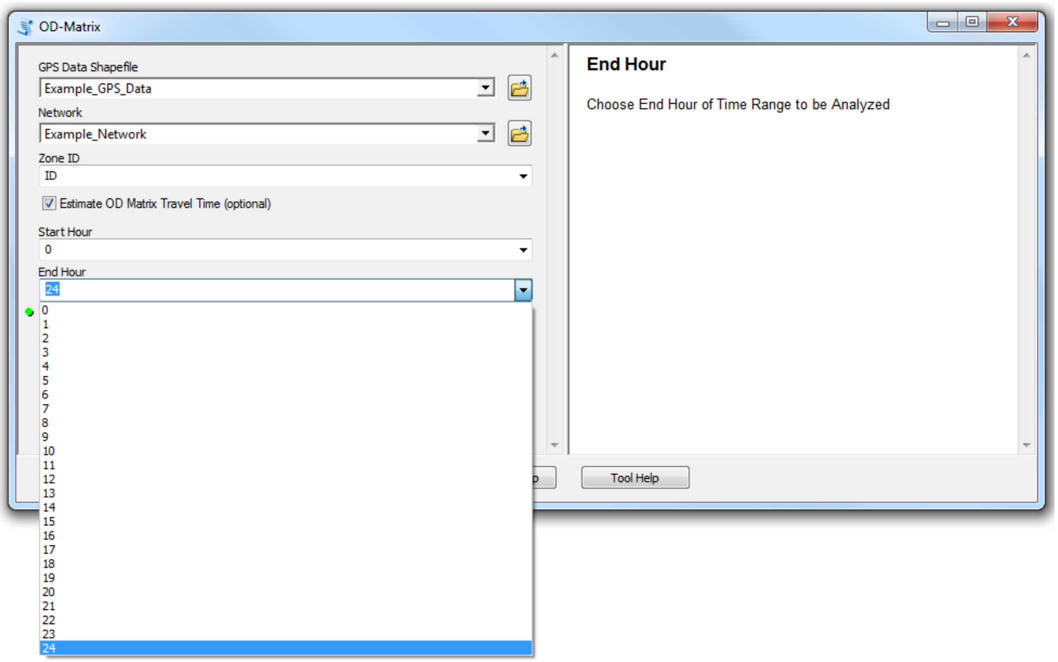


Figure 4-8. Select End Hour

STEP 7

In toolbox Output Folder parameter input output folder path where processed shapefiles will be exported after toolbox analysis (see Figure 4-9).

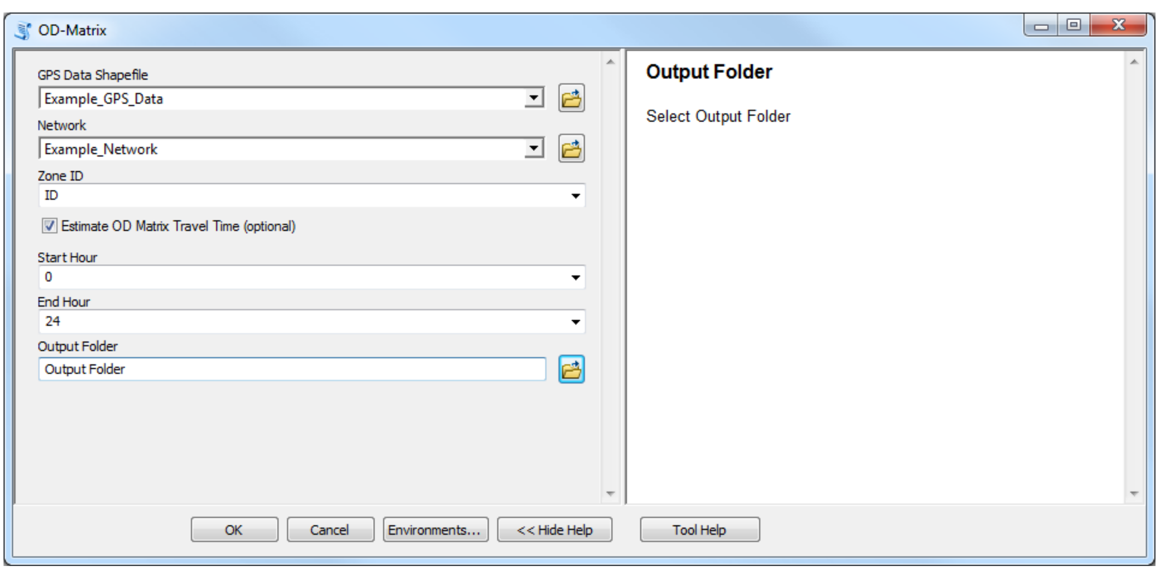


Figure 4-9. Input Output Folder

STEP 8

Once all required parameters are inputted, press OK to execute the application. The ArcGIS application invokes a task completion window, which reports status of each task (see Figure 4-10). In addition, processed shapefiles will be imported to ArcMap Display (see Figure 4-11).

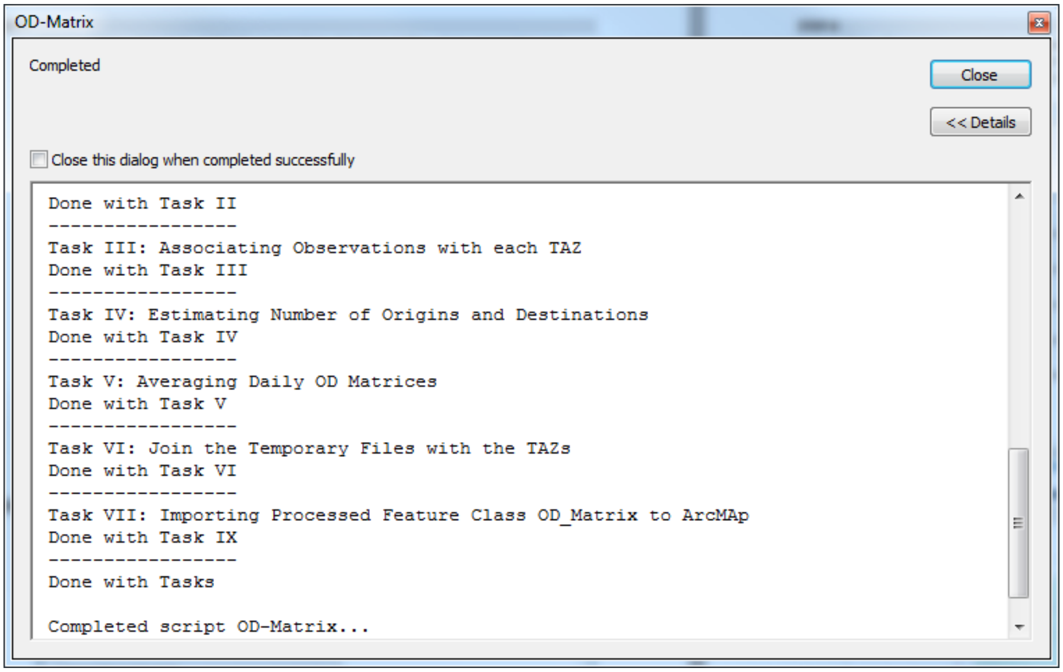


Figure 4-10. Application performed task window

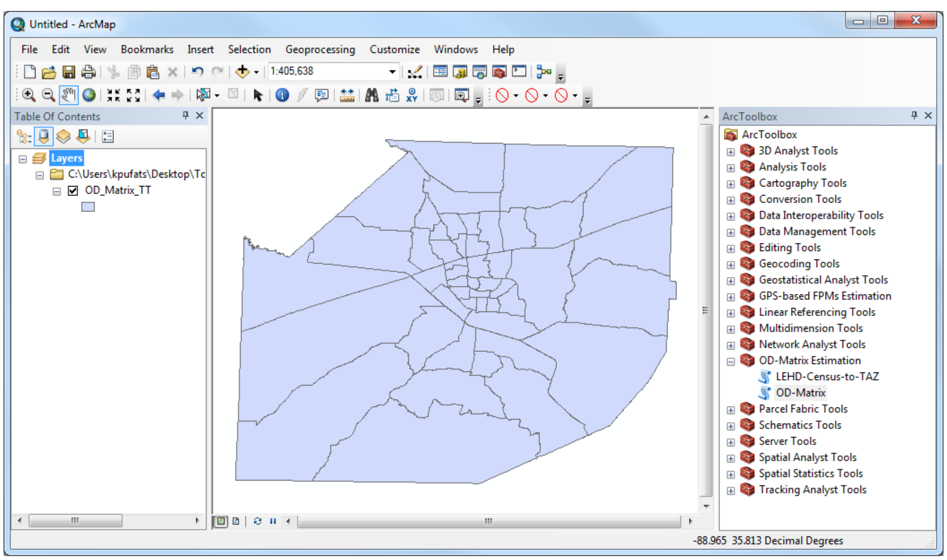


Figure 4-11. Displayed processed shapefile

LEHD-Census-to-TAZ tool

This section presents a step-by-step example of how to use the developed ArcGIS application.

EXAMPLE INPUTS

Following shapefiles were used in executing freight generation example (see Figure 4-12):

- **Example_Census_Network.shp** – Shapefile containing Census Blocks.
- **Example_TAZ_Network.shp** – Shapefile containing Traffic Analysis Zones.
- **LEHD_Table.csv**– Table containing Longitudinal Employer-Household Dynamics (LEHD) Data.

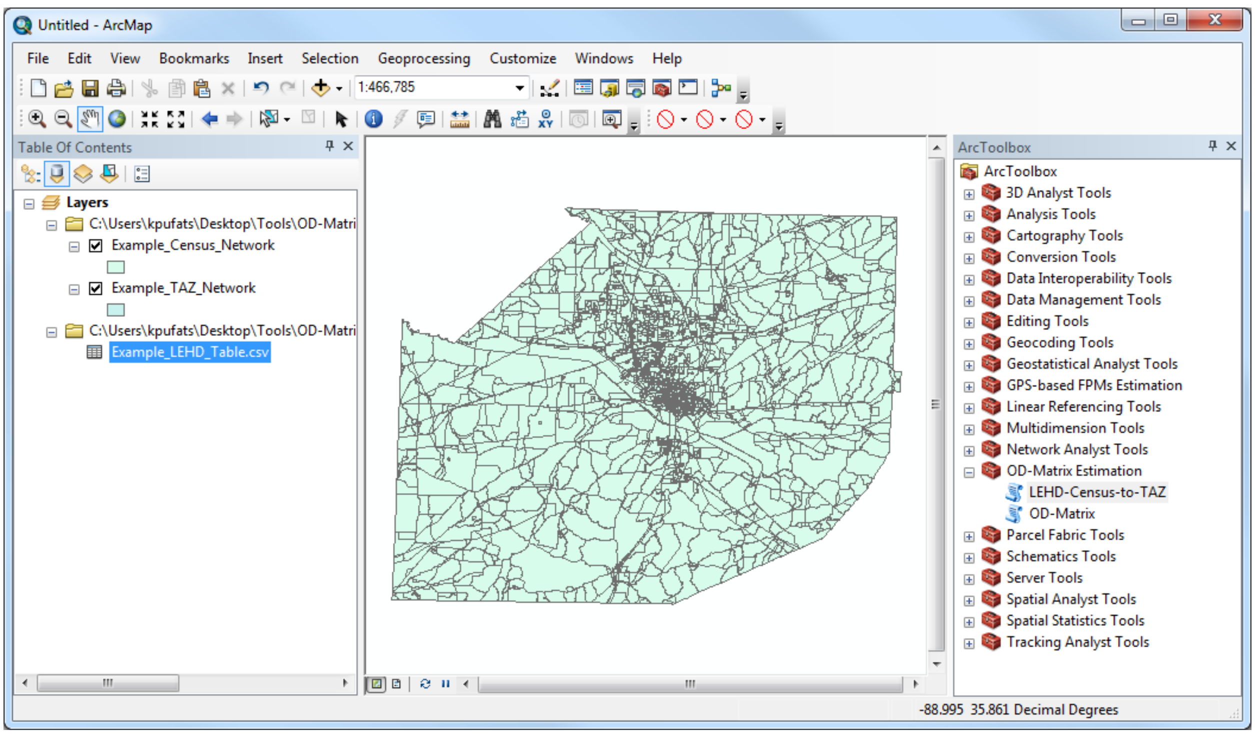


Figure 4-12. Example inputs

STEP 1

Open newly added OD-Matrix Estimation toolbox and lunch LEHD-Census-to-TAZ function (see Figure 4-13).

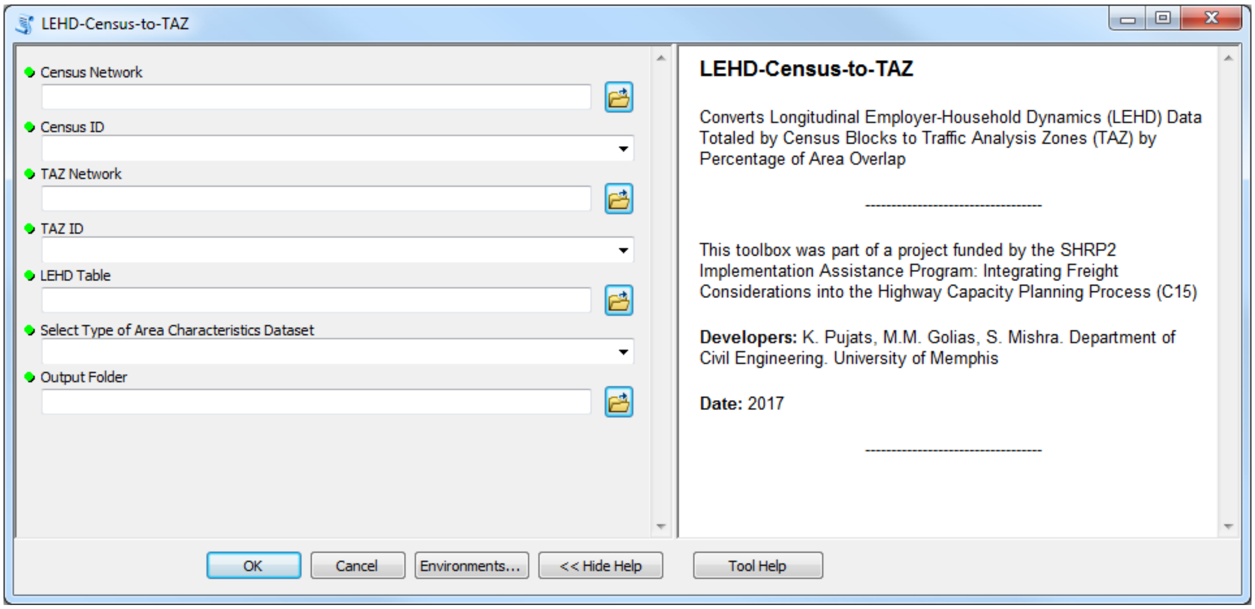


Figure 4-13. LEHD-Census-to-TAZ function

STEP 2

Input path to Network of Census Block shapefile into LEHD-Census-to-TAZ second input parameter Census Network (see Figure 4-14).

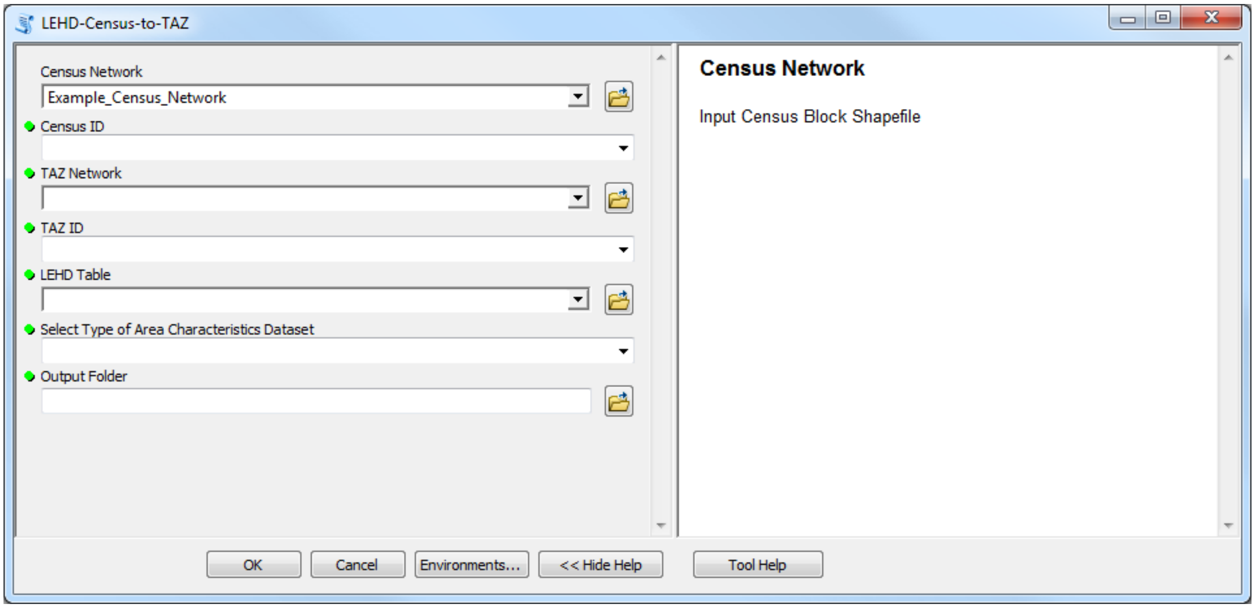


Figure 4-14. Input Census Block shapefile

STEP 3

Select unique Census Block attribute field identifier from input parameter Census ID (see Figure 4-15).

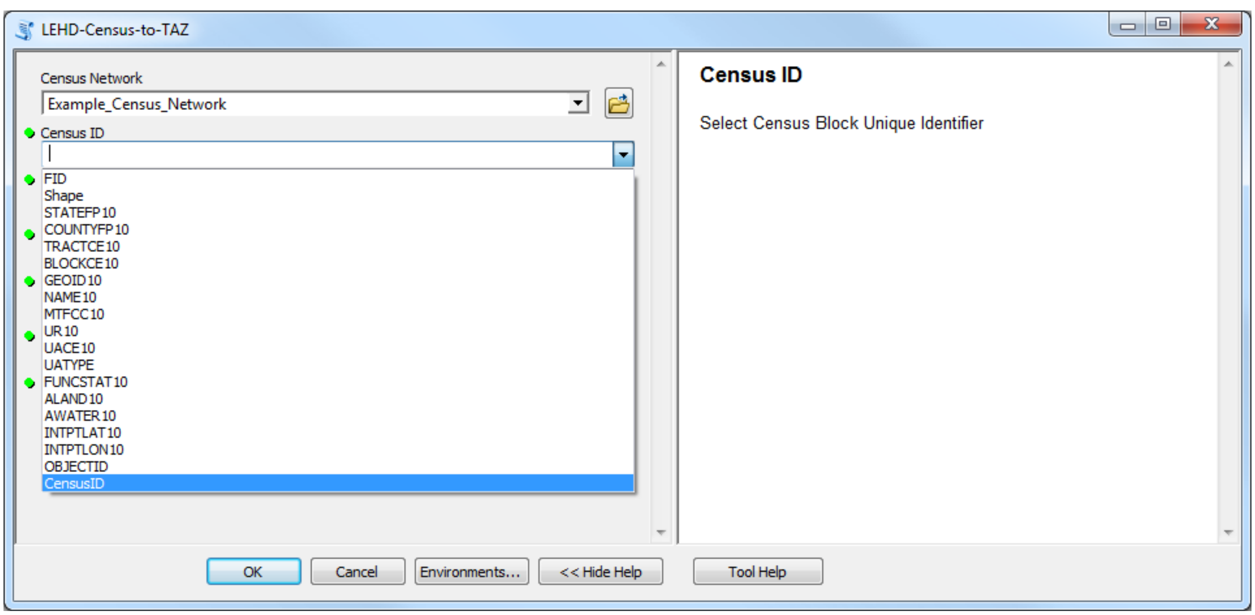


Figure 4-15. Select Census Block Unique Identifier

STEP 4

Input path to Network of Traffic Analysis Zones (TAZ) shapefile into LEHD-Census-to-TAZ input parameter TAZ Network (see Figure 4-16).

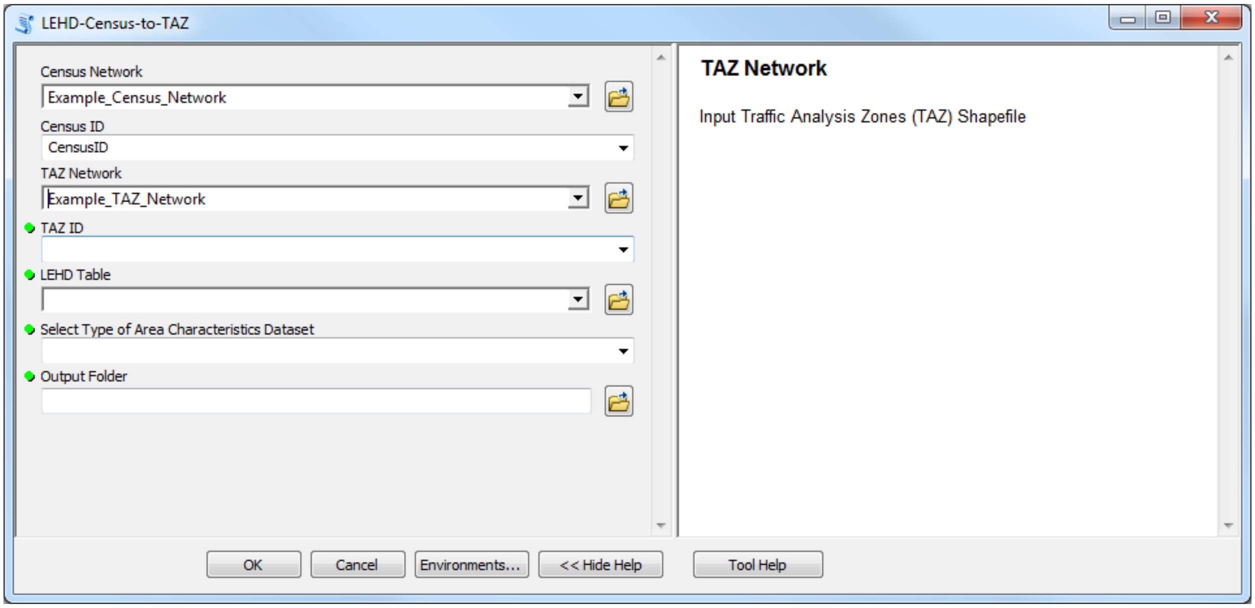


Figure 4-16. Input Traffic Analysis Zones (TAZ) shapefile

STEP 5

Select unique TAZ attribute field identifier from input parameter TAZ ID (see Figure 4-17).

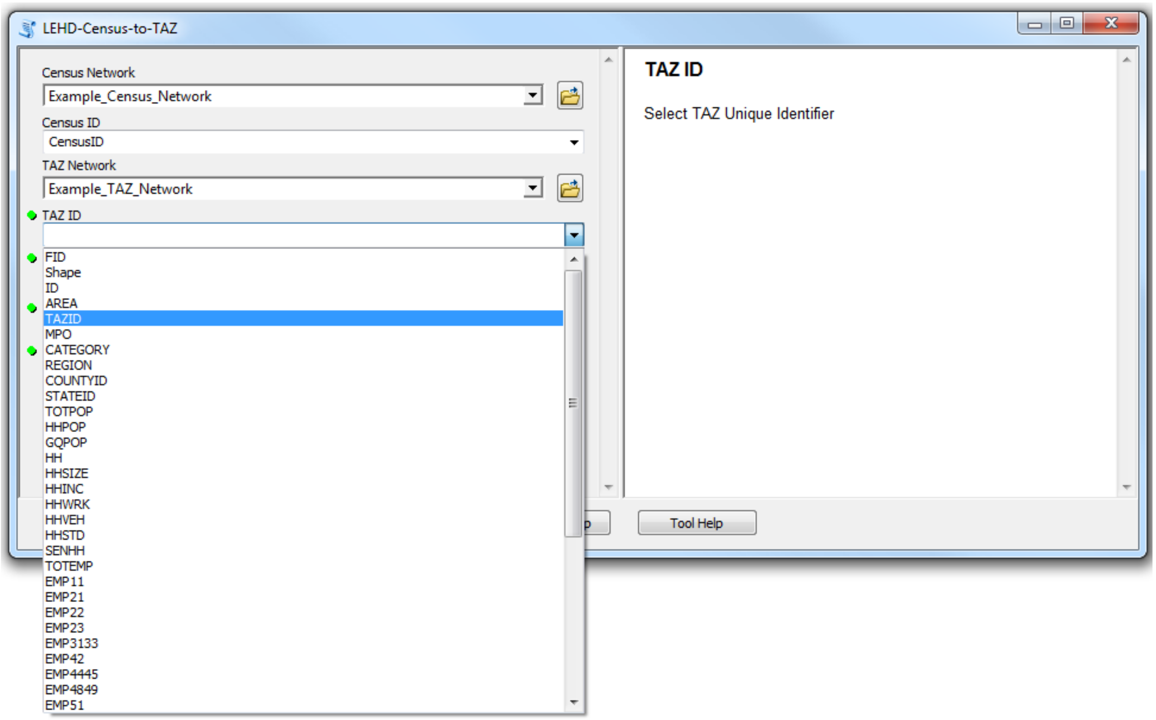


Figure 4-17. Select TAZ Unique Identifier

STEP 6

Input path to Longitudinal Employer-Household Dynamics (LEHD) Dataset into LEHD-Census-to-TAZ input parameter LEHD Table (see Figure 4-18).

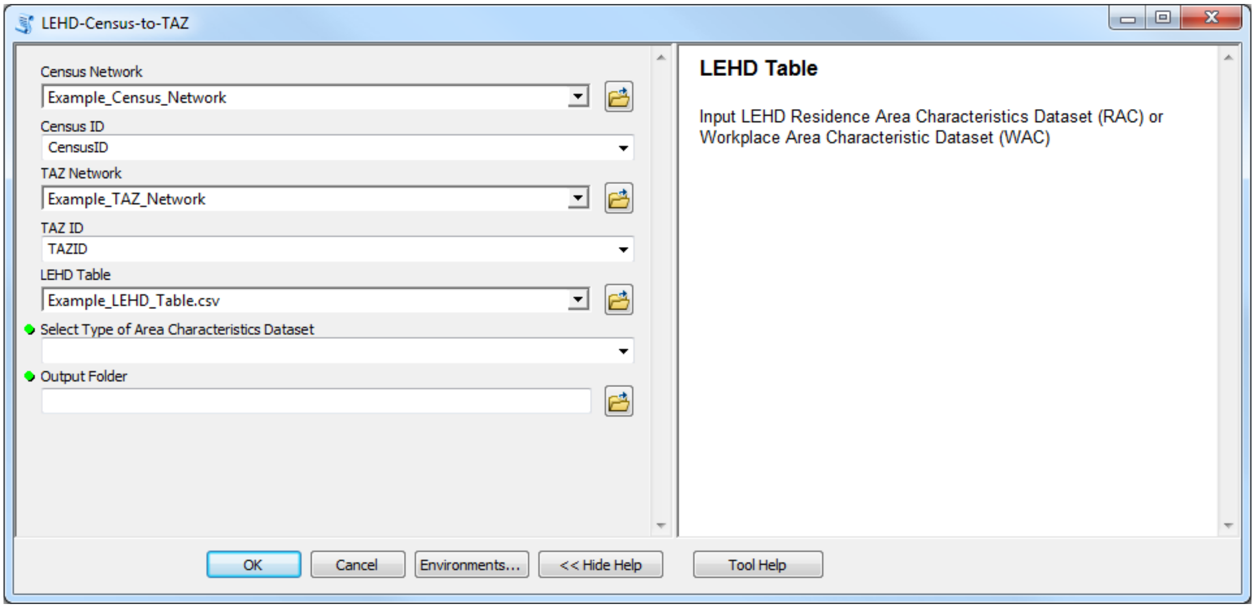


Figure 4-18. Input LEHD dataset

STEP 7

Select type of loaded LEHD area characteristics dataset in LEHD-Census-to-TAZ function (see Figure 4-19).

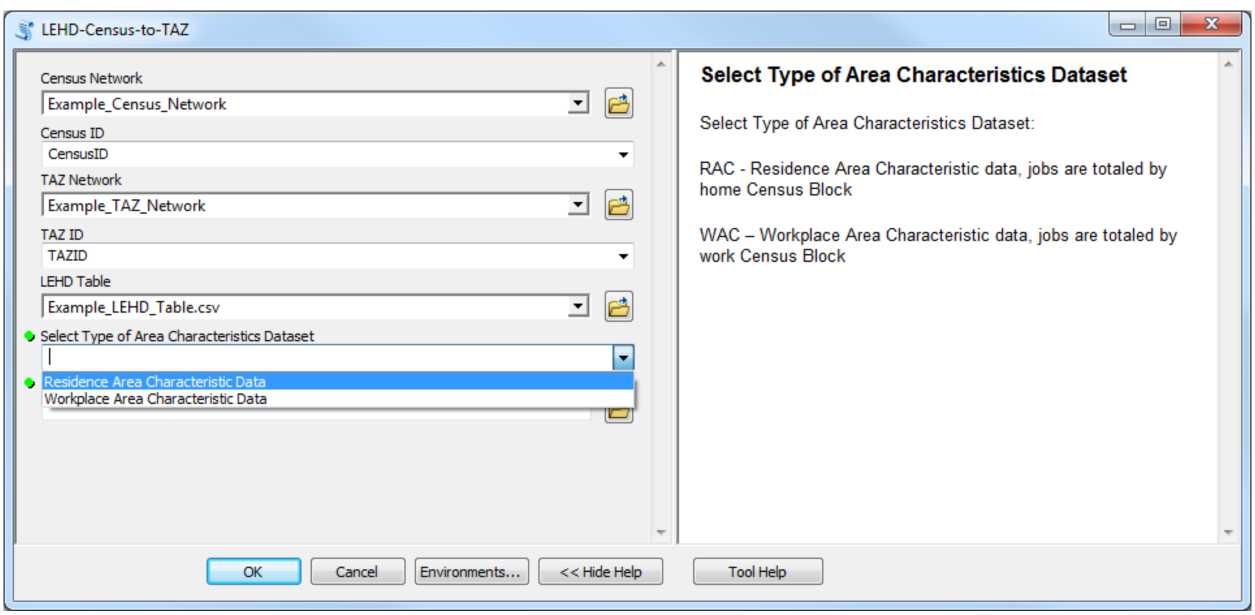


Figure 4-19. Select Type of LEHD Area Characteristics Dataset

STEP 8

In toolbox Output Folder parameter input output folder path where processed shapefiles will be exported after toolbox analysis (see Figure 4-20).

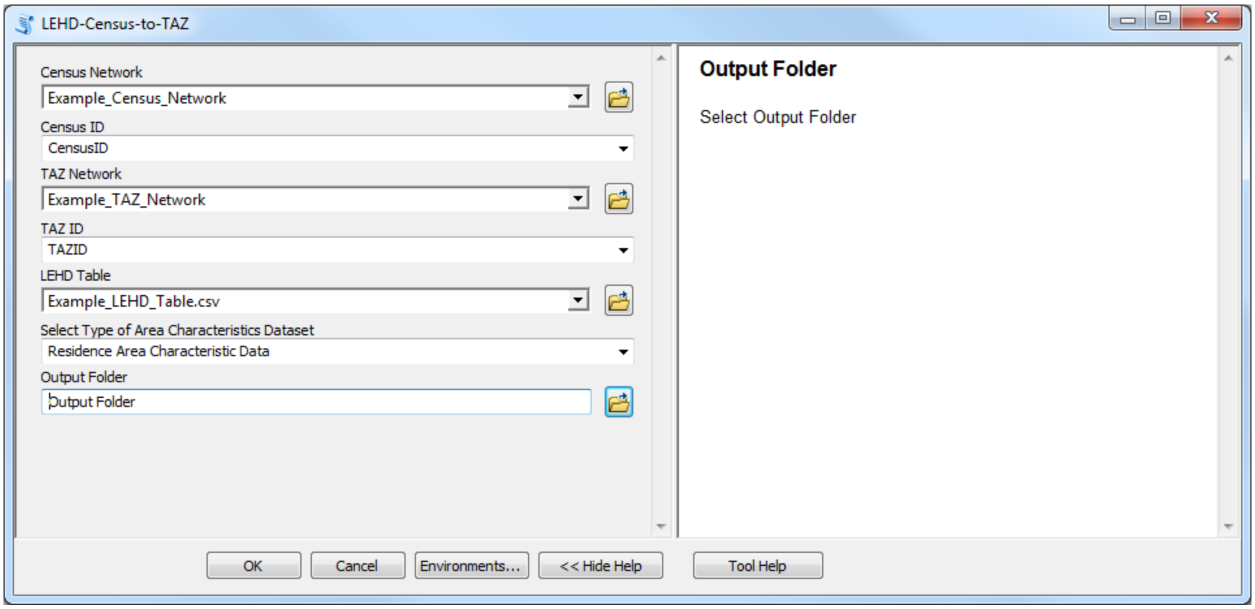


Figure 4-20. Input Output Folder

STEP 9

Once all required parameters are inputted, press OK to execute the application. The ArcGIS application invokes a task completion window, which reports status of each task (see Figure 4-21). In addition, processed shapefiles will be imported to ArcMap Display (see Figure 4-22).

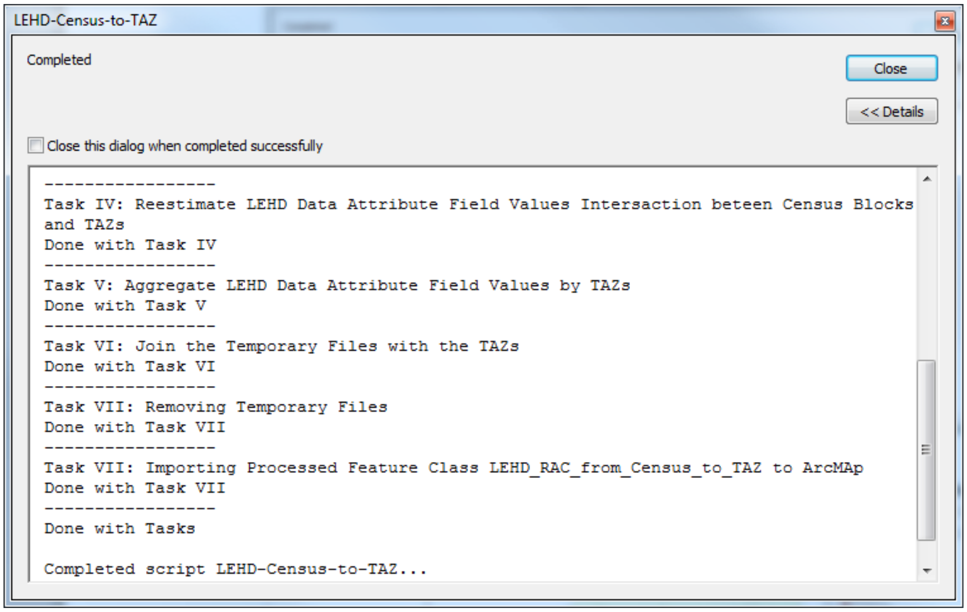


Figure 4-21. Application performed task window

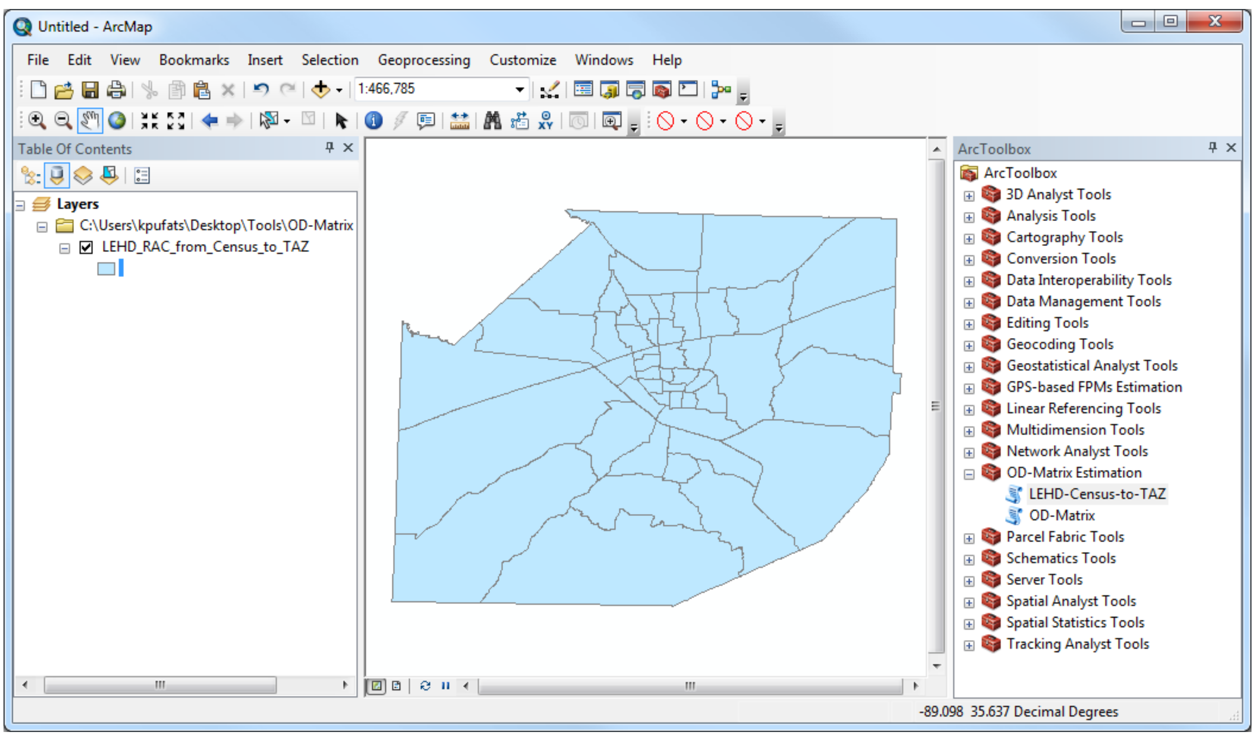
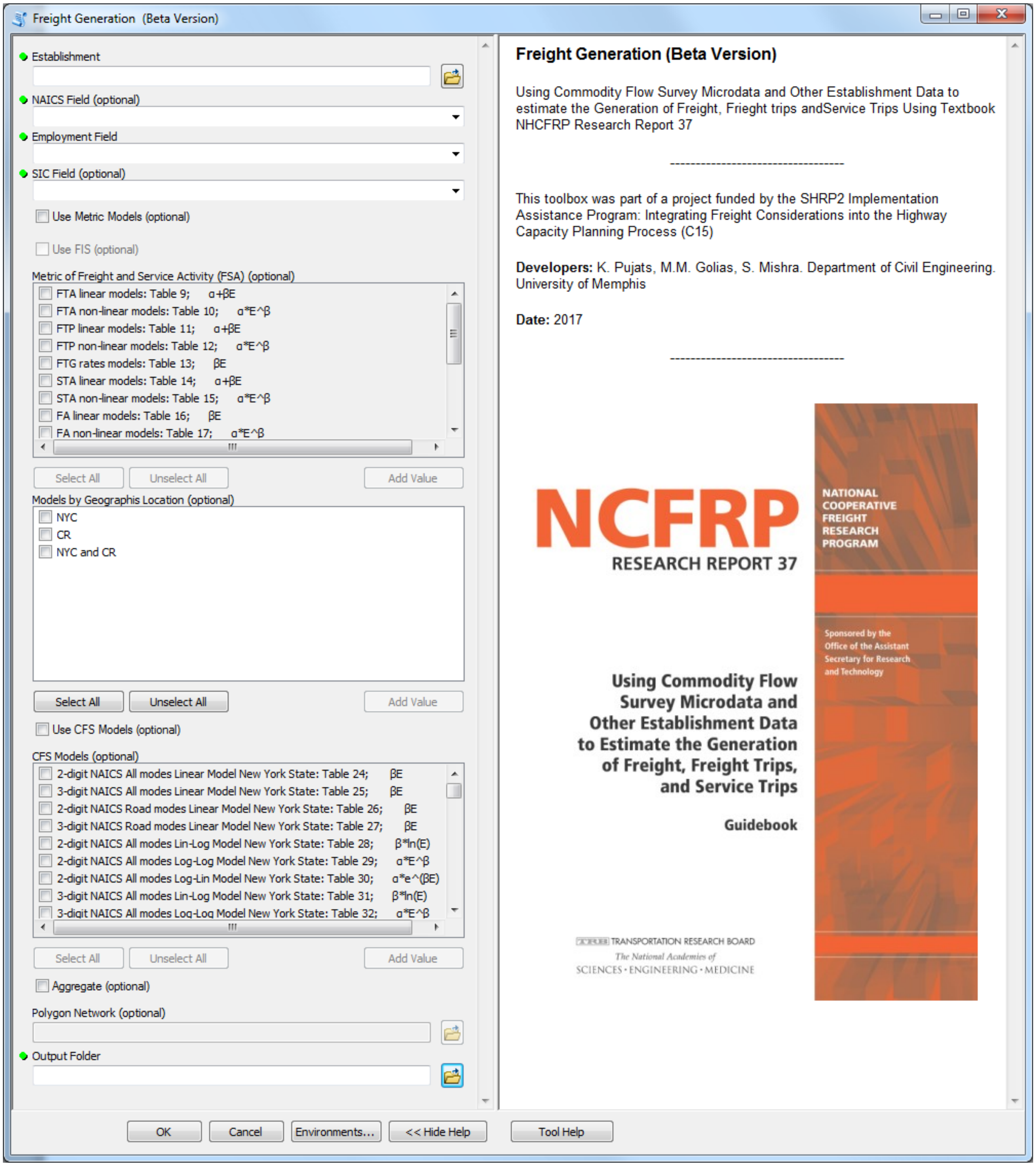


Figure 4-22. Displayed processed shapefile


Freight Generation (Beta Version)
Establishment
NAICS Field (optional)
Employment Field
SIC Field (optional)
Use Metric Models (optional)
Use FIS (optional)
Metric of Freight and Service Activity (FSA) (optional)
FTA linear models: Table 9; α+βE
FTA non-linear models: Table 10; α*E^β
FTP linear models: Table 11; α+βE
FTP non-linear models: Table 12; α*E^β
FTG rates models: Table 13; βE
STA linear models: Table 14; α+βE
STA non-linear models: Table 15; α*E^β
FA linear models: Table 16; βE
FA non-linear models: Table 17; α*E^β
Select All
Unselect All
Add Value
Models by Geographis Location (optional)
NYC
CR
NYC and CR
Select All
Unselect All
Add Value
Use CFS Models (optional)
CFS Models (optional)
2-digit NAICS All modes Linear Model New York State: Table 24; βE
3-digit NAICS All modes Linear Model New York State: Table 25; βE
2-digit NAICS Road modes Linear Model New York State: Table 26; βE
3-digit NAICS Road modes Linear Model New York State: Table 27; βE
2-digit NAICS All modes Lin-Log Model New York State: Table 28; β*ln(E)
2-digit NAICS All modes Log-Log Model New York State: Table 29; α*E^β
2-digit NAICS All modes Log-Lin Model New York State: Table 30; α*e^(βE)
3-digit NAICS All modes Lin-Log Model New York State: Table 31; β*ln(E)
3-digit NAICS All modes Log-Log Model New York State: Table 32; α*E^β
Select All
Unselect All
Add Value
Aggregate (optional)
Polygon Network (optional)
Output Folder
OK
Cancel
Environments...
<< Hide Help
Tool Help
Freight Generation (Beta Version)
Using Commodity Flow Survey Microdata and Other Establishment Data to estimate the Generation of Freight, Frieght trips andService Trips Using Textbook NHCFRP Research Report 37

This toolbox was part of a project funded by the SHRP2 Implementation Assistance Program: Integrating Freight Considerations into the Highway Capacity Planning Process (C15)
Developers: K. Pujats, M.M. Golias, S. Mishra. Department of Civil Engineering. University of Memphis
Date: 2017

NCFRP
RESEARCH REPORT 37
NATIONAL COOPERATIVE FREIGHT RESEARCH PROGRAM
Sponsored by the Office of the Assistant Secretary for Research and Technology
Using Commodity Flow Survey Microdata and Other Establishment Data to Estimate the Generation of Freight, Freight Trips, and Service Trips
Guidebook
TRANSPORTATION RESEARCH BOARD
The National Academies of
SCIENCES · ENGINEERING · MEDICINE

Example of Freight Generation Execution

This section presents a step-by-step example of how to use the developed ArcGIS application.

EXAMPLE INPUTS

Following shapefiles were used in executing freight generation example (see Figure 4-23):

- **Example_Facilties.shp** – Shapefile containing establishments with following attribute fields: SIC_CODE, NAICS_CODE and EMPLOYMENT.
- **Example_Counties.shp** – Shapefile containing polygon shapes.

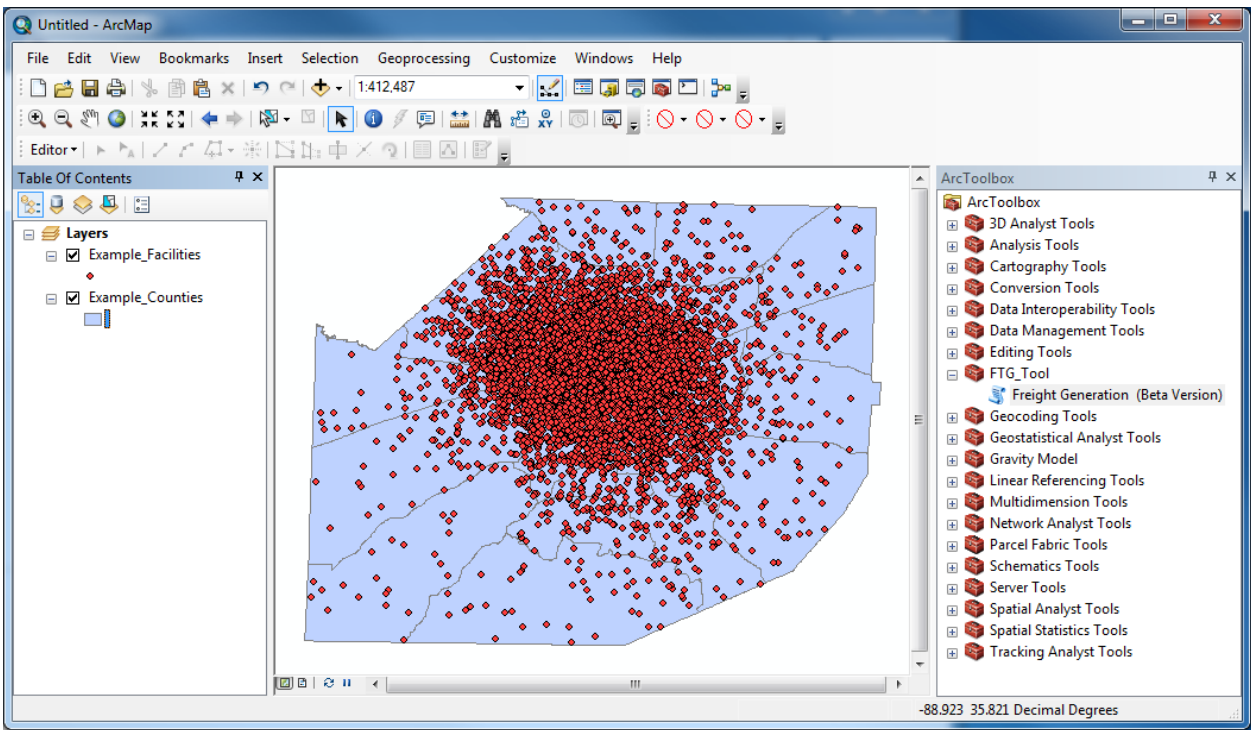


Figure 4-23. Example inputs

STEP 1

Open newly added FTG_Tool toolbox and launch Freight Generation function (see Figure 4-24).

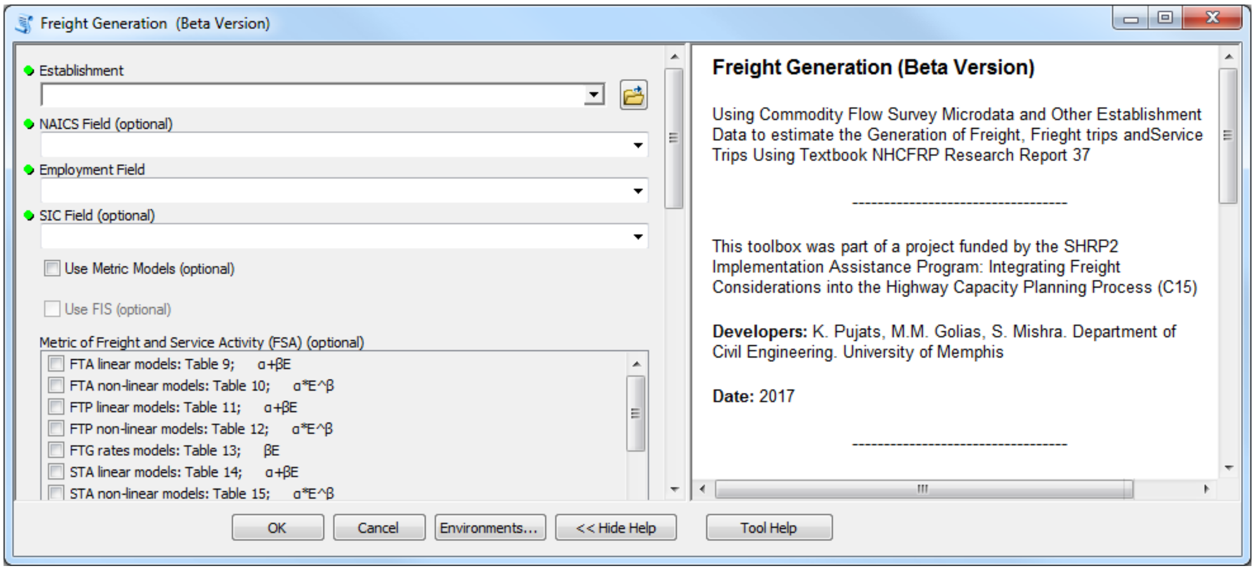


Figure 4-24. Freight Generation function

STEP 2

Input Establishment shape file or feature layer into Freight Generation tool first input parameter Establishment (see Figure 4-25).

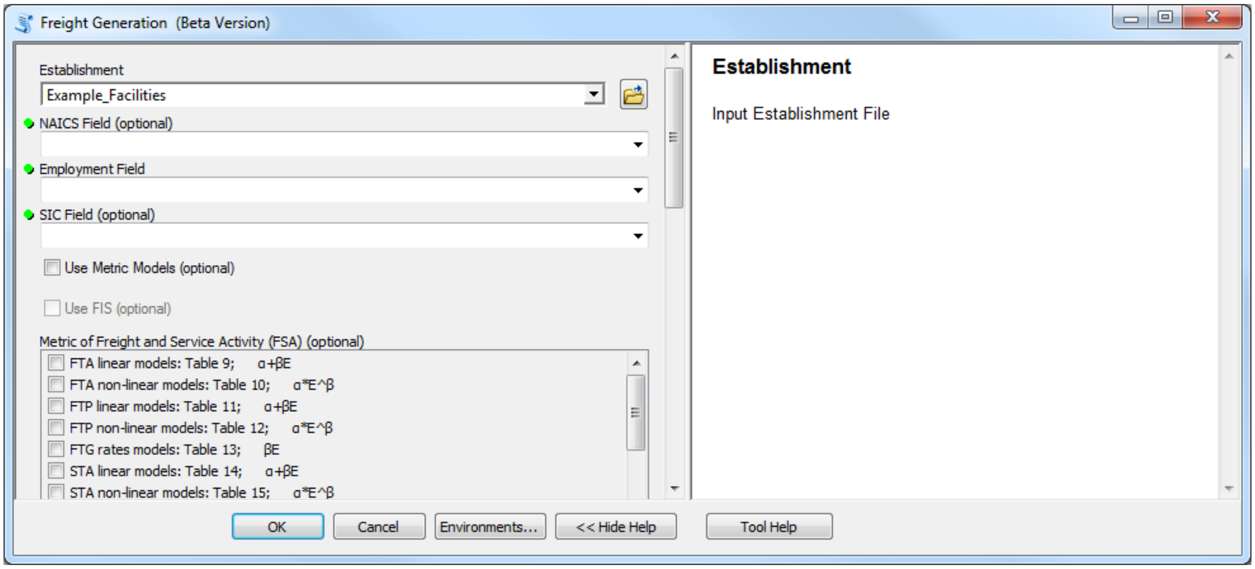


Figure 4-25. Input Establishment feature layer or shapefile

STEP 3 (optional)

Select NAICS Field from Input Parameter NAICS Field (see Figure 4-26).

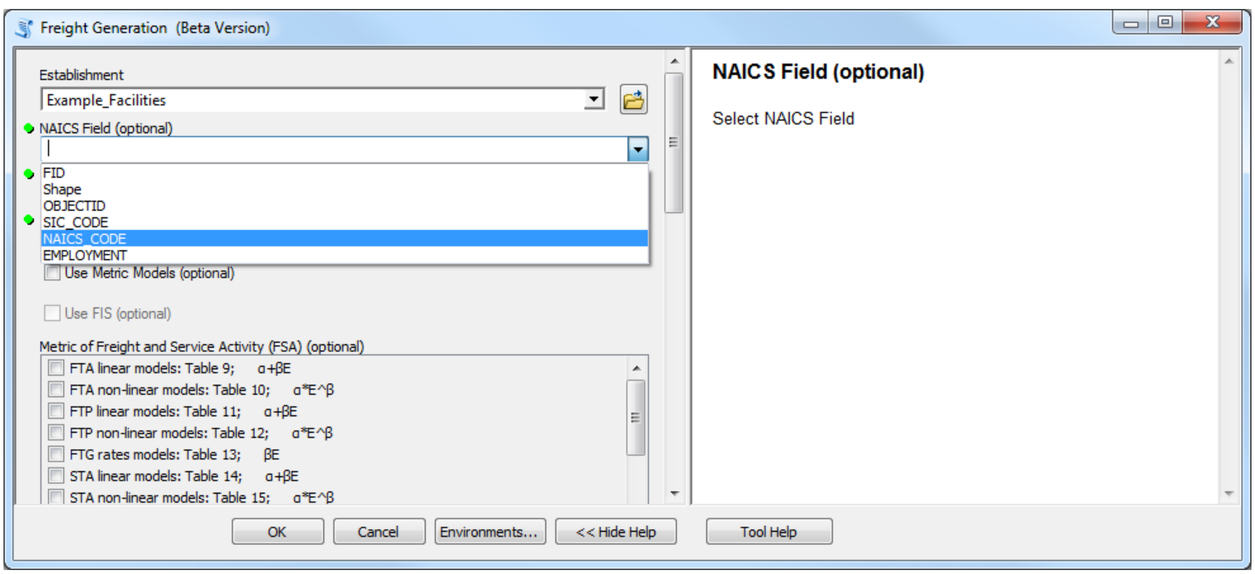


Figure 4-26. Select NAICS Field

STEP 4

Select Employment Field from input parameter Employment Field (see Figure 4-27).

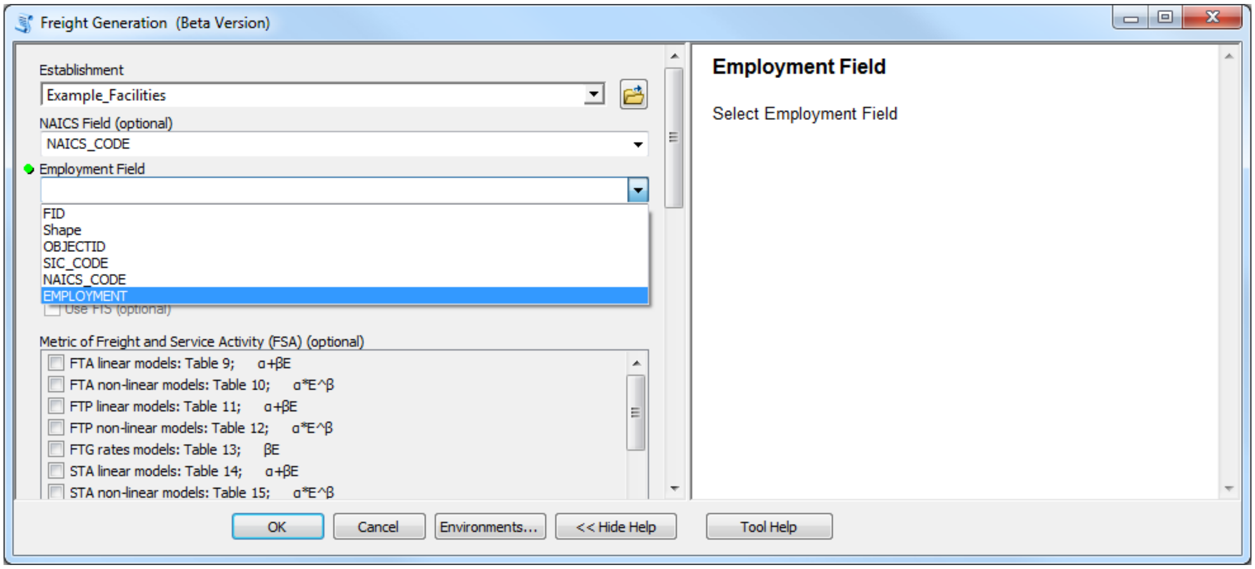


Figure 4-27. Select Employment Field

STEP 5 (optional)

Select SIC Field from input parameter SIC Field (see Figure 4-28).

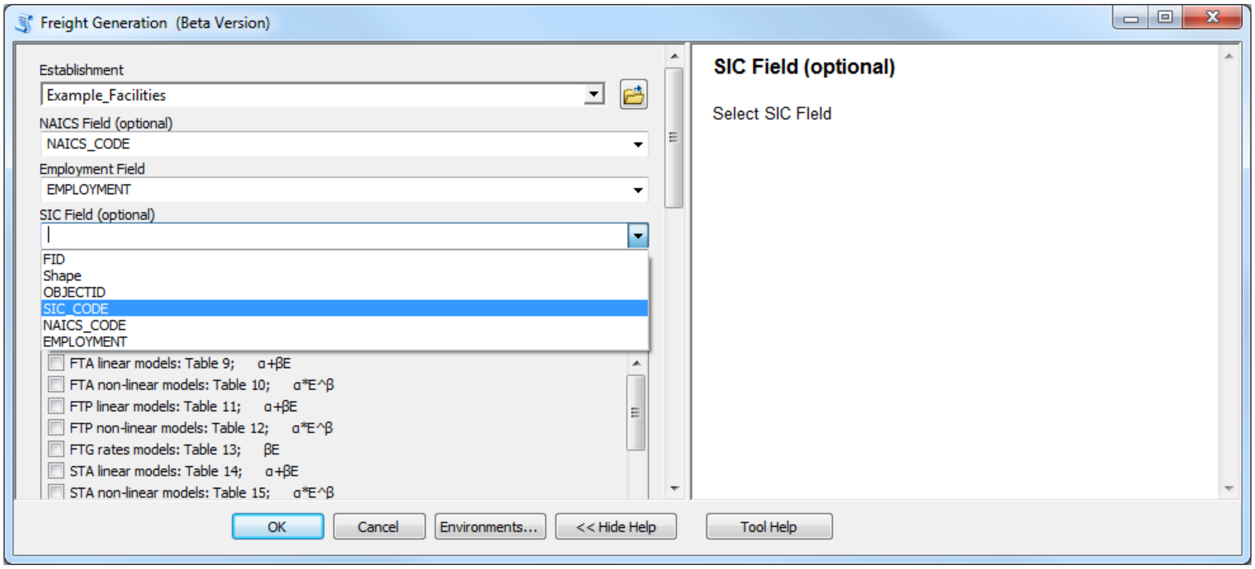


Figure 4-28. Select SIC Field

STEP 6

Select Use Metric Models checkbox whether Metric Models will be used for the calculation (see Figure 4-29).

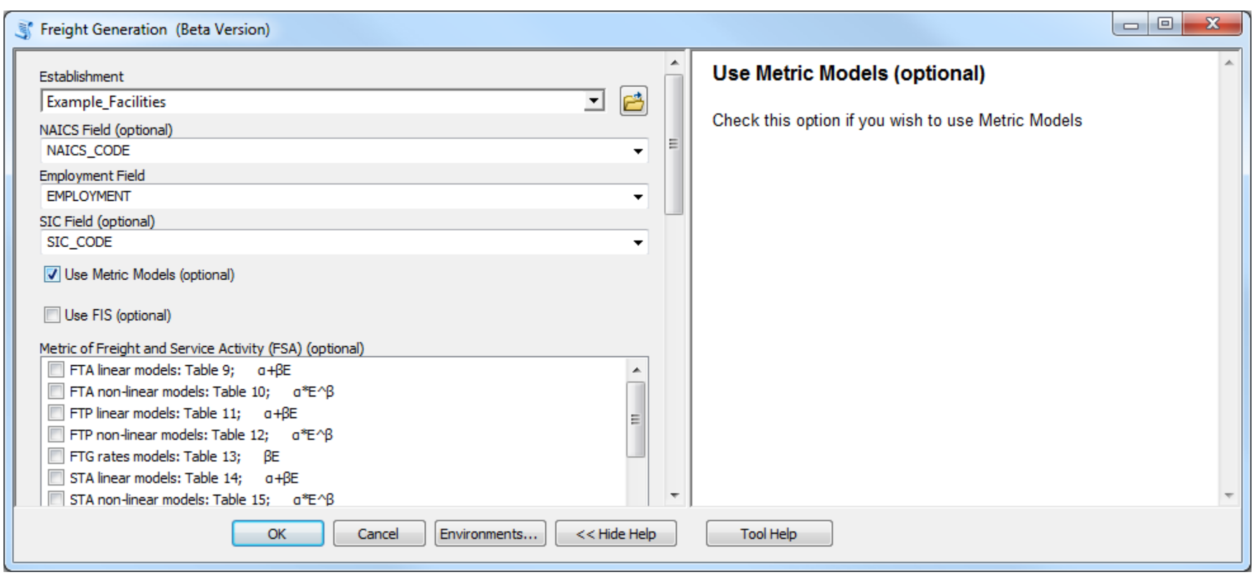


Figure 4-29. Select Metric models

STEP 7

Select the Use FIS option to use each table's ALL Freight Sector row and fill in missing NAICS codes (see Figure 4-30).

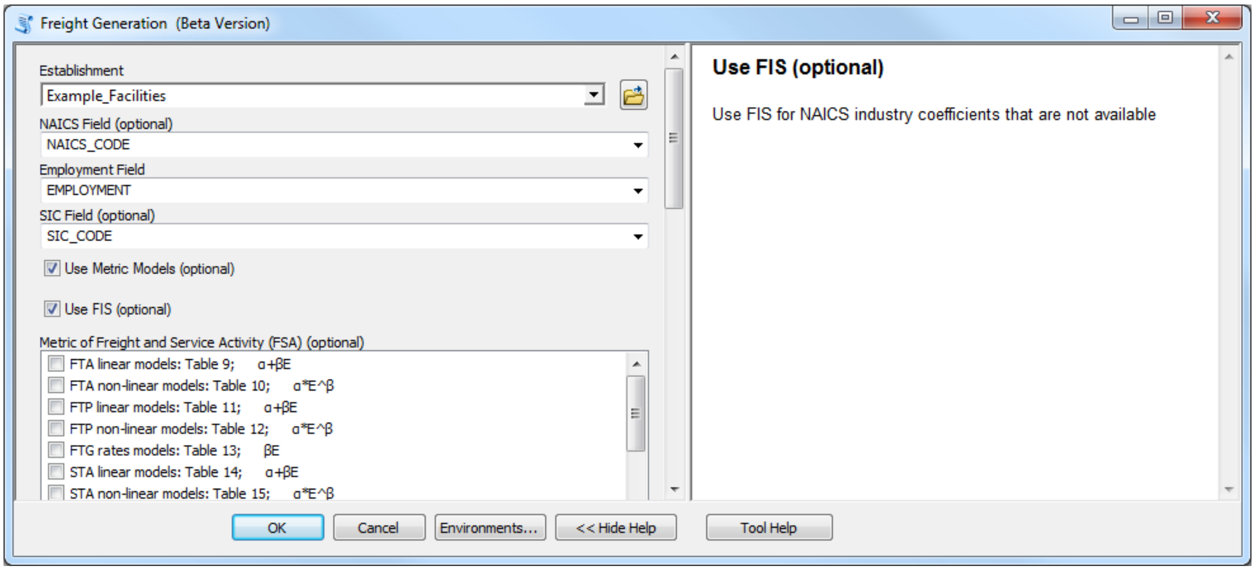


Figure 4-30. Select ALL freight modes

STEP 8

Select metric tables to use in Metric of Freight and Service Activity (FSA) input parameter (see Figure 4-31).

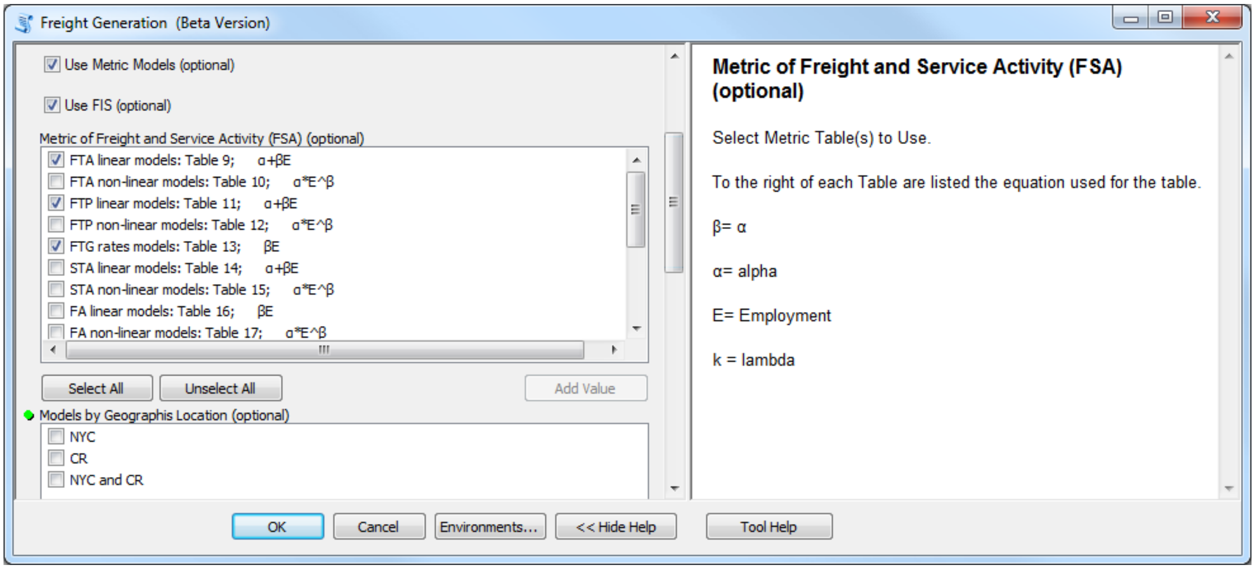


Figure 4-31. Select Metric Table(s)

STEP 9

Select geographic models to use for the metric tables in Models by Geographic Location input parameter (see Figure 4-32).

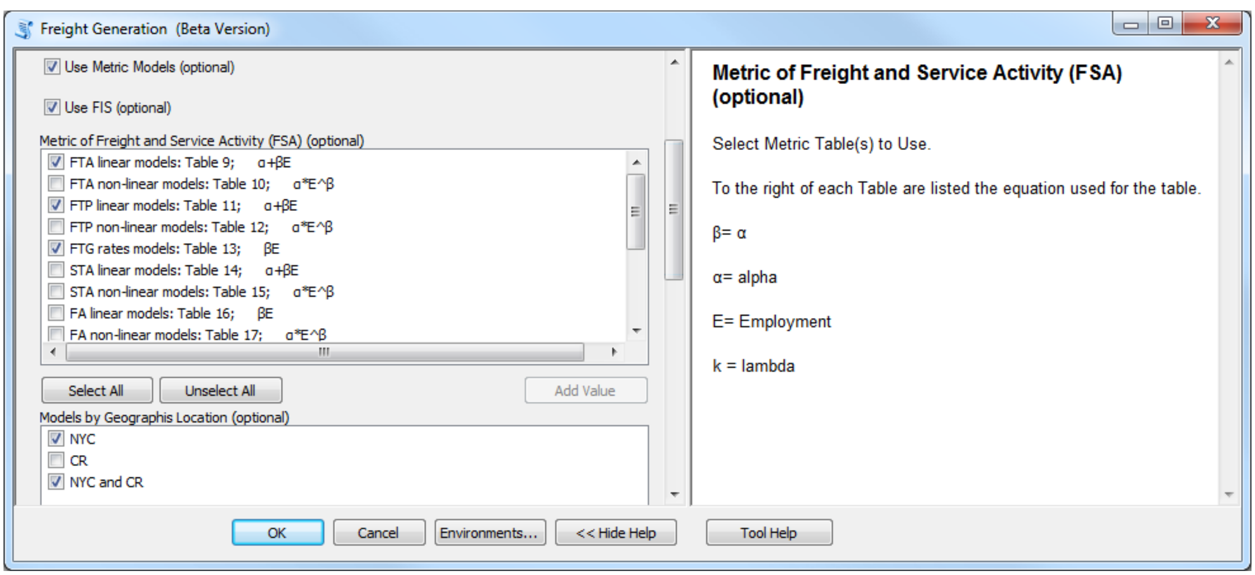


Figure 4-32. Select Metric Geographic model(s)

STEP 10

Select Use CFS Models checkbox whether Commodity Flow Survey (CFS) models will be used for the Calculations (see Figure 4-33).

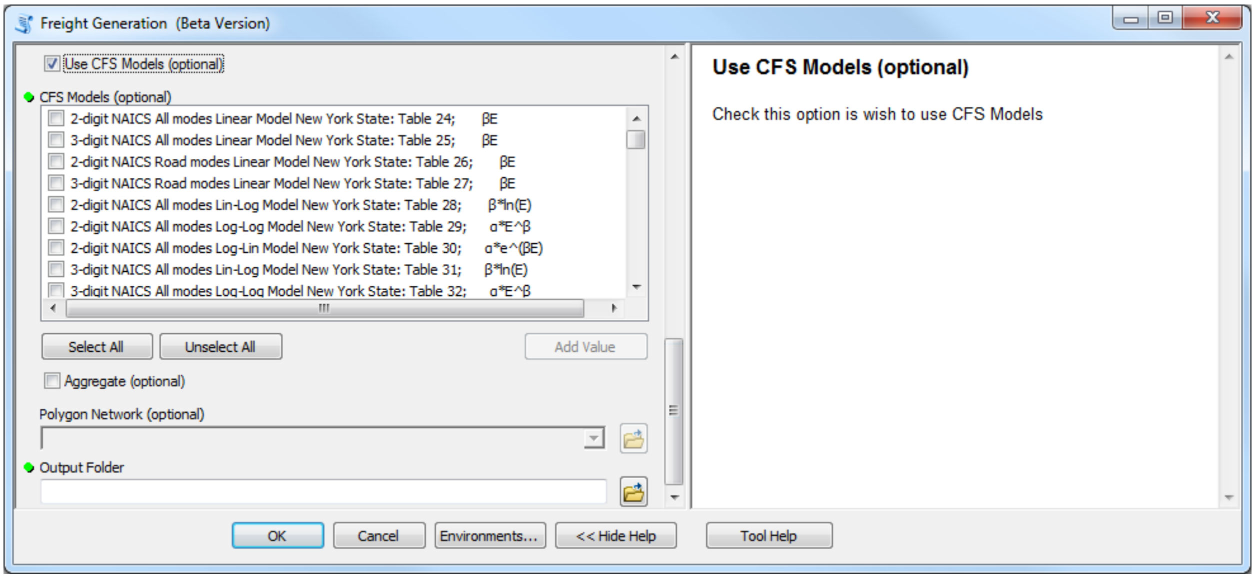


Figure 4-33. Select to Use CFS models

STEP 11

Select Commodity Flow Survey (CFS) models to use in CFS Models input parameter (see Figure 4-34)

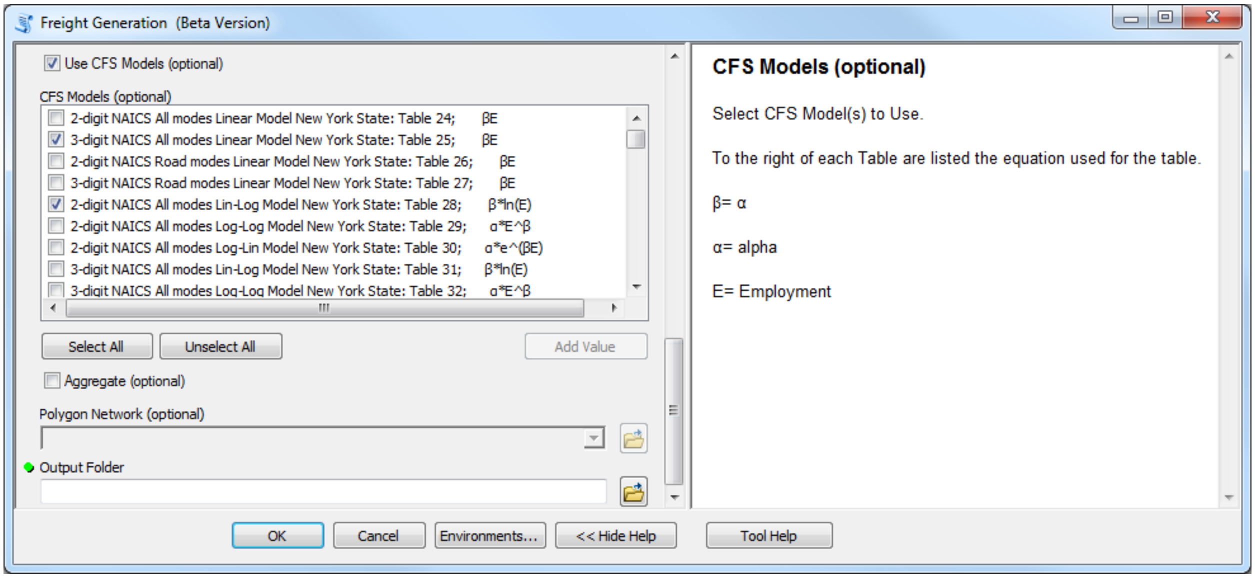


Figure 4-34. Select CFS model(s)

STEP 12

Select toolbox Aggregate check box weather to aggregate estimated trip generation output over user provided polygon network for each user selected model and by NAICS code and/or SIC Code (see Figure 4-35).

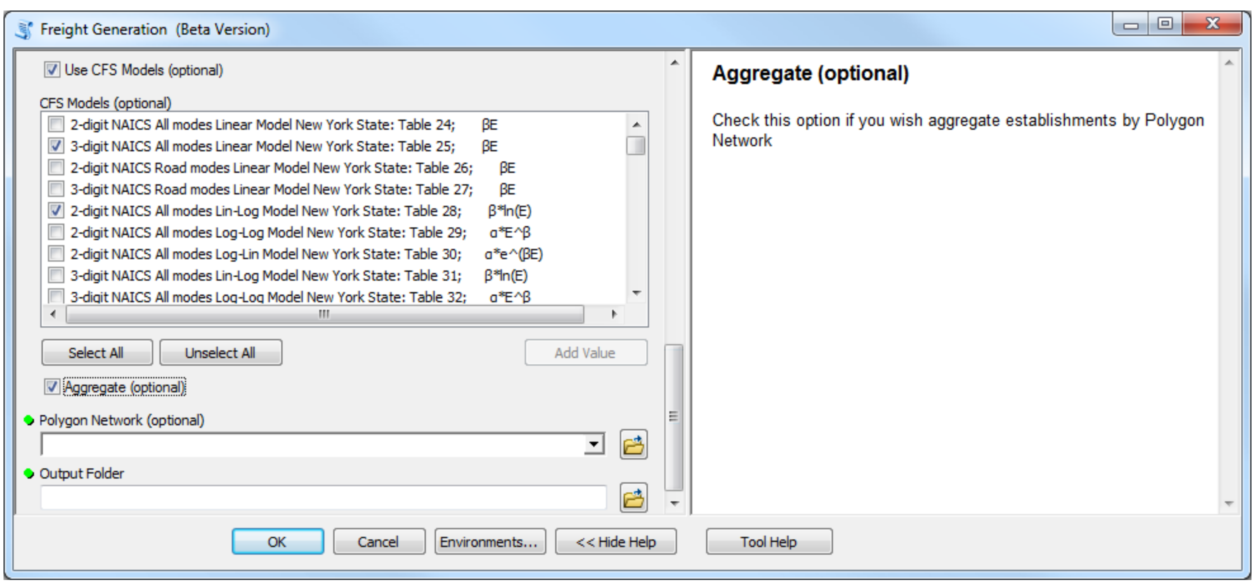


Figure 4-35. Select Aggregate check box

STEP 13

In toolbox Polygon Network parameter, input path to polygon network for what establishments model outputs by NAICS code and/or SIC code will be aggregated (see Figure 4-36).

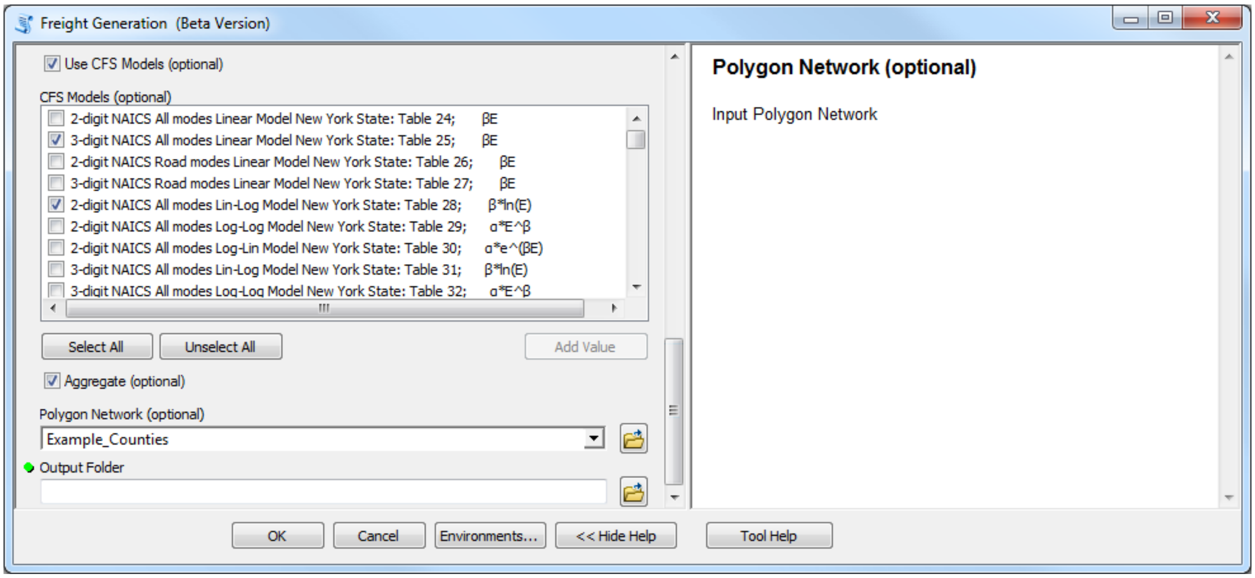


Figure 4-36. Input Polygon Network

STEP 14

In toolbox Output Folder parameter input output folder path where processed shapefiles will be exported after toolbox analysis (see Figure 4-37).

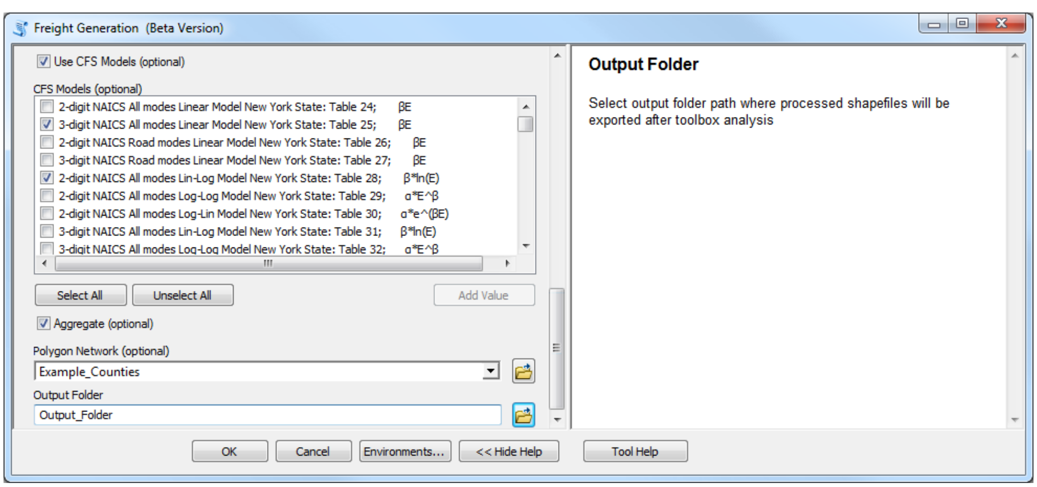


Figure 4-37. Input Output Folder

STEP 15

Once all required parameters are inputted, press OK to execute the application. The ArcGIS application invokes a task completion window, which reports status of each task (see Figure 4-38). In addition, shapefiles with truck trip generation will be imported to ArcMap (see Figure 4-39) as point shapefiles or as polygons (the latter if the option to aggregate is selected - Figure 4-40).

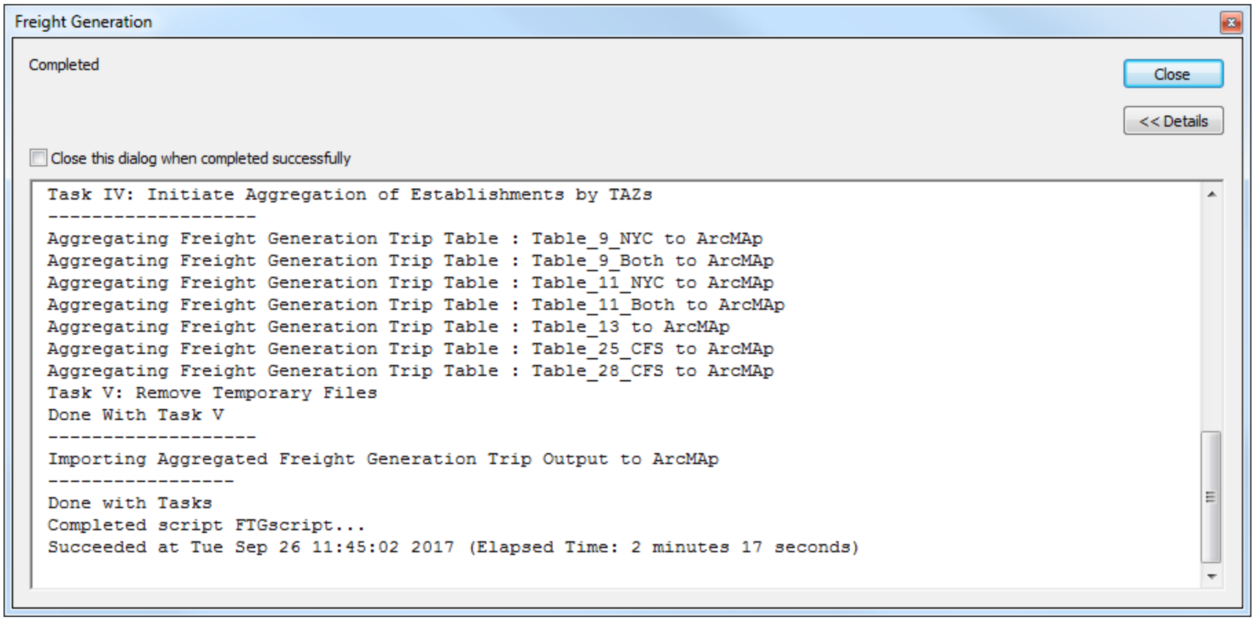


Figure 4-38. Application performed task window

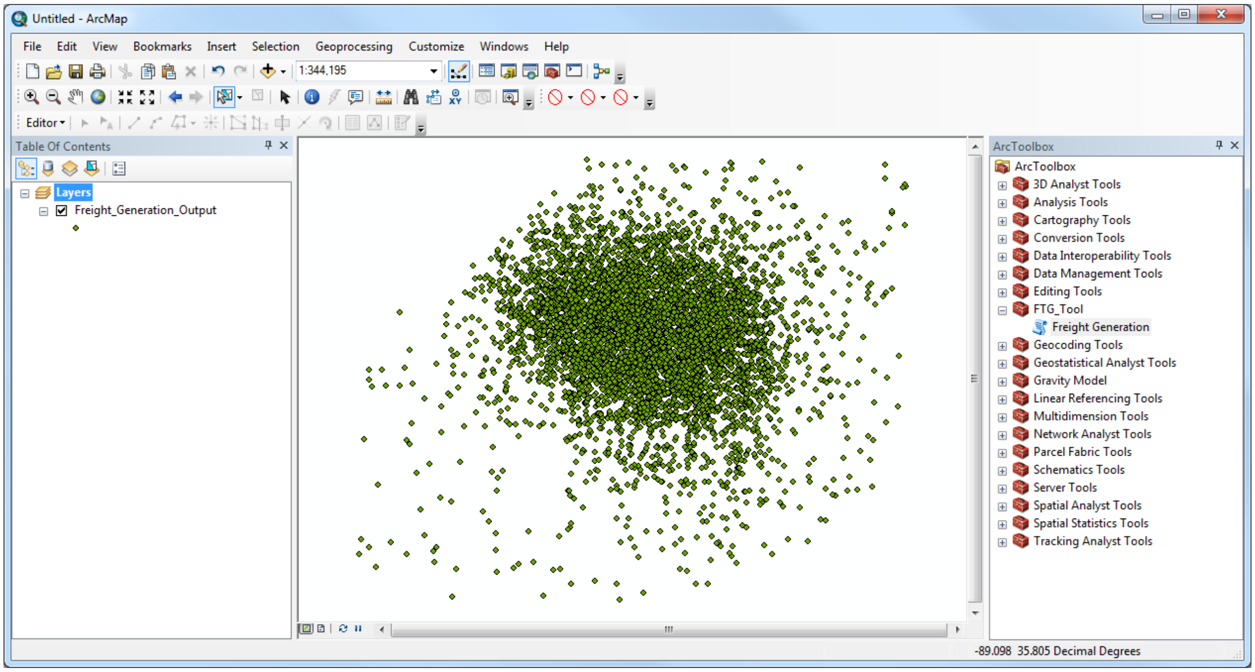


Figure 4-39. Facility level shapefile with truck trip generation

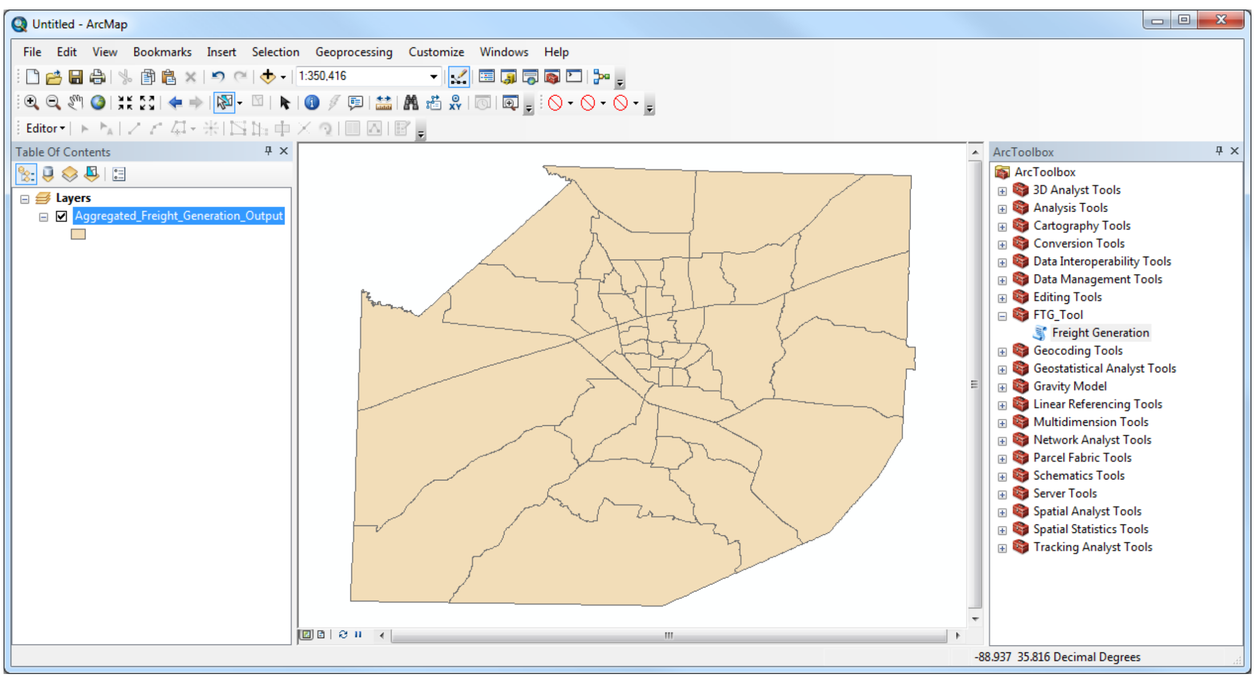


Figure 4-40. Zone level aggregate truck trip generation shapefile

Gravity-Model Tool

This section presents a step-by-step example of how to use the developed ArcGIS application.

EXAMPLE INPUTS

Following shapefiles were used in executing freight generation example (see Figure 4-41):

- **Example_Network.shp** – Feature class containing polygon network with trip productions and attractions.
- **Example_OD_Matrix_Format_1.shp**– Feature class containing origin-destination (OD) measured in travel time between different zones.
- **Example_OD_Matrix_Format_2.dbf**– Database File table (.dbf) containing origin-destination (OD) measured in travel time between different zones.

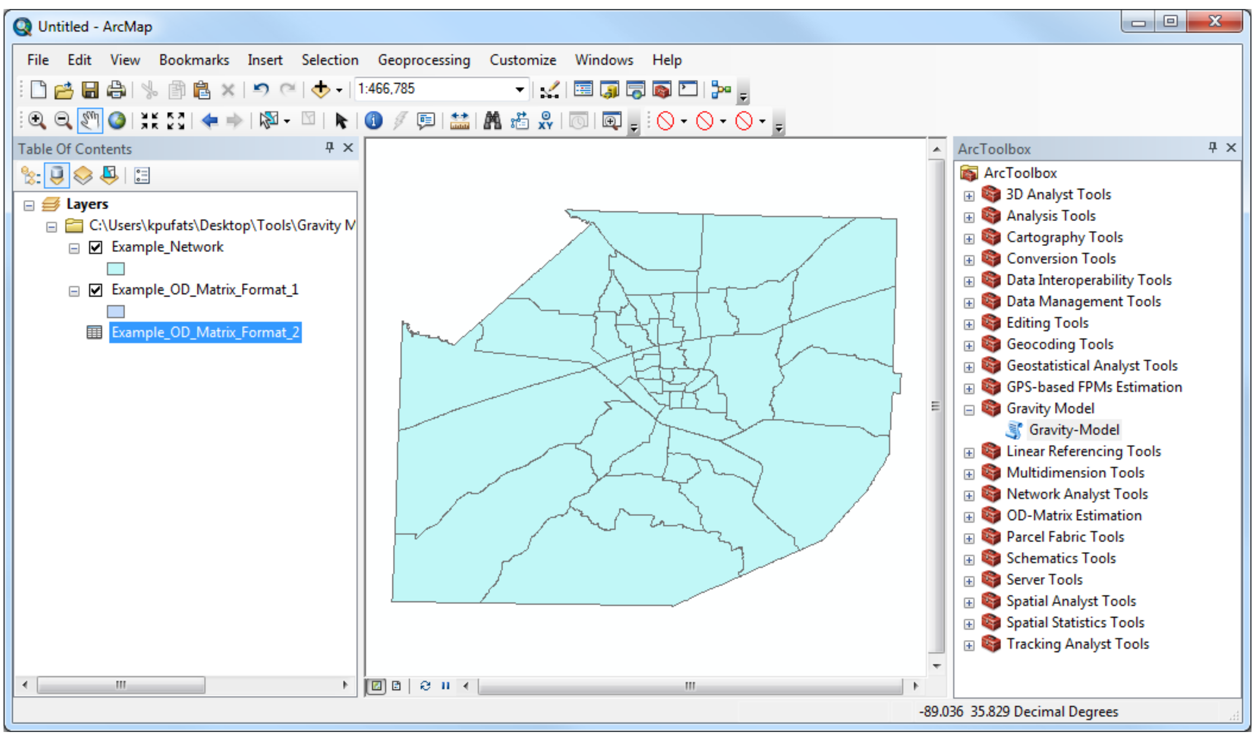


Figure 4-41. Example inputs

STEP 1

Open newly added Gravity Model toolbox and lunch Gravity-Model function (see Figure **4-42**).

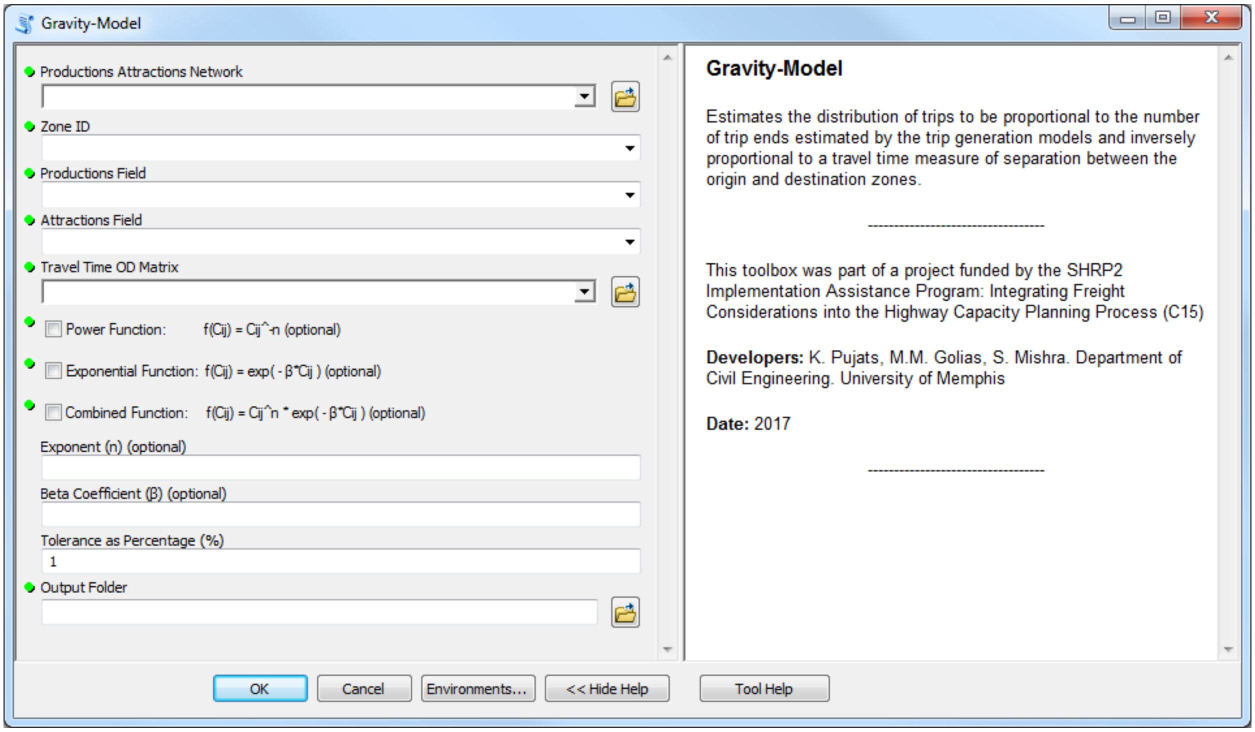


Figure 4-42**. Gravity-Model function**

STEP 2

Input path to network containing trip productions and attractions Feature Class into Gravity-Model first input parameter Productions Attractions Network (see Figure 4-43).

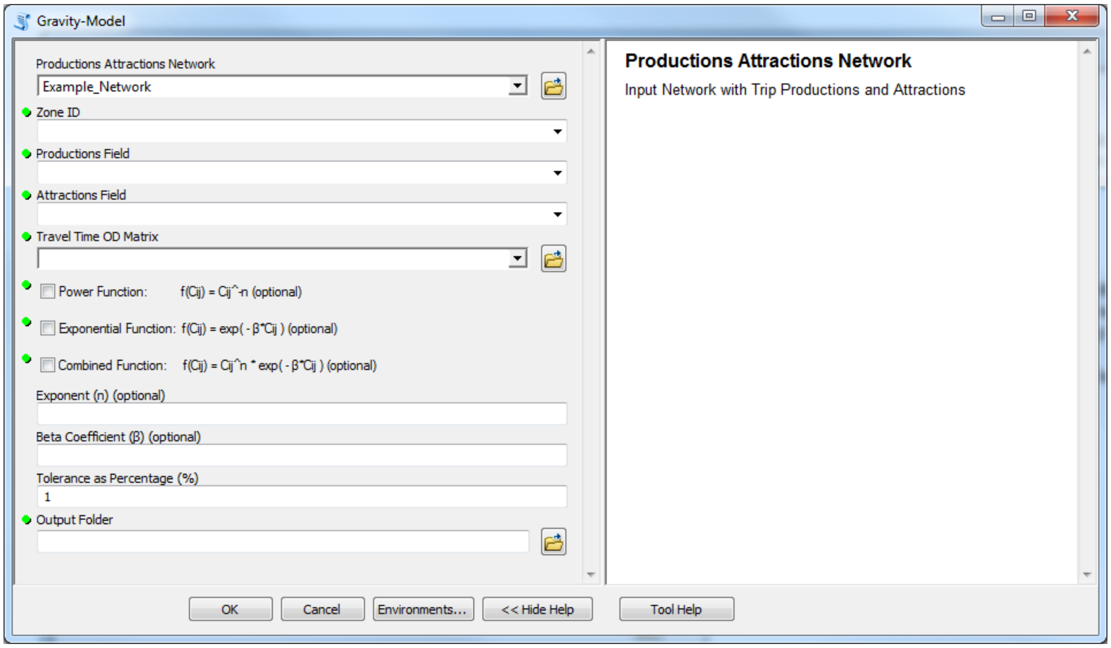


Figure 4-43. Input Productions and Attractions Network shapefile

STEP 3

Select zone identifier field from the second input parameter Zone ID (see Figure 4-44).

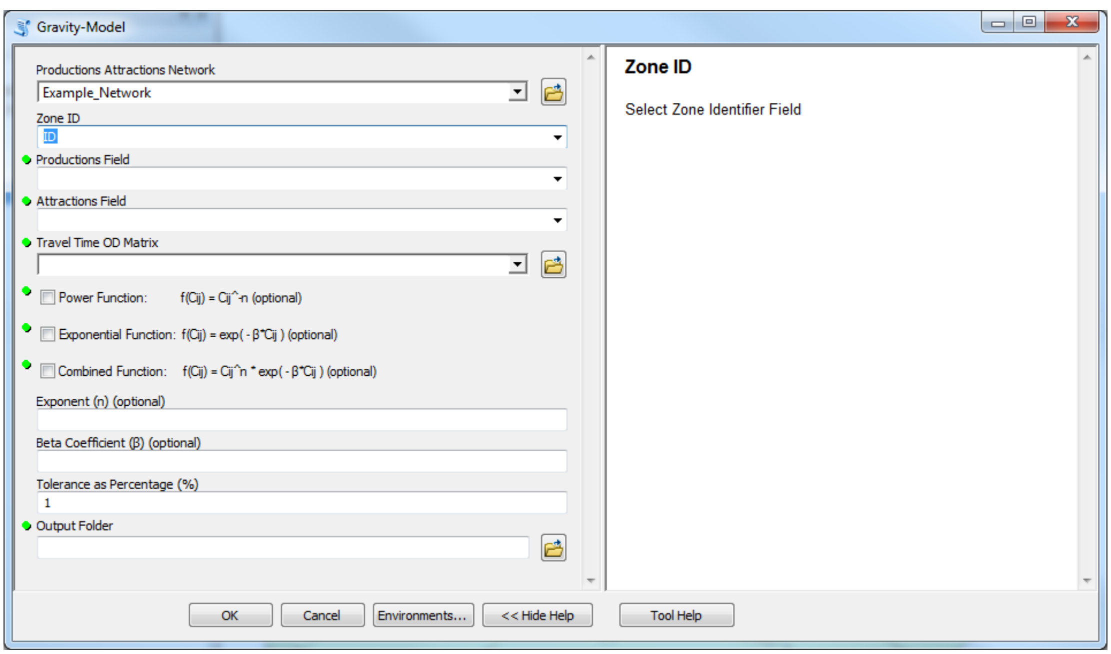


Figure 4-44. Select Zone Identifier field

STEP 3

Select attribute field for trip productions in the third input parameter Productions Field (see Figure 4-45).

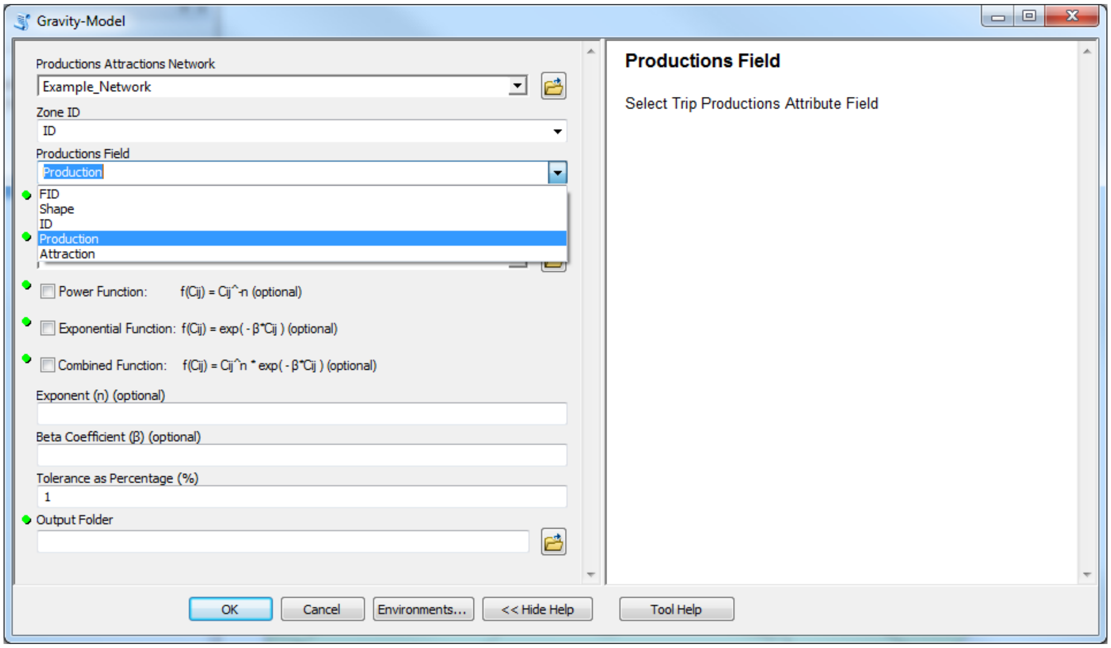


Figure 4-45. Select Trip Productions attribute field

STEP 4

Select attribute field for trip attractions in input parameter Attractions Field (see **Error! Reference source not found.**).

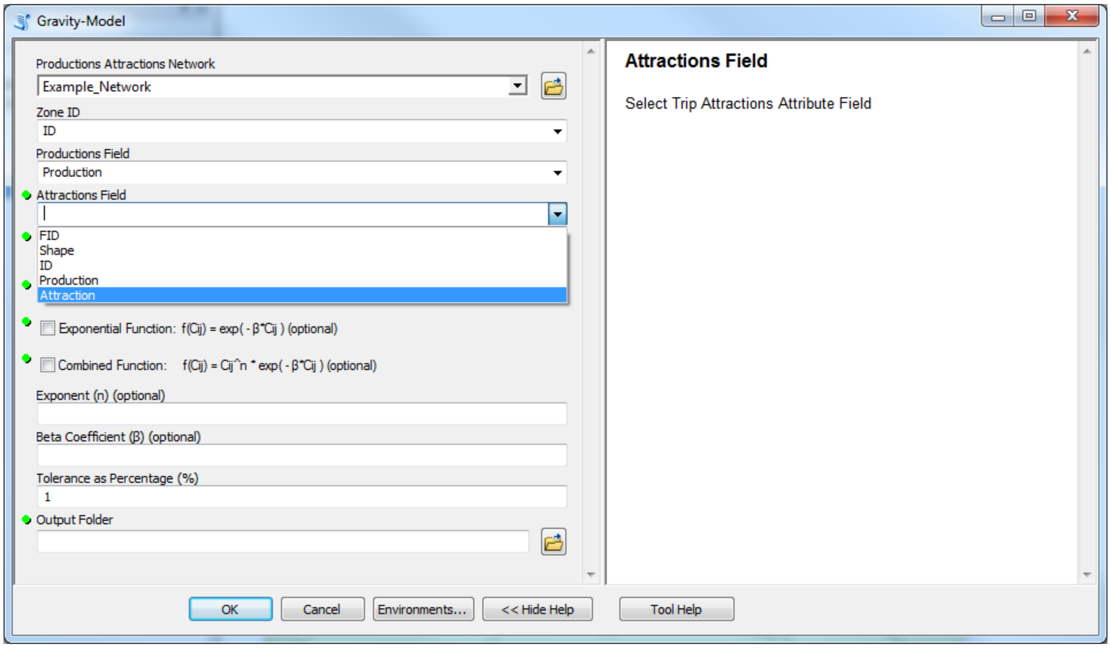


Figure 4-46. Select Trip Attractions attribute field

STEP 5

Input path to OD matrix Feature Class or Database File (.dbf) into Gravity-Model input parameter Travel Time OD Matrix (see Figure 4-47).

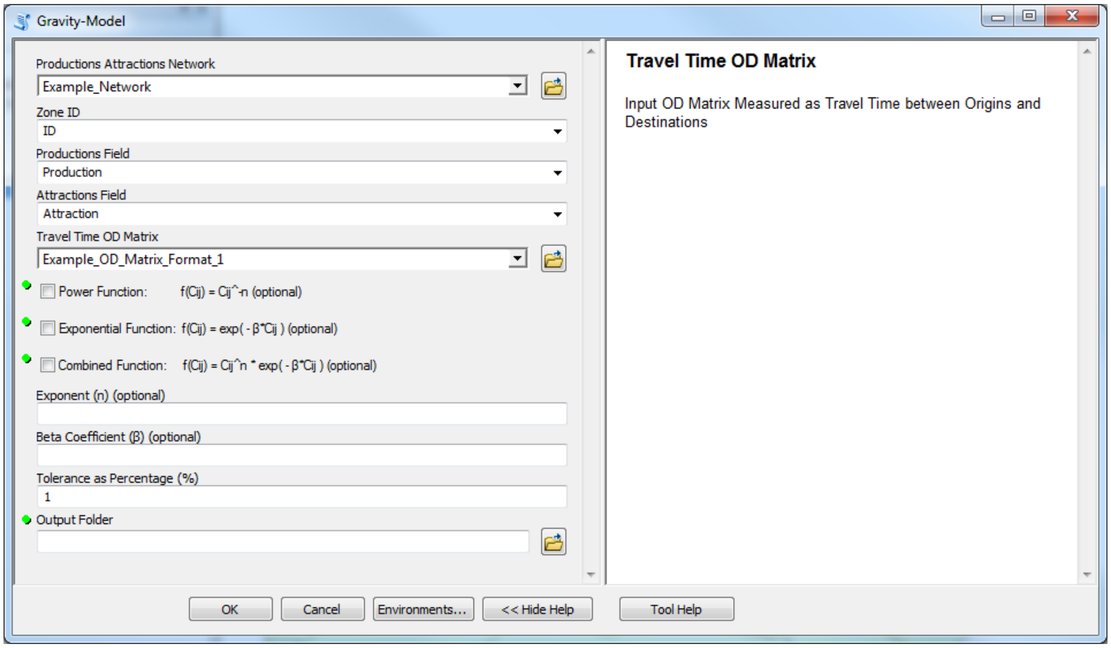


Figure 4-47. Input Travel Time OD Matrix

STEP 6

Check one of the following travel impedance functions: Power Function (see Figure 4-48), Exponential Function (see Figure 4-49), or Combined Function (see Figure 4-50).

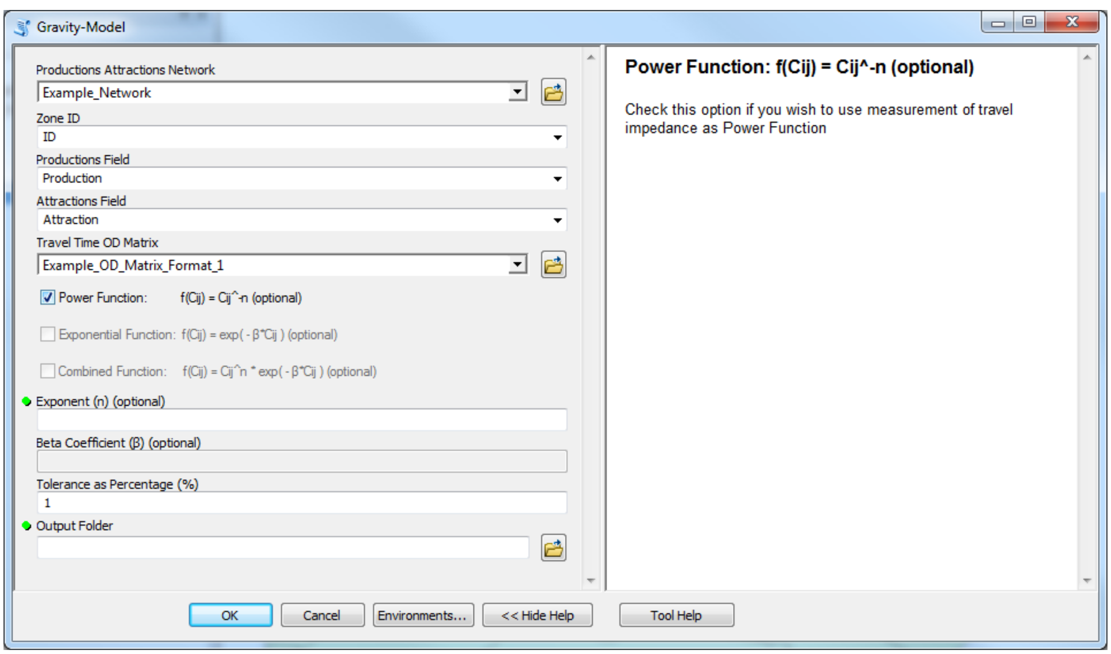


Figure 4-48. Select Power Function

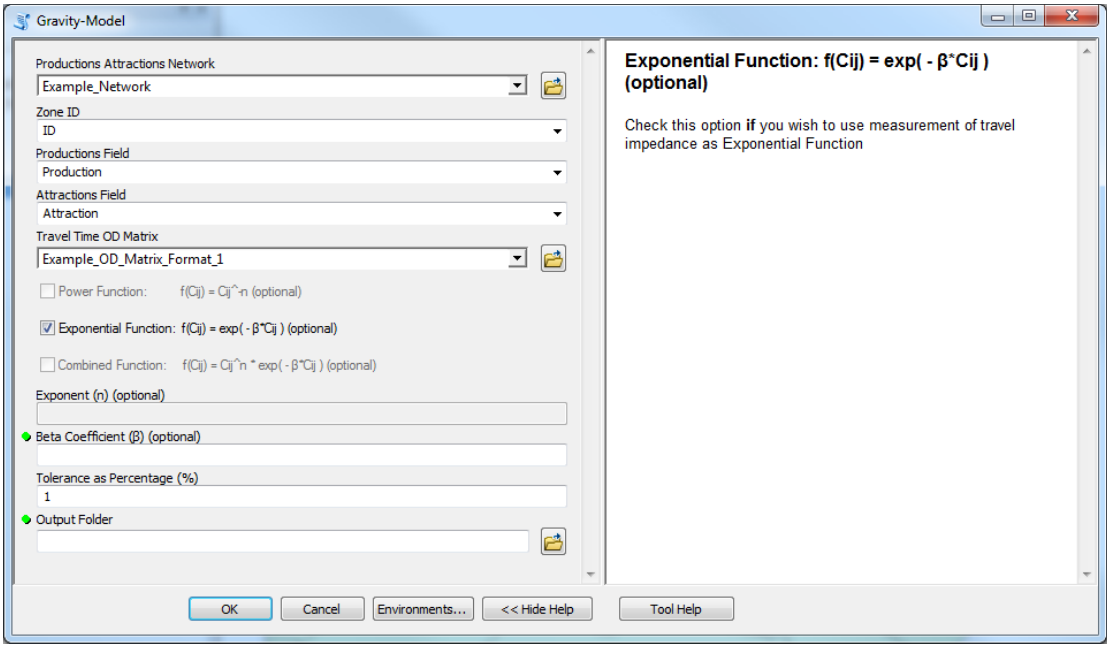


Figure 4-49. Select Exponential Function

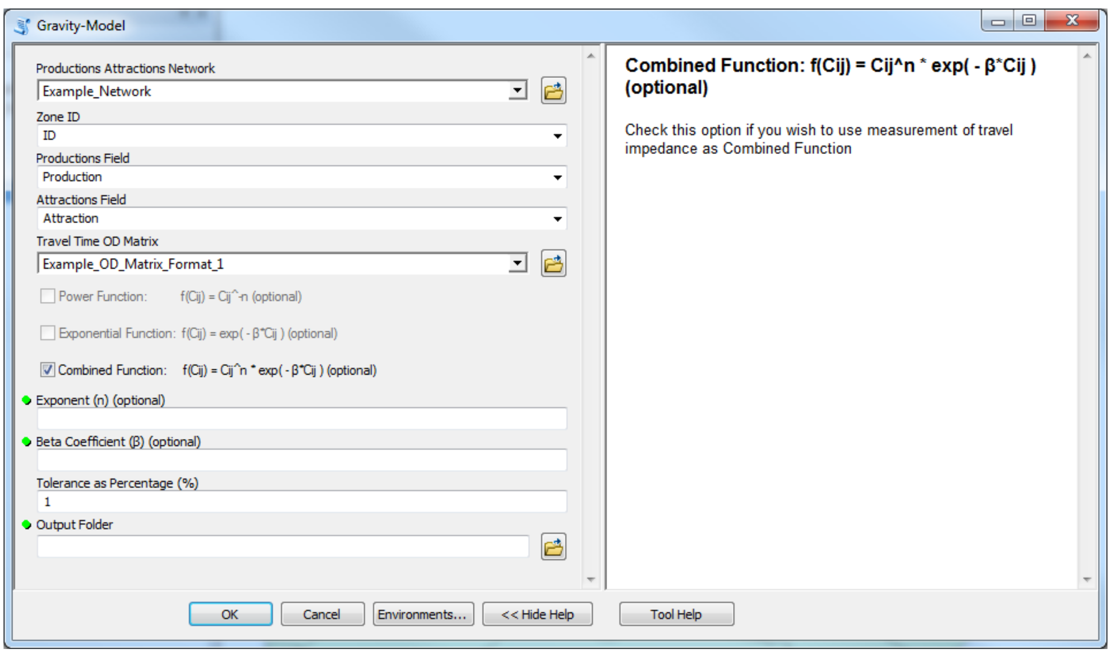


Figure 4-50. Select Combined Function

STEP 7

Input exponent in toolbox input parameter Exponent used in Power and Combined Functions (see Figure 4-51)

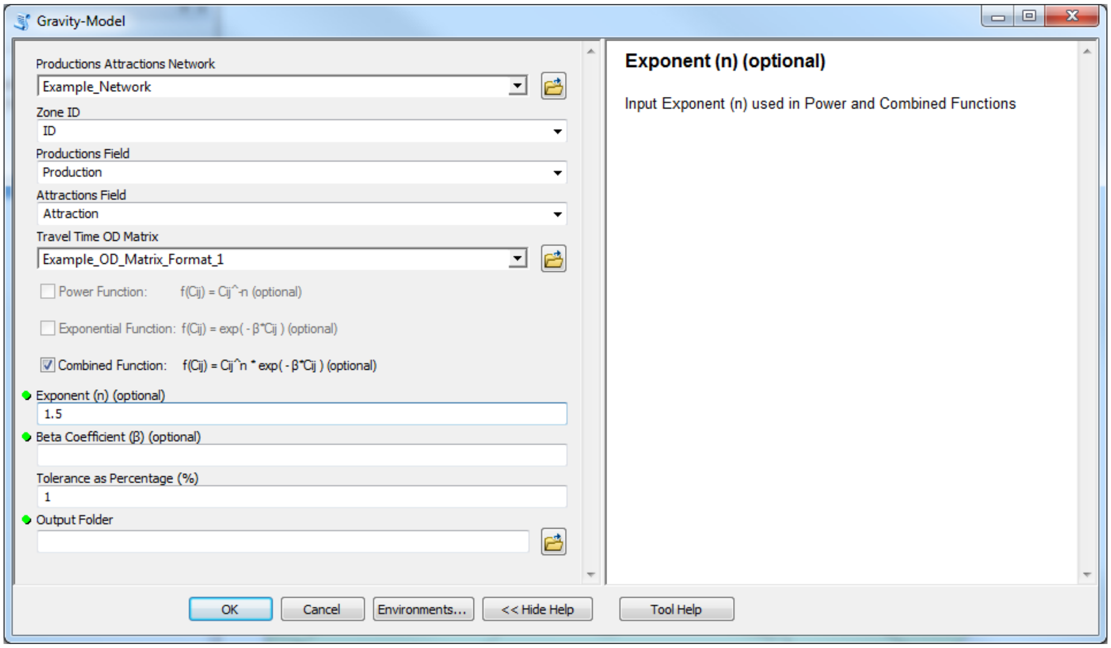


Figure 4-51. Input Exponent in Power or Combined Function

STEP 8

Input beta in toolbox input parameter Beta Coefficient used in Exponential and Combined Functions (see Figure 4-52)

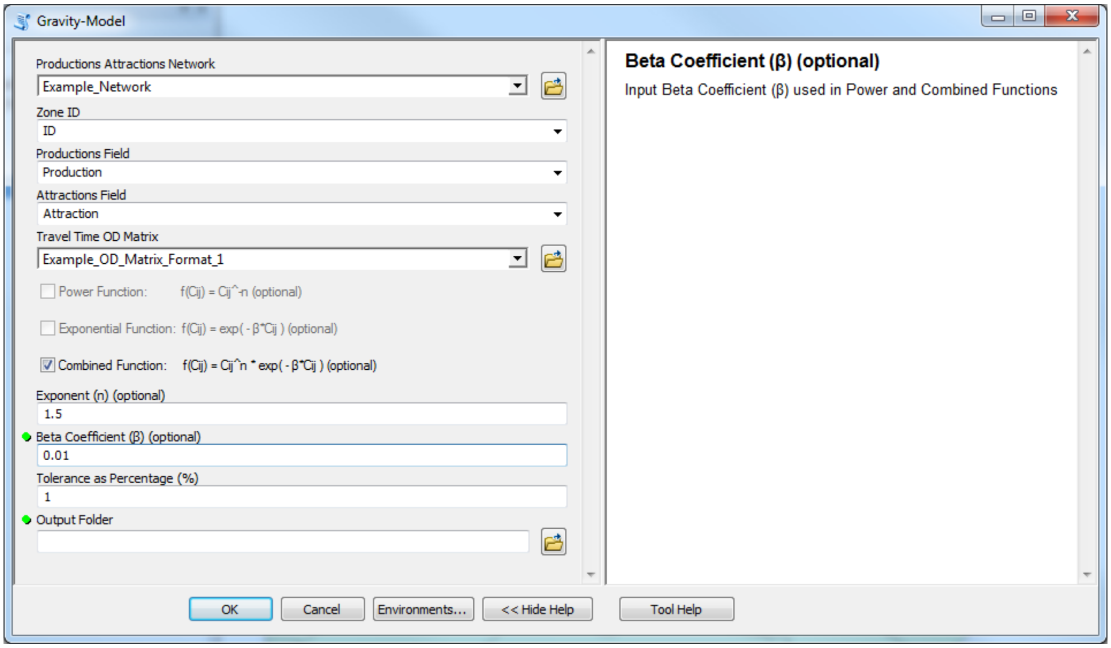


Figure 4-52. Input Beta Coefficient

STEP 9

Input a percentage of tolerance to balance matrix in input parameter Tolerance as Percentage (see Figure 4-53). (Default: 0.01 %).

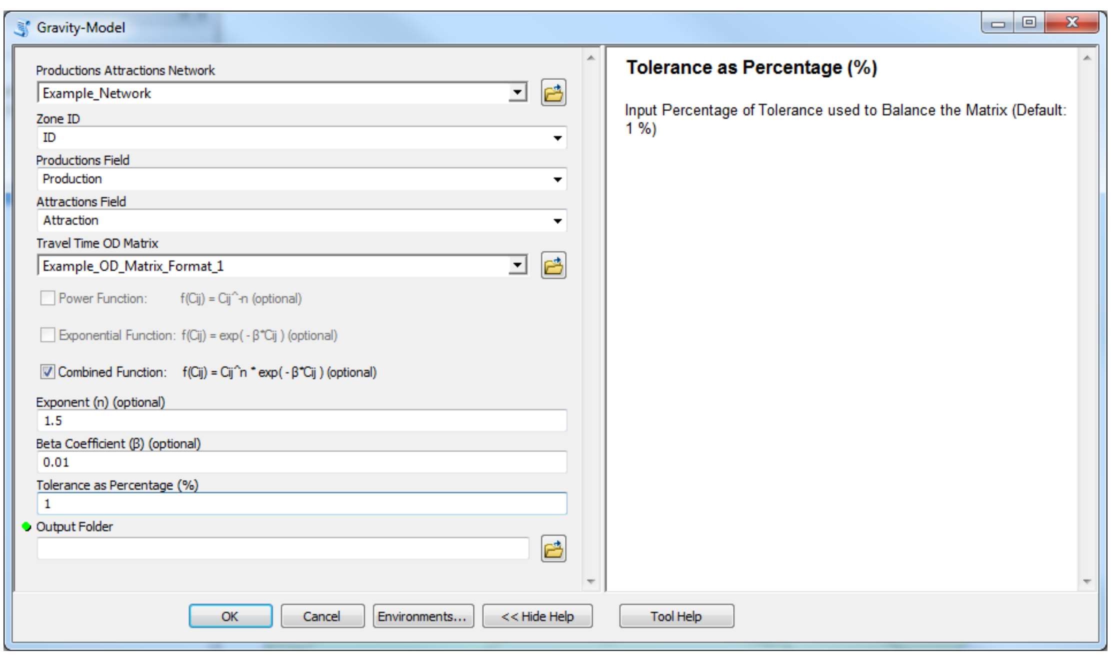


Figure 4-53. Input Tolerance

STEP 9

In toolbox Output Folder parameter input output folder path where processed shapefiles will be exported after toolbox analysis (see Figure 4-54).

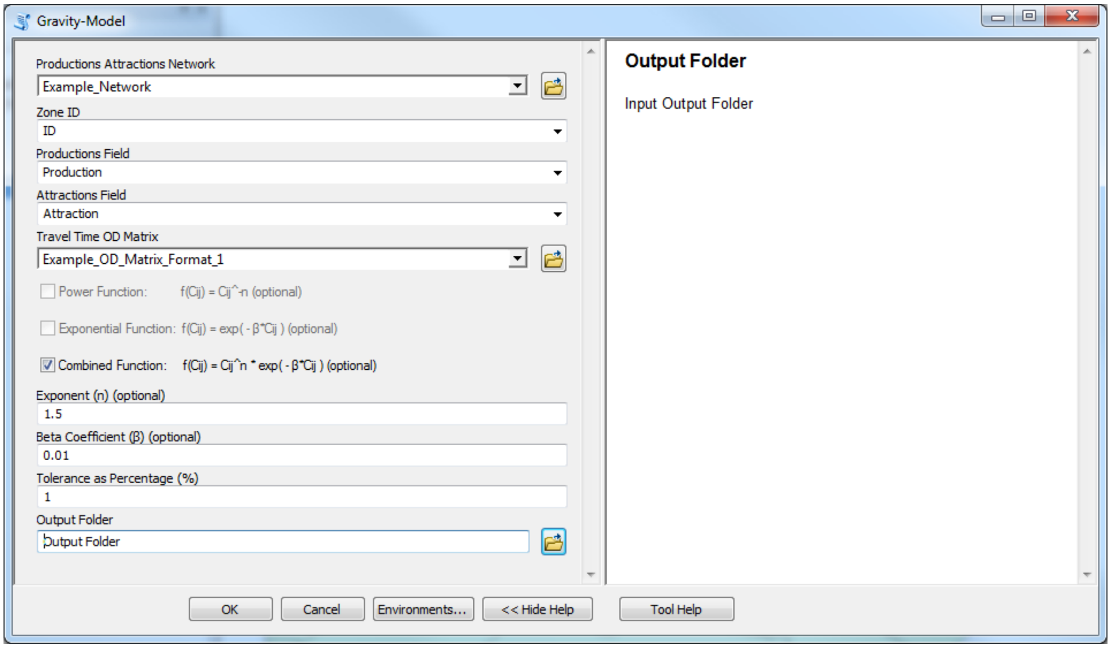


Figure 4-54. Input Output Folder

STEP 6

Once all required parameters are inputted, press OK to execute the application. The ArcGIS application invokes a task completion window, which reports status of each task (see Figure 4-55). In addition, processed shapefiles will be imported to ArcMap Display (see Figure 4-56).

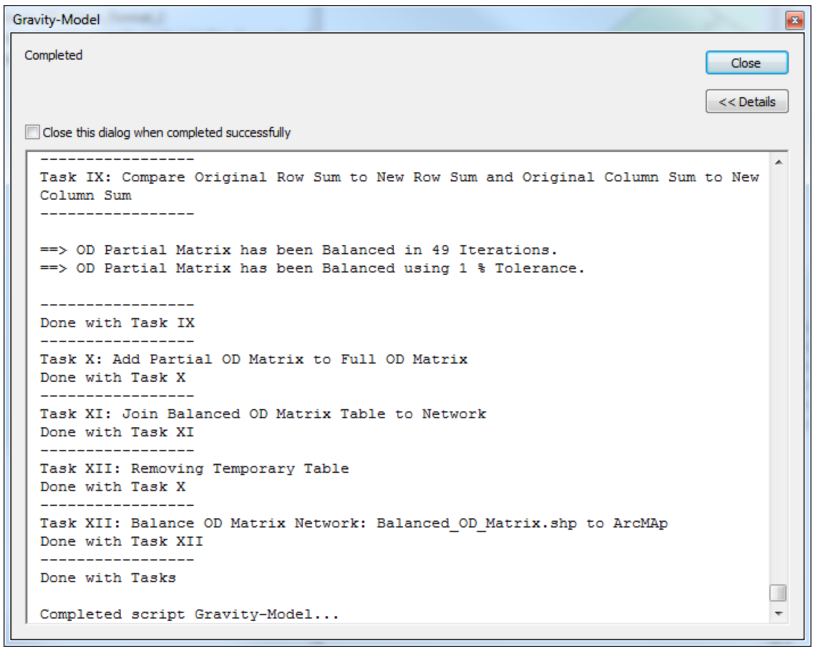


Figure 4-55. Application performed task window

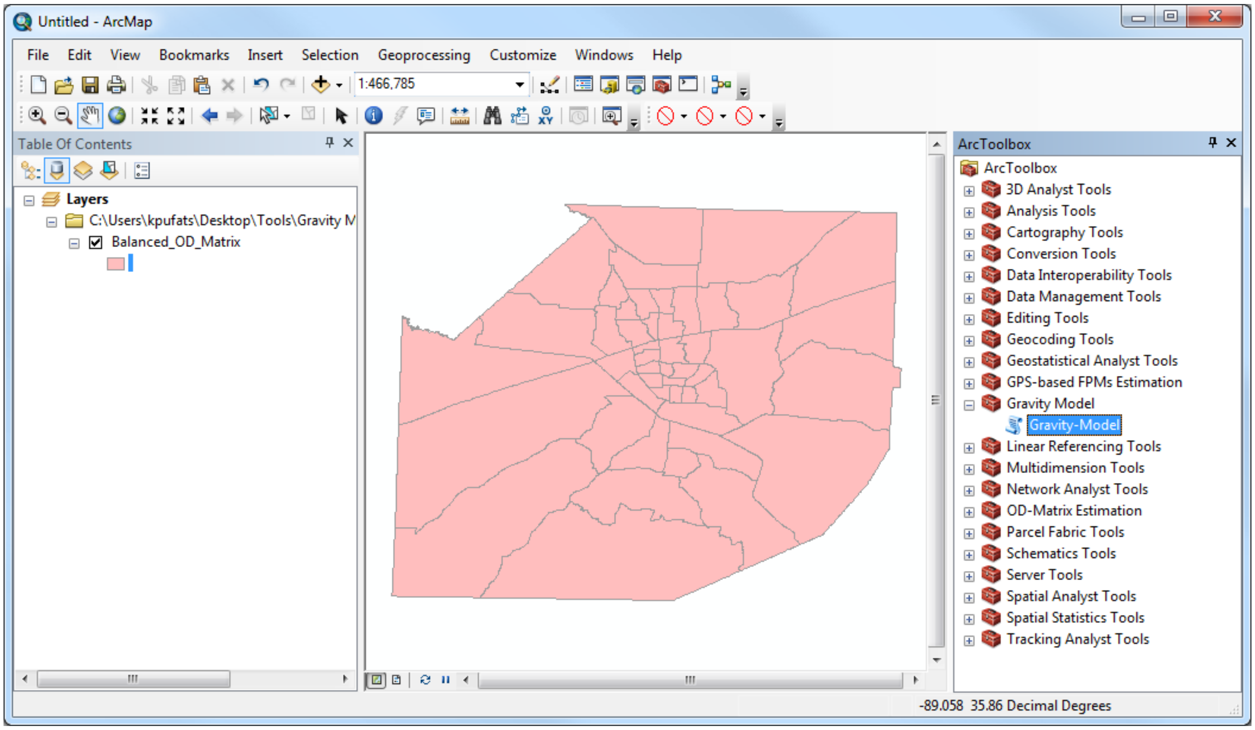


Figure 4-56. Displayed processed shapefile

4.5 Results: freight flows by NAICS code and TAZs in Jackson MPO

Above four GPS tools are used to estimate the freight flows in Jackson MPO of Tennessee. The flow is estimated for each TAZs of Jackson MPO based on establishment categorized by North American Industry Classification System (NAICS). Only four NAICS establishments based on three major categories, manufacturing, retail trade, and accommodation and food are found to exist within Jackson MPO. These are manufacturing food, beverages, textile (NAICS 31), manufacturing metal, machine, computer, furniture (NAICS 33), retail trade of motor vehicles, electronics, furniture (NAICS 44), and accommodation and food services (NAICS 72). The freight flows are represented conveniently by desire lines. These lines simply represent the magnitude of flows based on color and thickness of the lines connecting two regions.

The vehicle trips is highest for NAICS 31 (Figure 4-57) commodity followed by NAICS 33 (Figure 4-58), NAICS 44 (Figure 4-59), and NAICS 72 (Figure 4-60). The flows are concentrated around the Jackson city which is intuitive as the vehicle movements are directly proportional to the population and urbanization. Although, the vehicle movements were present outside the Jackson city, it was insignificant compared to the movements at Jackson city and hence, the desire lines were presented in such a way that it represents the major flows by avoiding the obscure state of the picture.

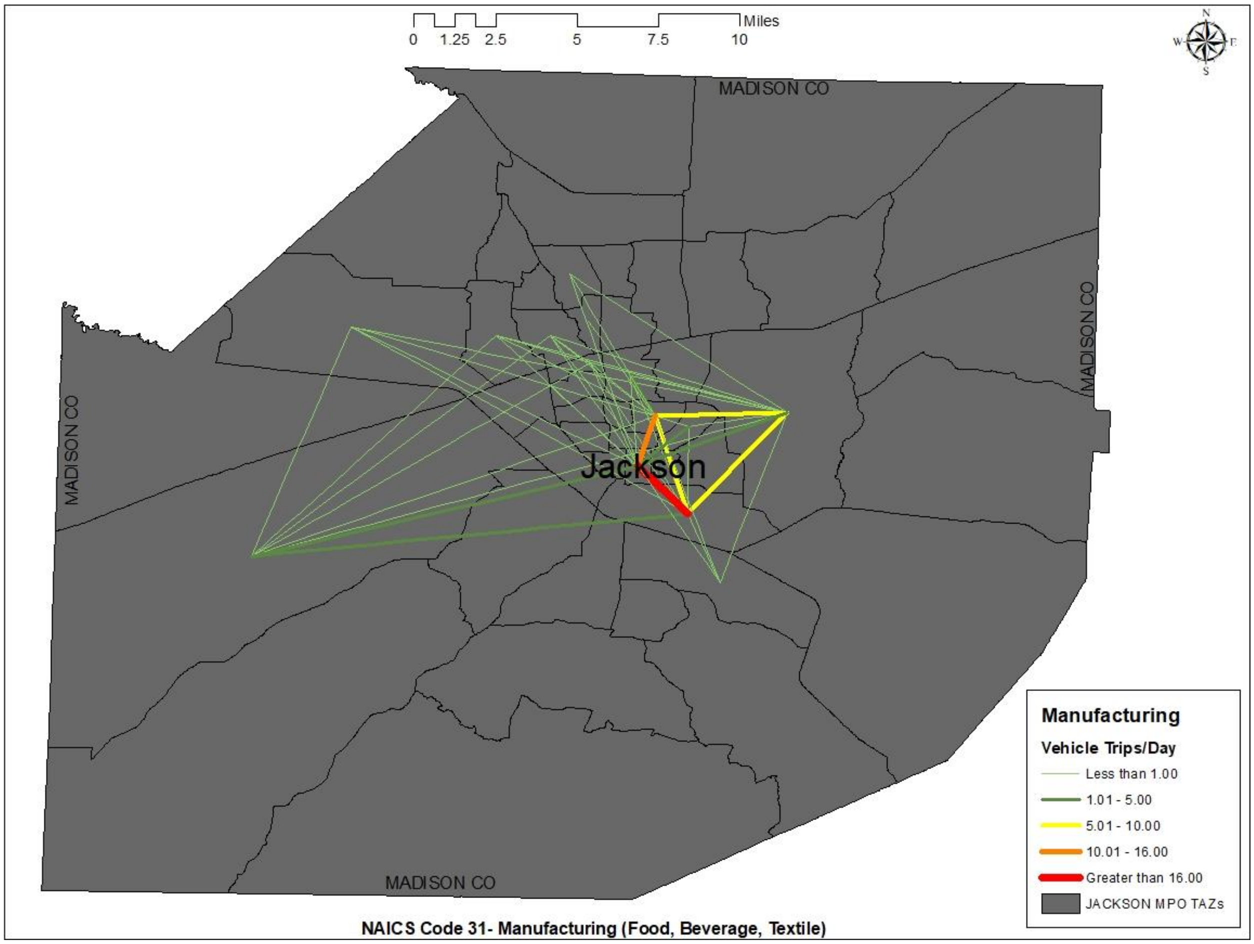


Figure 4-57. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 31"

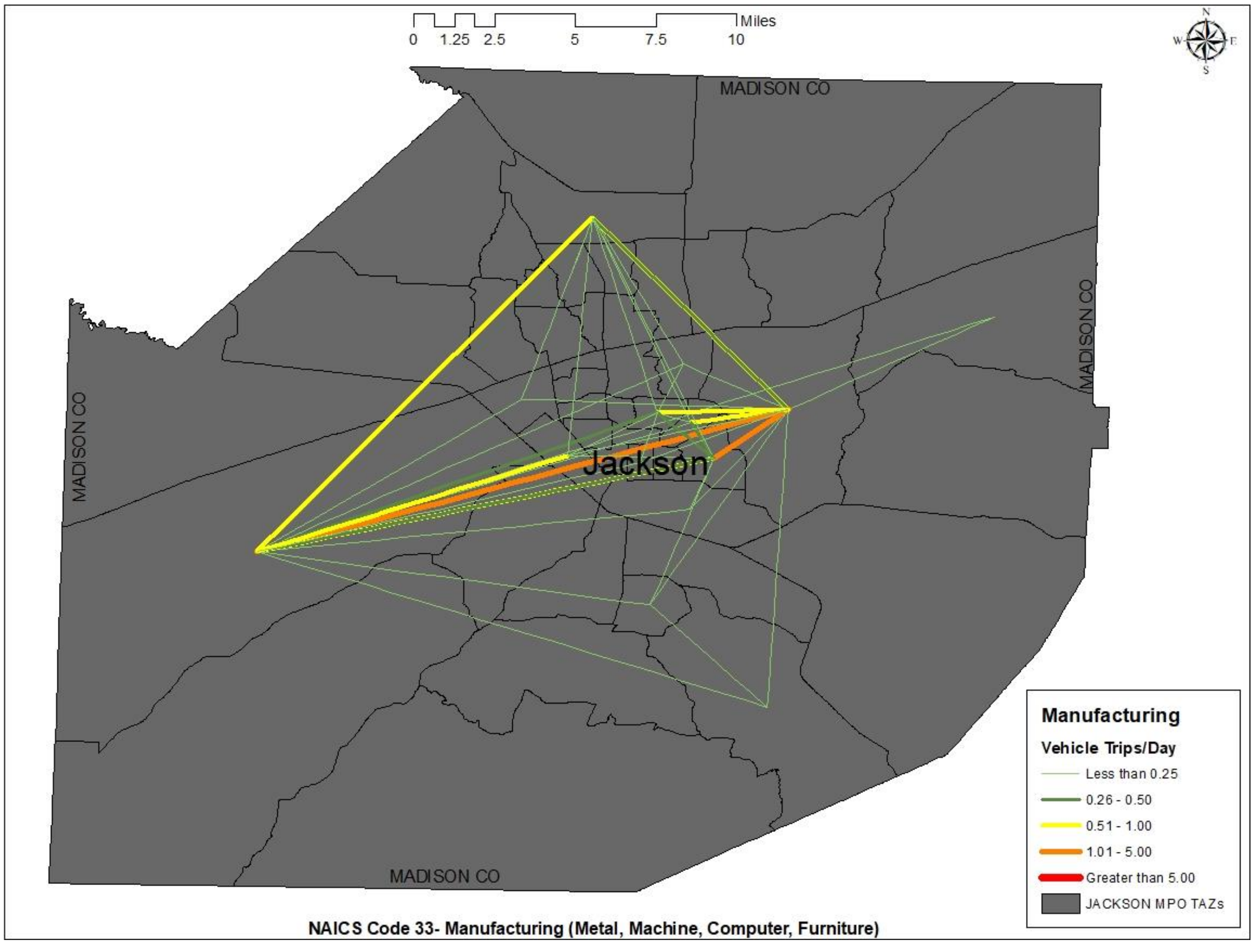


Figure 4-58. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 33"

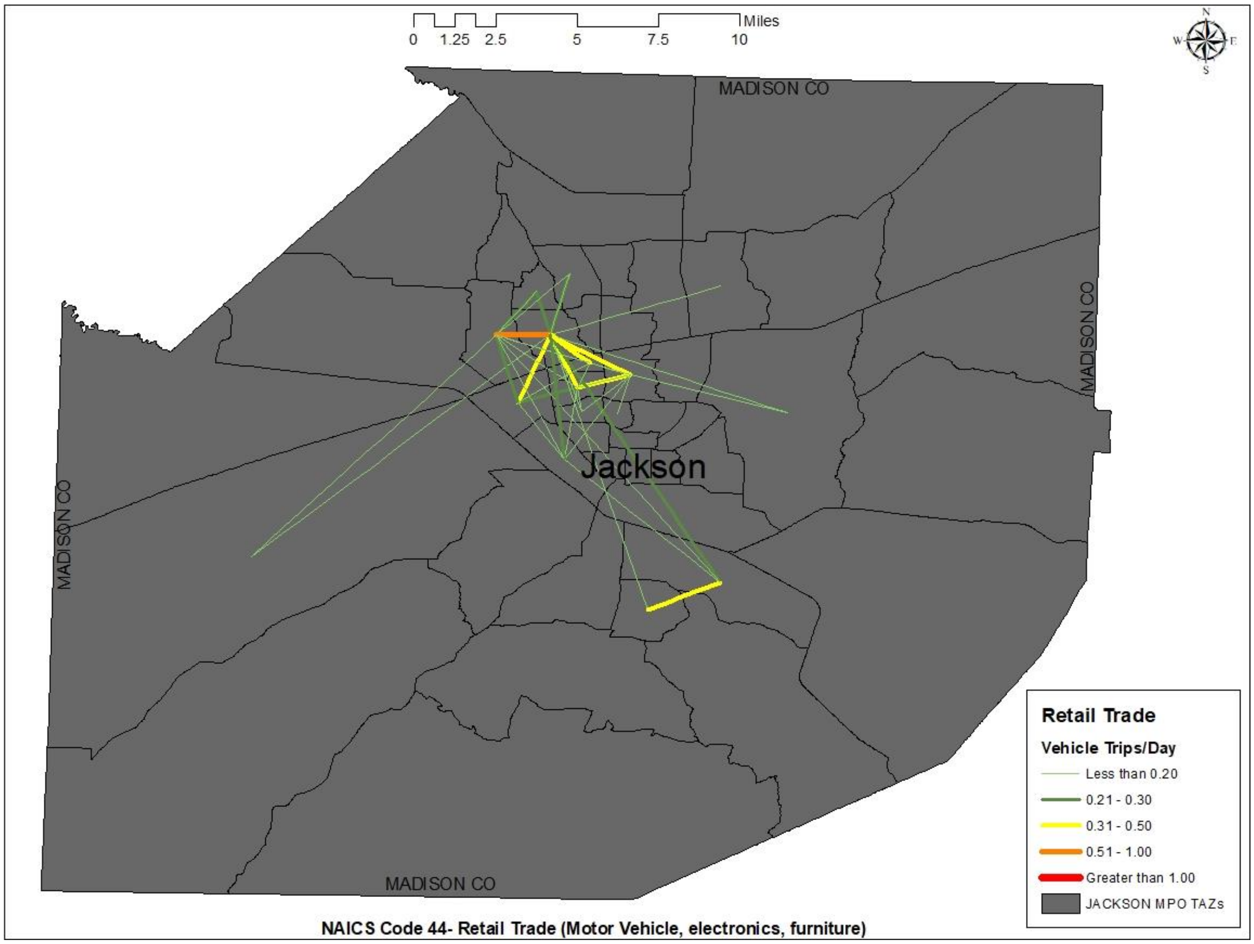


Figure 4-59. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 44"

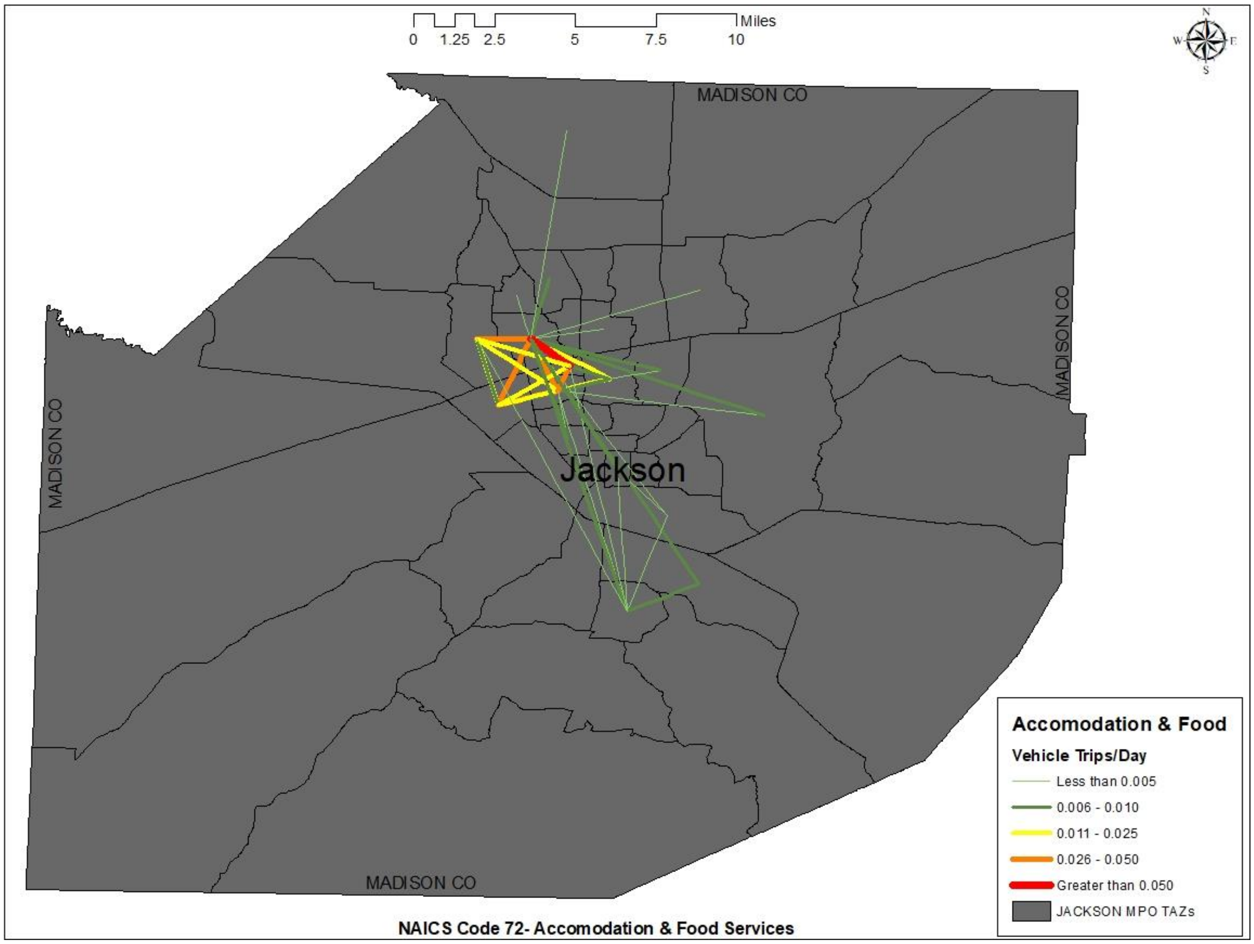


Figure 4-60. Daily vehicular trips at TAZ level for commodity indicated by "NAICS 72"

4.6 Conclusion

Through the availability of truck GPS data, it is possible to obtain commodity based origins and destinations by linking this data with freight establishment data which can be used effectively for local planning areas. In this chapter, freight movement was integrated with land use by collecting the freight establishment data and characteristics of each establishment. This establishment data was aggregated in TAZ level with the help of freight generation tools to execute the trip productions and attractions. Further with use of truck GPS data, travel time between specific O-D pairs was obtained which was useful for calibration of trip length distribution of gravity models producing the O-D matrices. The case study presented the O-D flows at Jackson MPO of TN where there were 48 sublevels

(TAZs) and four establishments by NAICS code. It was clear that the vehicle trips was concentrated in the city area highlighting the importance of land in freight planning.

Typically in planning models or for planning purposes, truck trips are available in the form of productions and attractions (or origins-destinations at a county level). While such data is helpful for statewide and regional planning purposes, it could have limited application for local levels. By developing the various GIS tools in this chapter, it is now possible to obtain the commodity based O-D matrices at local levels which clears the hindrances at local planning process. The direction for the future research would be to use the developed GIS tools in various regions of the state as well as the whole country and validate the commodity specific O-D such that the models can be used for highway capacity planning purposes. To further strengthen freight land use integration, vehicle registration data can be collected in the study area to develop a truck trip origin pattern by vehicle type.

CHAPTER 5: FREIGHT PLANNING AND COMMUNITY VISIONING

5.1 Background

To understand the current state of practice by public agencies in TN, we conducted a community visioning survey. The survey included a number of questions such as freight planning data, vision, goals, planning practices, etc. Below we present the survey results from 45 public agencies in TN. The survey is attached in appendix.

5.2 Findings

Figure 5-1 summarizes that the major participants of the survey belong to the DOT (37%) followed by MPO (27%), RPO (15%), other agencies (9%) with TPO and City or County Department of Transportation sharing the least and equal participants (6%). About 79% of total respondents seem to include comprehensive set of community visioning and goals in their Long Range Transportation plan (LRTP) and out of them, 83% address a multimodal transportation system (see Figure 5-2 and Figure 5-3). From these responses, it can be concluded that around 65% agencies address multimodal transportation system in their LRTP and major contribution to this comes from DOT and MPO. Efforts should be made to include multimodal transportation into LRTP especially in the lower level public agencies like City or County Department of Transportation. And, agencies are reluctant in answering the question about the alignment of previously established goals and visions into the current community visioning. 79% have escaped this question and only 21% have responded with alignment of previous visions and goals. This may be the reason that the agencies are either not sure of inclusion of their previous goals and visions into the current visions or they are changing their goals and visions every time and they do not want to disclose this (Figure 5-4).

Figure 5-5 highlights the importance of freight in community visioning process being given the highest response (17%) followed by location of new development (16%), and economic development and diversification (15%) among top three issues. But the most agencies (70%) have not assessed themselves from the community in the freight domain (Figure 5-6) although more than half of the agencies (52%) receive the request from the freight users (Figure 5-7). Out of those requests, 26% comes from the truck, 17% from the Shippers, and 15% from both the carrier and rail among the top three freight stakeholders (Figure 5-8) with the requests mostly in operations (50%) and capacity (39%), (see Figure 5-9). Figure 5-10 once again explains the importance of freight and its movement in the community's vision and goals.

Figure 5-11 shows the problem of truck parking in the agency's community with 61% of them facing this problem. Question 12 is about ranking the seven key elements recommended by Highway Capacity Planning process to account the important market driven behavior and interests of the private sector freight community. Figure 5-12 summarizes safety as most important element and the environment the least important with all other elements in between. Besides public, the major participants of the community visioning process are local government (15%), transportation agencies like FHWA, State DOTs (14%), and private sector and economic development agencies (both 13%), (see Figure 5-13). Then, the three major platforms for engaging the freight stakeholders are Freight Advisory Committee (FAC)-31%, workshop, freight stakeholder meetings etc. (24%), and outreach, interviews etc. (20%), (see Figure 5-14). Public workshops (23%), public surveys (22%), and a social media page along with one on one stakeholder interviews (18%) are three major strategies to encourage the community participation in the transportation planning process (Figure 5-16). Although three quarters of the agencies seem to disregard the citizen committee (Figure 5-15), almost four quarters (79%) agencies have a website to display the community visioning activities and engagement (Figure 5-17).

About the agencies which does not have a travel demand model, just above half of them (53%) seem not to use other travel demand model at all (Figure 5-22). Unexpectedly, the agencies use the NPMRDS (25%) more than the FAF (21%) to assist with the freight planning (Figure 5-23). Development or implementation of a Freight Action Plan is the outcome of the visioning process which lacks in 68% of the agencies (Figure 5-24) and hence these agencies are failing to measure the effectiveness of the community visioning which must be highlighted.

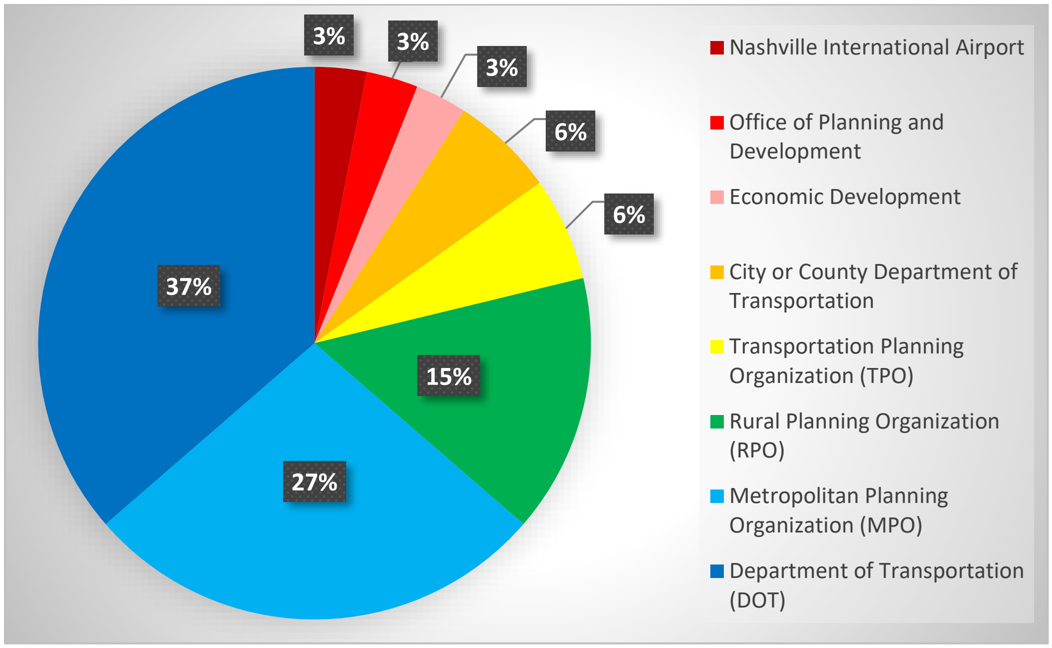


Figure 5-1. Responses to agency's survey, "What is the type of organization your agency represent?"

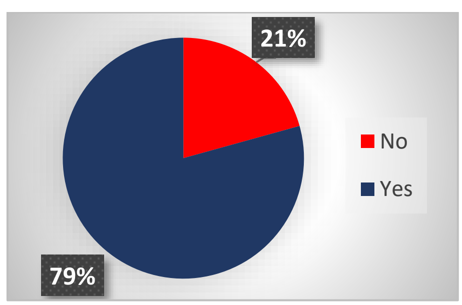


Figure 5-2. Responses to agency's survey, "Does your agency's Long Range Transportation Plan (LRTP) have a common, comprehensive set of community visioning and goals?"

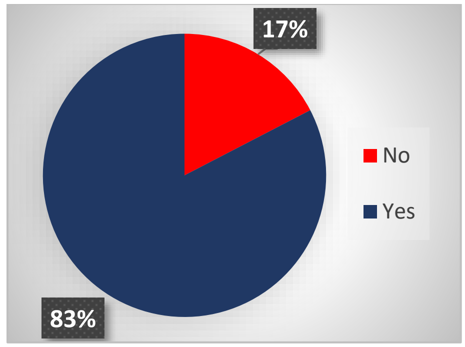


Figure 5-3. Responses to agency's survey, "If 'Yes', are these visions and goals diverse and wide-ranging enough to address a multimodal transportation system?"

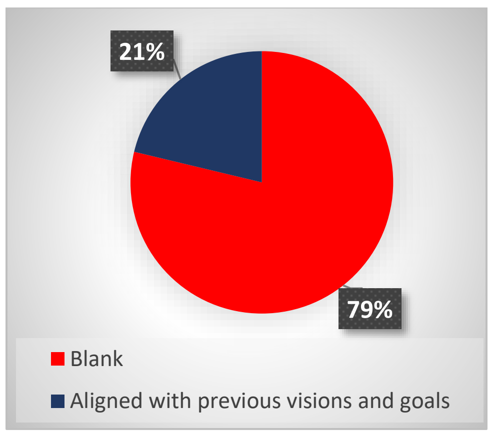


Figure 5-4. Responses to agency's survey, "How do these reflect previously established vision and goals?"

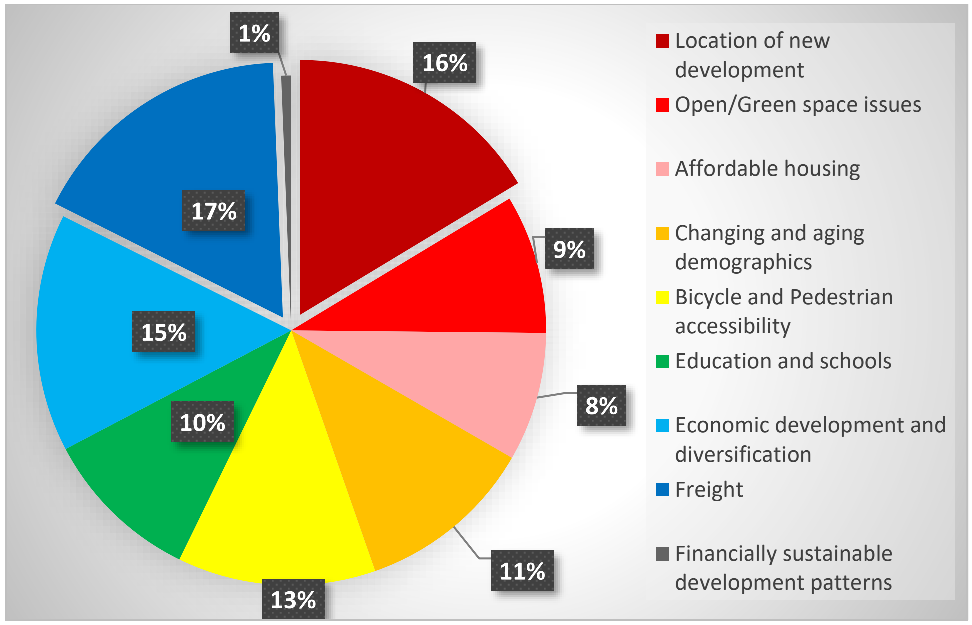


Figure 5-5. Responses to agency's survey, "What issues should the community address in visioning process?"

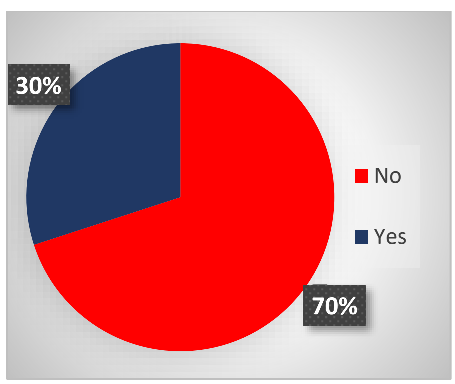


Figure 5-6. Responses to agency's survey, "Has your agency carried out '*Freight self-assessment'* for your community?"

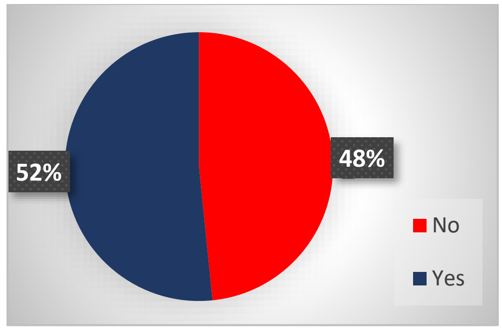


Figure 5-7. Responses to agency's survey, "Does your agency receive any request from freight users in your community?"

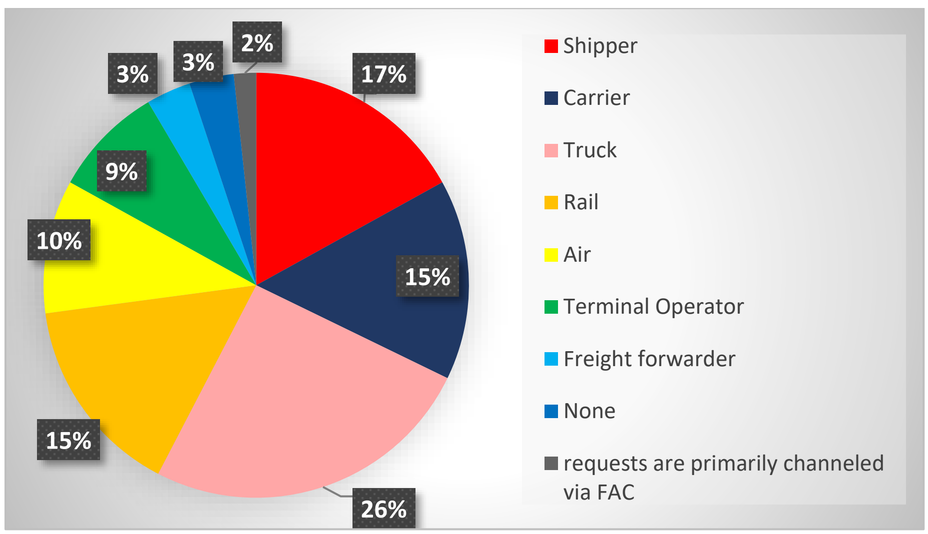


Figure 5-8. Responses to agency's survey, "If you answered 'Yes' in question 7, what type of freight stakeholders has made a request?"

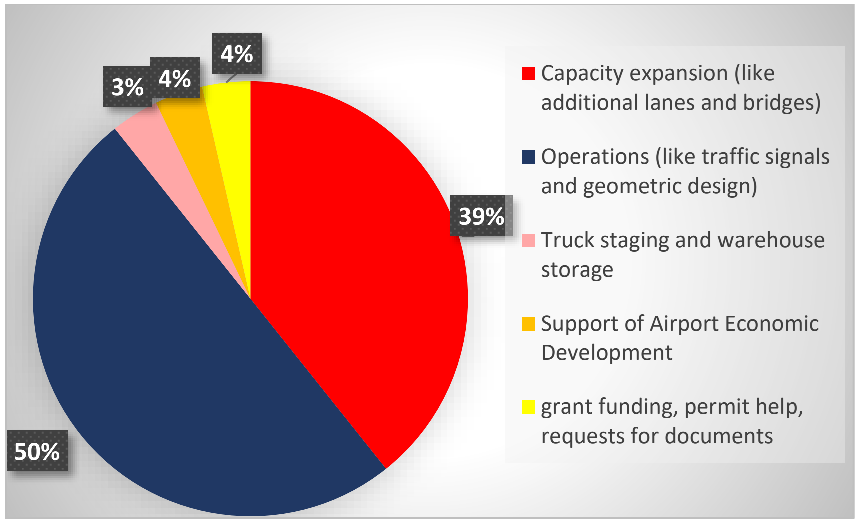


Figure 5-9. Responses to agency's survey, "If you answered 'Yes' in question 7, what type of request have you received?"

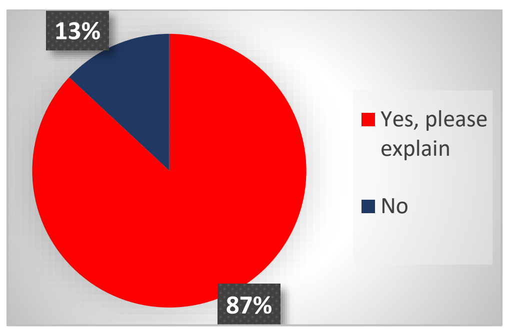


Figure 5-10. Responses to agency's survey, "Does freight movement impact your community's vision and goals?"

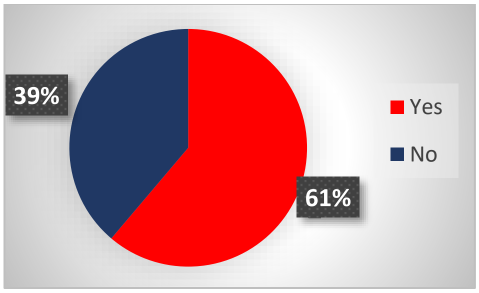


Figure 5-11. Responses to agency's survey, “Is truck parking a problem in your community or region?”

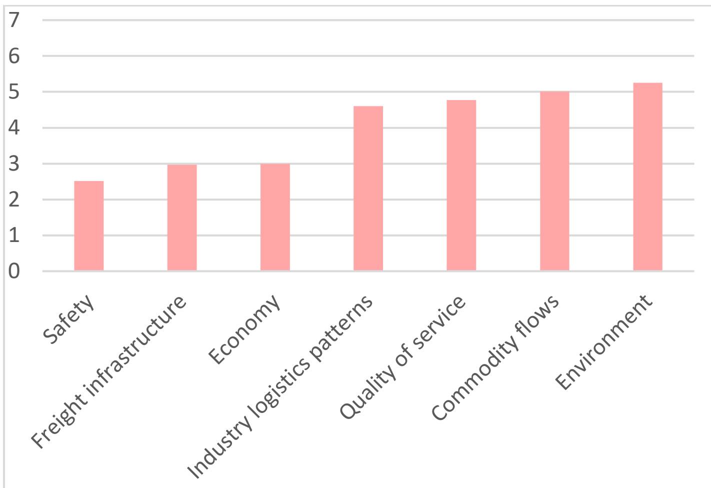


Figure 5-12. Responses to agency's survey, “To fully account for the important market-driven behavior and interests of the private-sector freight community, *Highway Capacity Planning* process recommends following key considerations. Please rank them (1—7, 1:Most Important, 7:Least Important) according to your community’s needs and visions”

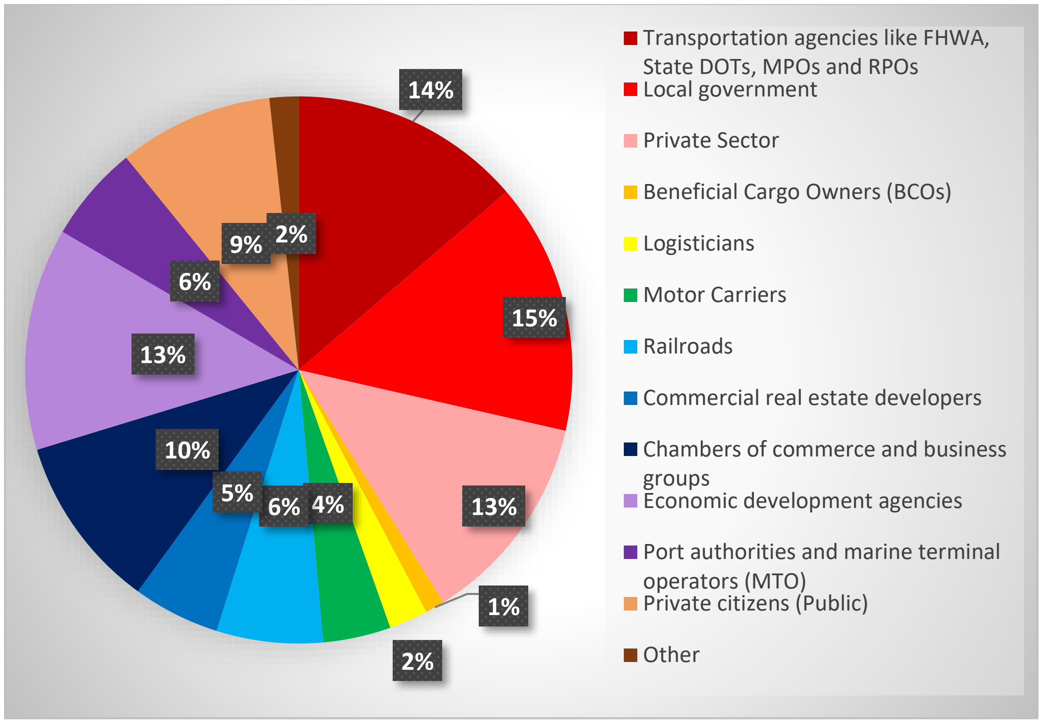


Figure 5-13. Responses to agency's survey, “Who are the participants in your community visioning process besides public?”

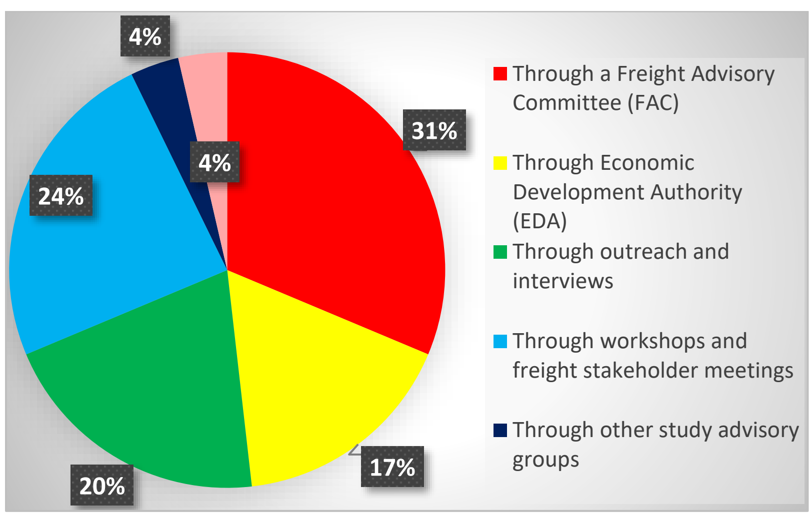


Figure 5-14. Responses to agency's survey, “How should the agency engage *Freight Stakeholders?*”

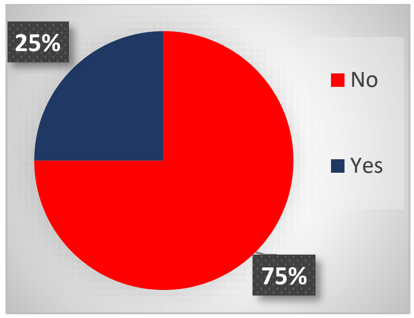


Figure 5-15. Responses to agency's survey, "Does your agency have a *Citizen Committee* or *Citizens Visioning Task Force* or *Steering Committee?"*

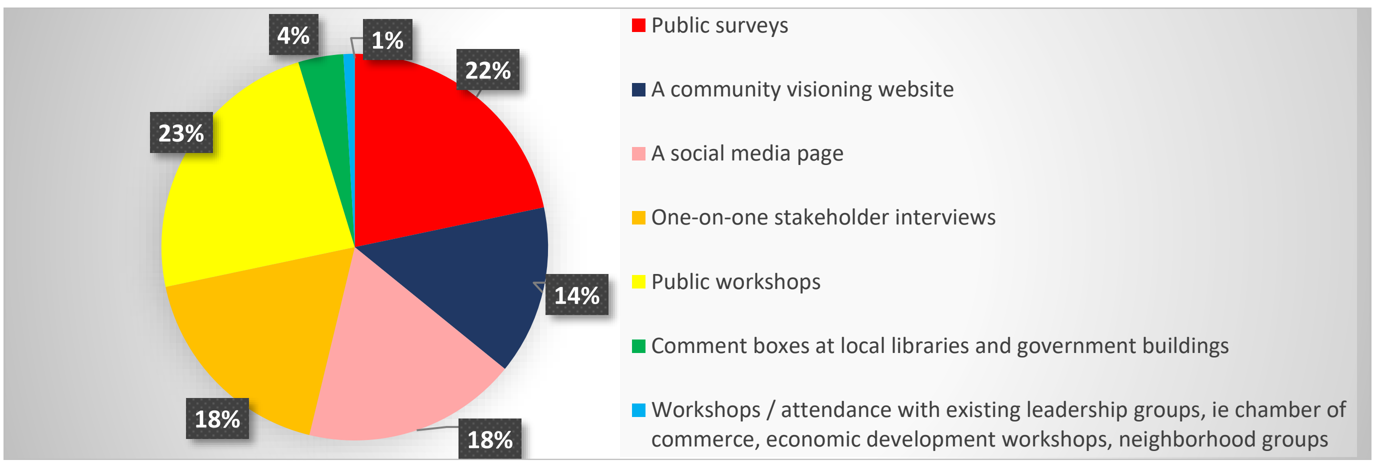


Figure 5-16. Responses to agency's survey, "What are the best strategies to encourage the community participation in the transportation planning process?"

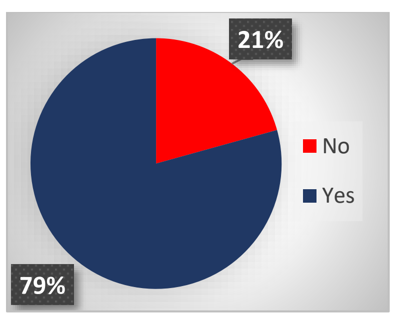


Figure 5-17. Responses to agency's survey, "Does your agency have a website to display community visioning activities and engagement?"

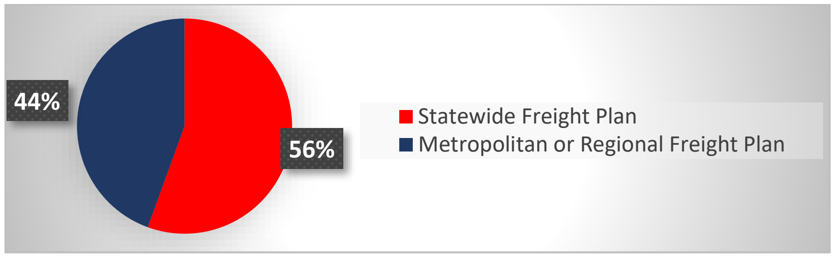


Figure 5-18. Responses to agency's survey, "Does your agency have one of the following?"

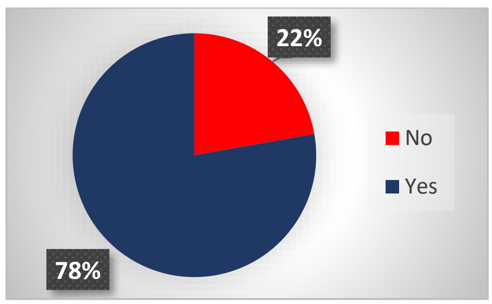


Figure 5-19. Responses to agency's survey, "Does your agency have a travel demand model for planning and decision making?"

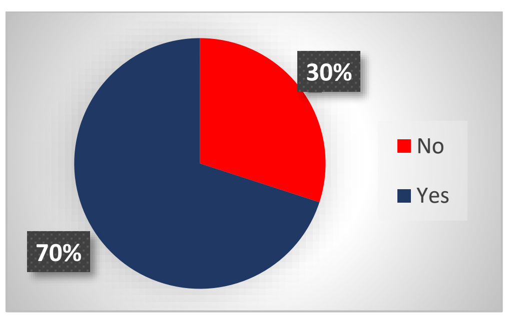


Figure 5-20. Responses to agency's survey, "If you answered yes to question 19, does your agency's travel demand model have a freight component?"

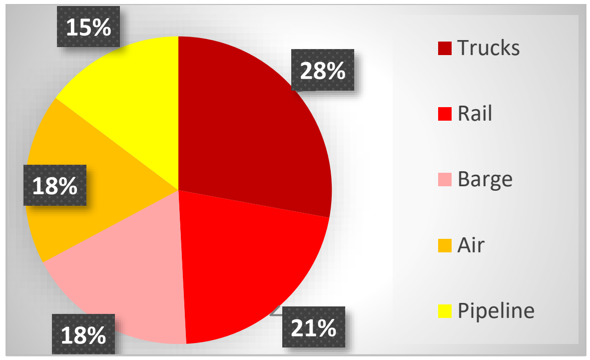


Figure 5-21. Responses to agency's survey, “If you answered yes to question 19, which modes are included in freight component of the model?”

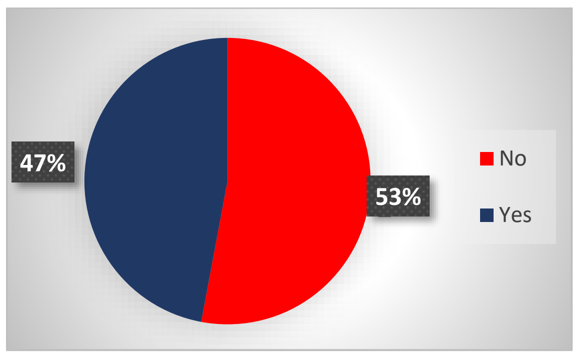


Figure 5-22. Responses to agency's survey, “If your agency does not maintain a travel demand model, does your agency use any other travel demand model at all developed by the state DOT or neighboring MPO?”

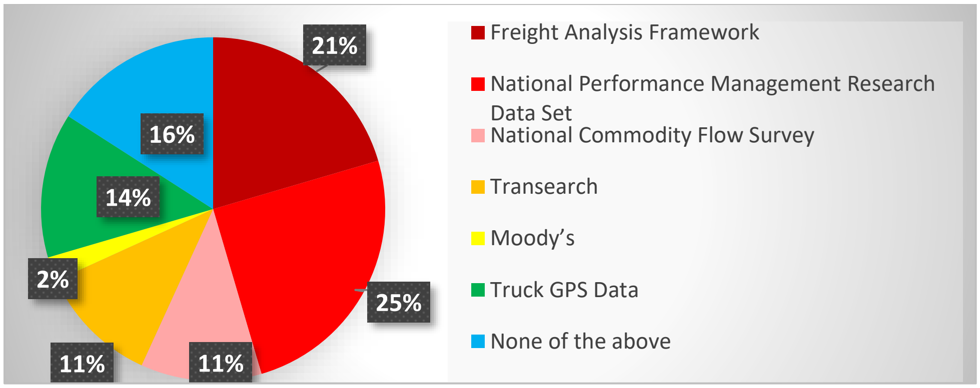


Figure 5-23. Responses to agency's survey, “Does your agency use any freely available or proprietary data or to assist with freight planning?”

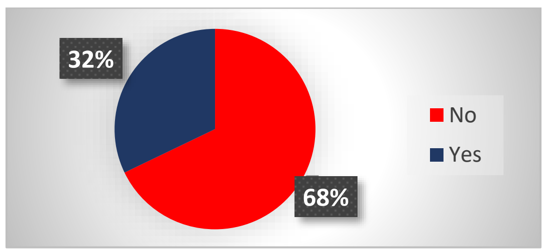


Figure 5-24. Responses to agency's survey, "Has your agency developed or implemented a Freight Action Plan according to the needs of community?”

5.3 Conclusion:

The survey represents a critical element to understand current agency practices on use of data, methods, and applications for freight planning. The statewide survey conducted as part of this study showed freight planning practices as well as needs and visioning by the agencies. Community visioning is a powerful way to identify agency needs as well as informing agencies with use of upcoming data and methods for freight planning.

CHAPTER 6: SUMMARY AND CONCLUSION

In effort to addressing the goal of SHRP2 round 5 project, three major performances measures were analyzed in order to integrate the freight considerations into the Highway Capacity Planning Process. The project was concluded with a brief community visioning survey from which we hope to identify freight indicators which will assist in institutionalizing the output of the implementation project, in TN. Truck GPS data obtained from ATRI serves as the basis of this project.

The first performance measure analyzed was truck parking within the rest areas of the interstates. Different econometric models were developed primarily to predict the truck parking utilization as a function of geometric and traffic characteristics of adjacent roadways and the rest area characteristics. In addition to this, the variation of truck parking utilization by time of day was also observed. To represent the nature of parking utilization, four different count models, Poisson (Model 1), Negative Binomial (Model 2), Poisson with Propensity (Model 3), and Poisson with propensity and threshold specific constant (Model 4) were developed, out of which Model 4 was found to be the best statistical fit. The major factors affecting the truck parking utilization were found to be truck volume, on ramp and off ramp violations, higher average speeds of the trucks passing the rest area, and presence of a two lane roadway adjacent to the rest area. Similarly, the early morning hours (immediately after the midnight) were found to be busier than other hours of the day in terms of parking which is very intuitive that the drivers want to take a rest in the night and start the journey again in the am peak hours (6-9 am). The interesting output of the model is that the increment of 100% truck volume increases truck parking utilization by only 1.33% in average. This explains that the parking space is very high compared to the truck volume. It will be interesting to see this increment number by different periods of the day which is expected to be higher during the night period. The developed models can play an important role in assessing the utilization of the various rest areas and the need for the enhancement.

The second performance measure was the freight corridor reliability in which truck GPS data was extensively used to predict the path based travel time and its reliability in ideal, recurring, and non-recurring conditions. Through the identification of shortest paths between each OD pairs connecting the FAF network of Shelby County within TN, the travel time and travel time variation within time of day for recurring and non-recurring congestion were studied. As expected, the travel time are higher in am and pm peaks with off peak hours being lowest of all. The standard deviation of travel time (travel time variation) for non-recurring congestion followed a similar trend to that of recurring congestion with higher time index. The main goal of this chapter was to predict the correlation of various roadway and crash characteristics with travel time and its variation for a freight corridor. All the results are self-explanatory like the increment of travel time and its variation with increase in VCR, arterial composition of paths, number of crashes on paths and number of vehicles involved in those crashes, and severity of the crashes occurred.

As a final performance measure of this study, land use and freight was studied in order to address the growth in land use by considering the current freight flows in a region. The main task in this study is the computation of first two steps of travel demand modeling, trips generation and trip distribution. For this, different GIS tools were developed based on truck GPS data with various assumptions acquired from NCHRP report 37. The model used for the trip distribution is the gravity model. This methodology was implemented in Jackson MPO of TN with 48 TAZs. The O-D trip matrices were computed on TAZ level for different establishments. Only four NAICS establishments are found to exist in the region with manufacturing food, beverages, textile (NAICS 31) and accommodation and food services (NAICS 72) being major and minor establishment respectively, based on the number of vehicle trips. The trips are mainly concentrated on the vicinity of the Jackson city indicating the importance of land use based on population and urbanization. This commodity specific O-D matrices can be integrated in the highway capacity planning process by prioritizing the importance of the lands.

To implement the above findings in the overall freight capacity planning process of a region effectively, the assessment of the current state of different agencies within the region is very helpful. Hence, a community visioning survey was carried out, presented in chapter 5. It was found that although 79% of the agencies' LRTP had community visioning and goals, only 65% address the multimodal transportation system in their LRTP. Also, various freight indicators like travel demand models, freight modes, proprietary data were identified along with some factors of the community visioning process such as issues and private participants, market driven behavior and interests**,** best strategies to encourage the community participation in the transportation planning process, etc.

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APPENDIX - COMMUNITY VISIONING SURVEY

Freight Planning and Community Visioning Survey Questionnaire

As a part of the Strategic Highway Research Program 2 (SHRP2) Round 6 project, this survey is designed to understand the freight planning and modeling exercises currently in place at various transportation planning organizations. The survey responses are anonymous and will be kept confidential. The results of the survey will be helpful for both TDOT, and FHWA to implement freight considerations in highway capacity planning process.

1. **What is the type of organization your agency represent?**
   - Department of Transportation
   - Metropolitan Planning Organization
   - Transportation Planning Organization
   - Rural Planning Organization
   - City or County Department of Transportation
   - Other issues, such as:______________________

2. **Does your agency's Long Range Transportation Plan (LRTP) have a common, comprehensive set of community visioning and goals?**
   - Yes
   - No

3. **If "Yes", are these visions and goals diverse and wide-ranging enough to address a multimodal transportation system?**
   - Yes
   - No

4. **How do these reflect previously established vision and goals?**
   - Aligned with previous visions and goals
   - Conflicts with certain visions and goals

5. **What issues should the community address in visioning process?**
   - Location of new development
   - Open/Green space issues
   - Affordable housing
   - Changing and aging demographics
   - Bicycle and Pedestrian accessibility
   - Education and schools
   - Economic development and diversification
   - Traffic congestion

- Freight
- Other issues, such as:______________________

6. **Has your agency carried out "*Freight self-assessment*" for your community?**
   - Yes
   - No

7. **Does your agency receive any request from freight users in your community?**
   - Yes
   - No

8. **If you answered "Yes" in question 6, what type of freight stakeholders has made a request. Select all that apply.**
   - Shipper
   - Carrier
   - Truck
   - Rail
   - Air
   - Terminal Operator
   - Freight forwarder

9. **If you answered "Yes" in question 6, what type of request have you received? Select all that apply.**
   - Capacity (e.g., additional lanes)
   - Operations (e.g., traffic signals, intersection geometry)
   - Others, please specify

10. **Does freight movement impact your community's vision and goals?**
    - Yes
    - No

11. **Is truck parking a problem in your community or region?**
    - Yes
    - No

12. **To fully account for the important market-driven behavior and interests of the private-sector freight community, *Highway Capacity Planning* process**

recommends following key considerations. Please rank them (1—7, 1:Most Important, 7:Least Important) according to your community's needs and visions

- Economy_____
- Industry logistics patterns_____
- Freight infrastructure_____
- Commodity flows_____
- Quality of service_____
- Environment_____
- Safety_____

13. Who are the participants in your community visioning process besides public? Select all that apply.

- Transportation agencies: FHWA, State DOTs etc.
- Local government
- Private Sector
- Beneficial Cargo Owners (BCOs)
- Logisticians
- Motor Carriers
- Railroads
- Commercial real estate developers
- Chambers of commerce and business groups
- Economic development agencies
- Port authorities and marine terminal operators (MTO)
- Other freight stakeholders, such as:_______________________________

14. How should the agency engage *Freight Stakeholders?*

- Through a Freight Advisory Committee (FAC)
- Through Economic Development Authority (EDA)
- Through outreach, interviews etc.
- Through workshop, freight stakeholder meetings etc.
- Through other study advisory groups

15. Does your agency have a *Citizen Committee* or *Citizens Visioning Task Force* or *Steering Committee?*

- Yes
- No

16. What are the best strategies to encourage the community participation in the transportation planning process? Check all that apply.

- Public surveys

- A community visioning website
- A community visioning site on a social networking site
- One-on-one stakeholder interviews
- Public workshops and/or design charrettes
- Comment boxes at local libraries and government buildings
- All of the above

17. Does your agency have a website to display community visioning activities and engagement?

- Yes
- No

18. Does your agency have one of the following?

- Statewide Freight Plan
- Metropolitan and Regional Freight Plan

19. Does your agency have a travel demand model for planning and decision making?

- Yes
- No

20. If you answered yes to question 18, does your agency's travel demand model have a freight component?

- Yes
- No

21. If you answered yes to question 19, which modes are included in freight component of the model? Select all that apply.

- Trucks
- Rail
- Barge
- Air
- Pipeline
- All modes

22. If your agency does not maintain a travel demand model, does your agency use any other travel demand model at all developed by the state DOT or neighboring MPO?

- Yes
- No

23. Does your agency use any freely available or proprietary data or to assist with freight planning? Check all that is appropriate.

- o Freight Analysis Framework
- o National Performance Management Research Data Set (NPMRDS)
- o National Commodity Flow Survey
- o Transearch
- o Moody's
- o Truck GPS Data
- o None of the above
- o Others (please list below)

24. Has your agency developed or implemented a *Freight Action Plan* according to the needs of community? (This is the outcome of the visioning process)

- o Yes
- o No