NCTSPM

NATIONAL CENTER FOR TRANSPORTATION SYSTEMS PRODUCTIVITY AND MANAGEMENT

Bringing Freight Components into Statewide and Regional Travel Demand Forecasting

Contract # DTRT12GUTC12 with USDOT Office of the Assistant Secretary for Research and Technology (OST-R)

Final Report

January 2016

Principal Investigator: David Jung-Hwi Lee, Ph.D.

National Center for Transportation Systems Productivity and Management
O. Lamar Allen Sustainable Education Building
788 Atlantic Drive, Atlanta, GA 30332-0355
P: 404-894-2236 F: 404-894-2278
nctspm@ce.gatech.edu nctspm.gatech.edu

Georgia Institute of Technology | FIU Florida International University | UAB The University of Alabama at Birmingham | University of Central Florida

TECHNICAL REPORT STANDARD TITLE PAGE

<table>
<tr><td>1. Report No.:
FHWA-GA-16-1223</td><td>2. Government Accession No.:</td><td colspan="2">3. Recipient's Catalog No.:</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle:
Bringing Freight Components into Statewide and Regional Travel Demand Forecasting: PART1</td><td colspan="2">5. Report Date: January 2016</td></tr>
<tr><td colspan="2">6. Performing Organization Code:</td></tr>
<tr><td colspan="2">7. Author(s):
Dr. David Jung-Hwi Lee, Principal Investigator
Dr. Catherine L. Ross, Co-Principal Investigator</td><td colspan="2">8. Performing Organ. Report No.: 12-23</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address:
Georgia Tech Research Corporation
College of Architecture
Center for Quality Growth and Regional Development (CQGRD)
760 Spring Street, Suite 213
Atlanta, GA 30332-0790</td><td colspan="2">10. Work Unit No.:</td></tr>
<tr><td colspan="2">11. Contract or Grant No.:
0011746</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address:
Georgia Department of Transportation
Office of Research
15 Kennedy Drive
Forest Park, GA 30297-2534</td><td colspan="2">13. Type of Report and Period Covered:
Final; January 2012 – July 2014</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code:</td></tr>
<tr><td colspan="4">15. Supplementary Notes:
Prepared in cooperation with the U.S. Department of Transportation, Federal Highway Administration.</td></tr>
<tr><td colspan="4">16. Abstract:
Transportation decision makers have the difficult task of investment decision making having limited resources while maximizing benefit to the transportation system. Given the growth in freight transport and its importance to national, state, and regional economies, public-sector agencies need improved capabilities to analyze freight movement. In general, freight modeling is not widely developed and operationalized, at the metropolitan planning organization (MPO) level in particular due to the complexity of freight movement and the lack of availability of detailed truck trip data. This study develops a methodological framework of a tour-based freight demand model at the MPO level using GPS truck data. Methodologically it is a more accurate model compared to trip based models allowing truck trips to be linked, which reflects how truck drivers and dispatchers often make multiple trips within a single ‘trip chain’ or ‘tour’. Disaggregate truck movement data can be obtained via truck global positioning system (GPS) records collected in this study by the American Transportation Research Institute (ATRI). The developed framework has been applied to two metropolitan areas in the southeast, one covering the region around Atlanta, Georgia, and the other around Birmingham, Alabama. The report illustrates, with examples, potential uses of the model with multiple performance measures and also shows possibilities of applying the model to corridor analyses, small geographic area analyses, and scenario planning. The report introduces performance measures to compare the results of the two classes of models namely, the tour-based and the trip-based models. The results of six scenarios of the Atlanta metropolitan area are presented and compared along with some important policy implications for practice. The numerical results demonstrate that GPS data is feasible for model calibration and that tour-based models provide conceptually robust forecasts that sustain empirical validation under multiple scenarios. Although the study focuses on the Atlanta Metropolitan area, policymakers at all levels of government in other state DOTs and MPOs can benefit from this study and develop their own truck demand model borrowing the framework used.</td></tr>
<tr><td colspan="2">17. Key Words: Tour-based truck model, GPS data based truck model, Disaggregate truck demand model</td><td colspan="2">18. Distribution Statement:</td></tr>
<tr><td>19. Security Classification
(of this report):
Unclassified</td><td>20.Security Classification
(of this page):
Unclassified</td><td>21. Number of Pages: 305</td><td>22. Price:</td></tr>
</table>

Form DOT 1700.7 (8-69)

GDOT Research Project No. 12-23

Final Report

BRINGING FREIGHT COMPONENTS INTO STATEWIDE AND REGIONAL TRAVEL DEMAND FORECASTING

By
Dr. David Jung-Hwi Lee
and
Dr. Catherine L. Ross
College of Architecture
Center for Quality Growth and Regional Development (CQGRD)
Georgia Tech Research Corporation

Contract with

Georgia Department of Transportation

In cooperation with

U.S. Department of Transportation
Federal Highway Administration

July, 2014

Bringing Freight Components into Statewide and Regional Travel Demand Forecasting

Table of Contents

About the Center for Quality Growth and Regional Development

The Center for Quality Growth and Regional Development (CQGRD) is an applied research center of the Georgia Institute of Technology. The Center serves communities by producing, disseminating, and helping to implement new ideas and technologies that improve the theory and practice of quality growth.

For more information visit www.cqgrd.gatech.edu

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

As global trades increase, the importance of freight demand forecasting gets more and more political attention from various levels of governments (federal, state, regional, and local). Proper freight planning based on dependable forecasting tools can lead policymakers to develop suitable strategies for regional economic development to strengthen regional economic competitiveness in the global economy. Freight modeling and forecasting can serve as a basis for private- and public-sector decision making for freight infrastructure and other long-term investments.

Although Federal law requires state departments of transportation (DOTs) and metropolitan planning organizations (MPOs) to account for freight in their long-range transportation plans (LRTP), transportation improvement programs (TIP), and annual work elements, in reality many MPOs and DOTs have faced difficulties in practice mainly due to a lack of data and appropriate models (Federal Highway Administration, 2007).

This study explores the possibility of a tour-based freight demand model at the state/regional level utilizing (1) recently available nationwide Global Positioning System (GPS)-based truck movement data, in conjunction with existing data sources such as Freight Analysis Framework (FAF), (2) detailed employment databases that provide North American Industry Classification System (NAICS) sector breakdowns, and (3) regional transport networks which can show all possible paths of freight movements.

In order to investigate the current state of the practice of freight demand modeling at state DOTs and MPOs, this study included a survey which was delivered to 50 state Department of Transportation (DOTs) and 381 Metropolitan Planning Organizations (MPOs). The survey questions included prevalence of models and studies, model characteristics, usage of Global Positioning System (GPS) data, challenges in modeling freight, and consideration of future improvements. The survey results reveal that freight models are still relatively rare in applications and most models in practice are vehicle based. Usage of GPS data also remains rare. And most importantly, the survey reveals that the lack of data remains a large obstacle in developing freight demand models.

In the literature review section, special focus was placed on several key points:

A primary focus was to review the increasing importance of freight modelling in MPO planning. Freight planning has significant impacts on regional economies, primarily since freight planning is closely associated with regional congestion, congestion mitigation and infrastructure development that influence livability, attractiveness, sustainability, and the economic competitiveness of a region.

Secondly, in addition to the survey, existing freight planning and modelling activities at the state DOT and MPO level were reviewed. It was found that freight modeling is not as advanced as passenger modeling especially at the MPO level and there are very few models of commodity flow other than truck movements. Compared to MPOs, state DOTs have relatively higher frequencies of freight modeling activities in practice, although commodity-based models are still rare.

Thirdly, challenges in implementing freight demand models were also reviewed. The lack of disaggregate freight/truck data availability is one of the largest challenges to effective freight model development at the metropolitan or regional level. Potential new data sources addressed include intelligent transportation systems (ITS) technologies, a series of truck and container trackers implemented by carriers through radio frequency identification (RFID), and GPS devices (Bronzini, 2006). Fundamental differences between freight and passenger travel behavior is also a fact to be considered in modeling.

Various modelling methodologies and their advantages and disadvantages were reviewed: these include trend and time series analysis, four-step models, truck, tour-based modelling, micro-simulation models, economic activity models, and supply-chain models. Choice of the most appropriate model depends on the area being modeled, including the size of the modeling area, the data available, the organizational structure, and the economic activity. Tour-based models, which are often referred as trip-chaining models, were reviewed with particular interest since the model proposed in this study is based on tour-based modeling structure.

Lastly, GPS data use in freight modeling was examined. The use of GPS-based data presents several opportunities: it provides disaggregate data; it can help to identify performance measures; it helps in modeling freight movements with spatial and temporal disaggregate details which have been largely neglected in travel demand models; it can be an inexpensive way to replace truck survey data collection.

After the literature review, a tour-based truck demand modeling framework was developed, because conventional trip-based models measure travel in terms of independent trips between pairs of zones and ignore the relationship between trips that may be segments of a tour. Many trucks make multiple stops to deliver goods, and therefore modeling tours is more reasonable and important for truck modeling than for personal travel modeling. The proposed model was intended to inform a transferrable framework for state/regional freight demand models and examine data sharing, modeling, and collaborative planning and integration of MPO freight activity in statewide freight planning.

The framework of the proposed model is composed of several key components. The *Tour Generation* step probability functions create a trip at a certain time and start location. *Tour Main Destination Choice* follows next, and *Number of Intermediate Stops* estimates how many stops if any a given truck makes. *Location of Intermediate Stops* estimates stop locations. *Time Period of Tour Start* follows the Atlanta Regional Commission's (ARC's) four time periods. *Trip Accumulator* breaks tours into individual trips for analysis. The *Traffic Assignment* step assigns truck and passenger traffic to roads simultaneously by traffic period. A series of logit models is applied and Monte Carlo simulation is used to identify the tour's main destination zone, the number of intermediate stops, the stop locations, and the time period of the tour's start.

The proposed model represents one of only a few truck modelling efforts to date to utilize real time GPS truck data. The study uses eight weeks of GPS data from 5,000 different trucks in calendar year 2011, based on sampling movements for 2 weeks in each of four seasons within the Atlanta MPO and Birmingham MPO boundaries. The study proposes improvements to a vehicle trip based freight demand model by utilizing a combination of GPS-based truck movement database, detailed employment data, and data describing regional transportation networks.

The research provides planners and decision makers with insights to improve regional and statewide freight demand modeling/planning and freight related regional strategies. Lessons learned from this research include: (1) Freight modeling remains underutilized in most MPOs; (2) Tour-based freight modeling retains a theoretical advantage over trip-based modeling; (3) Tour-based truck movement models capture underlying freight movement relationships more completely than conventional models; (4) GPS-derived truck movement data is a viable data source and has the advantage of being cheaper to collect than the use of trip diaries. It can be targeted to trucks operating in a specific area, and can collect data for a long period of time; (5) GPS data processing should carefully preserve data completeness and representativeness; (6) There is added benefit to integrating GPS data with other information on land use, destination characteristics, fleet characteristics, congestion levels etc.; (7) GPS data is very promising, but needs further improvement with regard to information on vehicle type, better geocoding of external trip ends, and a more consistent ping rate. GPS data provides greater positional accuracy and the importance of this will likely increase; (8) There is increasing need for tour-based and supply-chain models of freight and commercial vehicles activity; (9) New regional, national and international scale models of commodity flows/economic activity are needed; (10) Activity-based modeling integrates the various choices, considers tours, reduces aggregation error and is a better disaggregate input to dynamic traffic simulations; (11) Permits a more accurate means of analyzing traffic impacts of projects and can address intra-regional commerce or inter-regional goods shipments.

State and metropolitan transportation planners and engineers, policymakers at all levels of government in other state DOTs and MPOs can learn from this study and develop their own truck demand model borrowing the framework used. Researchers should also work with practitioners to implement tour-based truck models with GPS data in different settings to overcome local and regional differences. Researchers should examine the range of applications that improved truck modeling can have including impacts on air quality models, traffic congestion forecasts, and investment decisions.

ACKNOWLEDGEMENTS

The research presented in the following report was sponsored by Georgia Department of Transportation through Research Project Number 12-23. The authors would like to acknowledge Yusuf H. Ahmed, Transportation Engineering Associate, Georgia DOT for his assistance in completing this project.

The authors would also like to acknowledge the assistance from researchers and graduate students at the Center for Quality Growth and Regional Development at Georgia Tech in particular Dr. Amit Kumar, William G. Allen, Jr., Dr. Frank Southworth, Andrew J. Sullivan, Dr. Virginia P. Sisiopiku, Dr. Ozge Cavusoglu, Peter Hylton, and Fangru Wang.

The opinions and conclusions expressed herein are those of authors and do not represent the opinions, conclusions, policies, standards or specifications of the Georgia Department of Transportation or of the cooperating organizations.

SECTION I. INTRODUCTION

Research Background

Federal legislation such as the Intermodal Surface Transportation Efficiency Act (ISTEA), the Transportation Equity Act for the 21st Century (TEA-21), the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU), the Moving Ahead for Progress in the 21st Century Act ("MAP-21"; P.L. 112-141), and the recent Generating Renewal, Opportunity, and Work with Accelerated Mobility, Efficiency, and Rebuilding of Infrastructure and Communities throughout America Act (GROW AMERICA) have encouraged inclusion of freight components in the statewide and regional transportation planning processes.

Given the growth in freight transport and its importance to national, state, and regional economies, public-sector agencies need improved capabilities to analyze freight movement. A number of MPOs are becoming increasingly interested in developing formal freight models to include in transportation planning procedures.

In general, freight modeling is not widely developed and operationalized at the MPO level due to the complexity of freight movement and the lack of availability of detailed truck trip data. Most publicly available truck movement data is reported at the inter-county level and is represented as aggregated tonnages that need to be broken down into smaller geographies for more analysis and modeling. Existing public freight datasets are often used as the basis for capturing vehicle trip information. The current Freight Analysis Framework (FAF) provides freight data based on the Commodity Flow Survey (CFS) conducted every five years with commercial vehicle data collected from state DOTs and other proprietary data sources. The FAF provides aggregate information on commodity shipments between selected major cities and remainders of states, with otherwise limited geographic detail on shipment at smaller geographies. Commercial commodity flow databases are available (such as Global Insight's TRANSEARCH data), which themselves make use of the FAF or its principal data source. For example, the U.S. Commodity Flow Surveys uses FAF as well as some other data including the Annual Survey of Manufacturers (ASM) to establish production levels by state and industry; the Surface Transportation Board (STB) Rail Waybill Sample develops all market-to-market rail activity by industry; the Army Corps of Engineers Waterborne Commerce data develops all market-to-market water activity by industry; the Federal Aviation Administration (FAA) develops Enplanement Statistics; Airport-to-airport cargo volumes offer additional (e.g. county level) spatial detail, and have been purchased by a number of transportation planning agencies. However, for many agencies, such multi-sourced, commercial datasets represent a significant expense, while their construction is not entirely transparent and not readily amenable to in-house agency modification.

Freight transportation surveys (such as roadside interviews, intercept surveys, mail-back surveys, telephone call-in, focus and stakeholder group surveys, and commodity flow surveys) are often used to collect data on freight transportation. However, they are quite time-consuming and require a great amount of labor and budget to collect reasonable data. Also, insufficient capital resources is cited as a barrier to use of ITS technologies.

GPS-based truck travel data may lower the hurdle posed by the lack of detailed and disaggregated truck travel data, so that regional planning organizations can develop freight demand models in conjunction with their passenger travel demand forecasting models more easily. Incorporated with other existing data mentioned above, GPS data provide detailed Origin-Destination information, critical routes for goods movement, operating speed of a large sample of trucks along major highways, travel times, and sample flows for intercity truck traffic along significant truck corridors, etc. (Liao 2010; McCormack 2011). This study explores the possibility of developing a tour-based freight demand model at the state/regional level, utilizing recently available nationwide GPS-based truck travel data, in conjunction with existing data sources, detailed employment databases, and regional transport networks. With two case studies of Atlanta and Birmingham metropolitan area, this study investigates the current state of the practice and constructs a transferrable framework for state/regional freight demand models, which many DOTs and MPOs are looking for. The results would shed light on various issues such as data sharing, freight modeling, and collaboration of MPO freight planning activities within the statewide freight planning framework.

Report Organization

With GPS-based truck data, this study has developed a tour-based freight demand model and applied it to Birmingham and Atlanta metropolitan areas. The report starts with a literature review on various freight modeling techniques, their strengths and limitations, the challenges of implementing freight modeling, and the merits of employing GPS truck data for a tour-based freight demand modeling. The four major sections of the report are as follows:

Section II-Literature Review: This literature review lays the foundation for understanding the research background and the importance of this study by a thorough examination of the previous literature on 1) the significance of developing freight models; 2) existing application of freight planning and modeling; 3) challenges in implementing freight demand models at the MPO/State level; 4) the state-of-art of current modeling methodology; and 5) the application of GPS-based data in freight modeling.

Section III-Tour-Based Freight Demand Model: This section develops a methodological framework of a tour-based freight demand model at the MPO level using GPS truck data. The section provides an introduction to the architecture of the tour-based model and data used, which could serve as a prototype for future MPO level freight (truck) demand modeling. The developed framework has been applied to metropolitan areas in the southeast (Atlanta, GA; Birmingham, AL). The methodology could be easily applied to other metropolitan area with data availability.

Section IV-Planning Applications: This section shows some examples of potential uses of the model with multiple performance measures and also shows possibilities of applying the model to corridor analyses, small geographic area analyses, and scenario planning. The section introduces some important performance measures to compare the results of the two classes of models comprehensively and derives important policy implications from the comparison. The results of the tour-based model for six scenarios of the Atlanta metropolitan area are presented and compared with the trip-based model that is currently being used by ARC.

Section V- Recommendations: This section summarizes main findings and puts forward constructive recommendations for future research.

SECTION II. LITERATURE REVIEW

Significance to MPO Planning

Freight modelling matters because of the tangible effects freight has on urban and rural roadways in a framework of federal, state, and local transportation planning and funding allocation. Two entities typically perform transportation modeling: state transportation agencies, usually at the statewide level, and metropolitan planning organizations (MPO), at the urban level. Their work is part of much larger planning and programming processes, which respond to changing economic conditions, legal requirements, and political priorities to promote the most appropriate infrastructure investment. As such, the modeling output's influence on the process and changing conditions make freight modeling of particular importance to MPOs and state transportation agencies.

Growing Freight Traffic

Cities and states are facing the continuing increase of global trade and concomitant rises in domestic freight flows. The U.S. domestic freight volume is projected to increase 65-70% by 2020 and freight value by 300% in the same period (Lahsene, 2005). The projected increase in freight stresses the importance of performing freight demand modeling including truck modeling activities. Also, the growth is projected to occur across several modes. Rail traffic has increased steadily, and the increase is predicted to continue, especially as its links with international freight movement continue to strengthen (Congressional Budget Office, 2006). Moreover, the expansion of the Panama Canal may shift land-based traffic flows in new directions, modes, or facilities (KRCU, 2011). The great growth in freight traffic will likely also have significant impacts on pollution and roadway maintenance (to the extent that trucks accommodate the increases) (Transportation Research Board, 2007).

Economic Development

Freight planning has important impacts on regional economic development, mainly because freight planning is closely associated with the regional congestion level that has influences on the livability, attractiveness, and sustainability of a region, and freight planning is often also related to certain types of businesses as it determines the cost and mobility of commodities. Some jurisdictions are making efforts to address freight planning at a regional or state level. The Tennessee DOT’s 10-year strategic Investments Program recognizes the importance of the integration of passenger and freight transportation (TDOT, 2005). The improvement of freight transportation involves not only the public sector, but also the communities and freight carriers. One common challenge, as encountered recently by the Tennessee DOT, is the accelerating increase of truck traffic, especially on rural interstate systems; and the difficulties involved in coordinating information with freight carriers to alleviate the growing pressures on the highway system (Stewart, 2012). Moreover, the National Cooperation Freight Research Program recognizes the multi-jurisdictional nature of freight planning and economic development, notably citing multijurisdictional barriers as a major issue that needs to be addressed in freight planning (Stewart, 2012).

Support for Decision Making

Freight modeling and forecasting can serve as a basis for private- and public-sector decision making for freight infrastructure and other long-term investments. It will have an impact on policymakers, whose policies may take many years to reach fruition, and major infrastructure operators (e.g., for airports, sea ports, roads, and rails) who need to forecast freight growth appropriately to minimize and prepare for the investment risks (Lahsene, 2005).

Public-sector decision makers need at least eight types of freight analysis: 1) Costs and benefits of freight programs and projects, 2) Performance measures specific to freight movements, 3) Mode shifts, 4)Time-of-day shifts, 5) Route diversion estimates, 6) Freight forecasts, 7) Existing routings of freight vehicles, and 8) Facility flow information (Cambridge Systematics, 2010). Moreover, commodity-based/Input-Output (I-O) models, upon which many freight flow models are based, need additional data, including "existing and forecasted commodity flow data, traffic counts, employment data, characteristics of major freight generators, forecasts of economic activity, and technical coefficients to extrapolate existing production and trade patterns into the future" (Cambridge Systematics, 2010).

Freight modeling and forecasting can support public decision making and its links with the private sector. According to the National Cooperative Freight Research Program (Cambridge Systematics, 2010) , the two sectors too rarely coordinate presently. There needs to be more coordination between the private sector which is more directly managing the nation's freight flow, and the public sector, which makes decisions and policies affecting freight infrastructure (Cambridge Systematics, 2010).

Federal Laws and Regulations

Federal law requires state DOTs and metropolitan planning organizations (MPOs) to account for freight in "long-range plans, transportation improvement programs, and annual work elements," though many MPOs and DOTs have faced limitations including a lack of data and highly complex models that have made freight planning difficult (Beagan, Fischer, & Kuppam, 2007; Federal Highway Administration, 2007).

On July 6, 2012, President Barack Obama signed Public Law 112–141, the Moving Ahead for Progress in the 21st Century Act (*Moving Ahead for Progress in the 21st Century*, n.d.). Section 1116 of MAP–21 (Prioritization of Projects to Improve Freight

Movement) authorizes the Secretary to increase the Federal share payable for any project to 95 percent for projects on the Interstate System and 90 percent for any other project if the Secretary certifies that the project Demonstrates the improvement made by the project to the efficient movement of freight (including making progress on freight performance measures established under MAP–21) and is identified in a State Freight Plan developed pursuant to section 1118.

Section 1117 of MAP–21 (State Freight Advisory Committees) directs the Secretary to encourage each state to establish a State Freight Advisory Committee consisting of a representative cross-section of public and private freight stakeholders.

Section 1118 of MAP–21 (State Freight Plans) directs the Secretary of Transportation to encourage states to develop a comprehensive State Freight Plan that outlines both immediate and long-term freight planning activities and freight-related transportation investments. Section 1118 specifies certain minimum contents for State Freight Plans, and states that such a plan may be developed separate from or be incorporated into the statewide strategic long-range transportation plan required by section 135 of title 23, United States Code.

MAP-21 also provides for travel demand forecasting relating to federal funding. For example, it requires that "each State…develop a long-range statewide transportation plan, with a minimum 20-year forecast period for all areas of the State" and the "Establishment of a National Freight Network" (*Moving Ahead for Progress in the 21st Century*, n.d.). Linkages between funding and requirements for freight forecasting highlight the need for effective and approachable forecasting methods.

Unique Characteristics of Freight Modeling

While it is not uncommon to scale up projected passenger travel demand to account for freight demand at a very basic level, freight modeling is best addressed separately since many of its fundamental dynamics differ from those that drive passenger travel. Freight and passenger travel demand forecasting may benefit from different modeling and forecasting techniques because of the ways in which they differ, regarding several fundamental characteristics as follows (Cambridge Systematics, 1997; Eatough, Brich, & Demetsky, 1998; Wigan & Southworth, 2005).

- **Decision Making Processes:** Freight flows and passenger travel result from very different decision making dynamics. First, passenger travel typically results from the aggregation of many individuals' own choices and travel behavior. By contrast, freight movement results from the decision of a number of entities who decide a segment of the movement, such as agents, shippers, carriers, brokers, and receivers (Cambridge Systematics, 1997; Eatough et al., 1998) – hence it usually has more decision makers involved per trip. Moreover, the value of time influences decisions. Eatough et al. (1998) explain that freight demonstrates a wider variety of time value based on commodity type, perishability, and value than do passengers.
- **Physical Facilities:** The physical facilities required for freight and passenger transportation include both the vehicle types and the load/unloading facilities. Normally, only freight requires extensive loading and unloading facilities (Cambridge Systematics, 1997; Eatough et al., 1998).
- **Unit of Measure:** Passenger travel is normally measured by number of vehicles, whereas freight might be measured either by number of vehicles or commodity characteristics, such as volume, value, or weight (Cambridge Systematics, 1997; Eatough et al., 1998).

Existing Freight Planning and Modeling

2013 DOT/MPO Survey: Use of Freight Models and GPS Data

The research for this study includes a short survey that addresses the state of the practice in freight studies and modeling activities in regional and state transportation agencies around the country. The online survey questions included prevalence of models and studies, model characteristics, usage of Global Positioning System (GPS) data, challenges in modeling freight, and consideration of future improvements. The survey was delivered to 50 state Department of Transportation (DOTs) and 381 Metropolitan Planning Organizations (MPOs). Out of the targeted agencies, 44% of DOTs (22 agencies) and 39.4% of MPOs (150 agencies) responded (Figure 1: Survey Respondents).

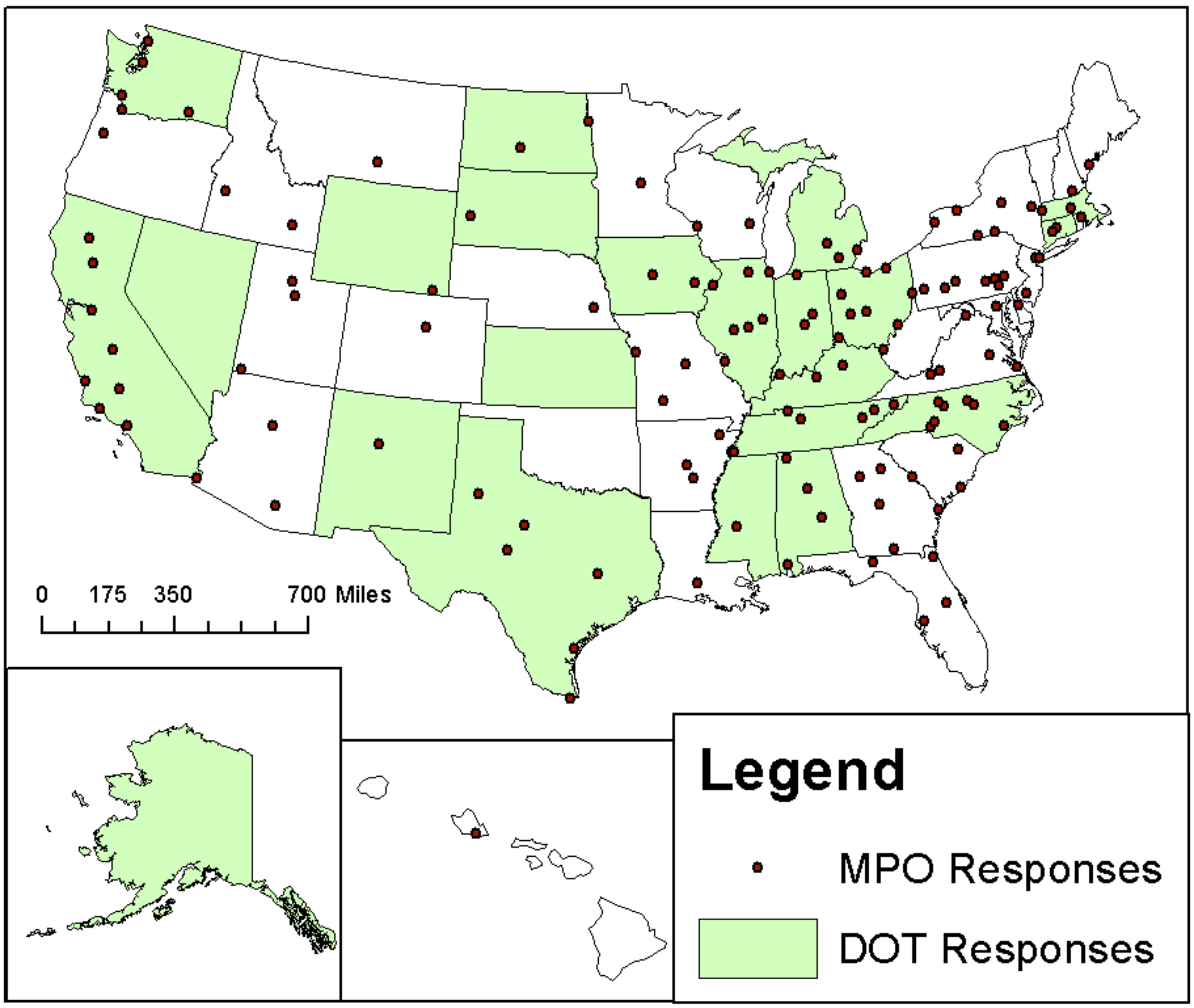


Figure 1: Survey Respondents

The survey explicitly distinguished freight modeling from freight studies and definitions were provided to survey respondents prior to questions being completed. Freight studies were defined as an analysis of freight data that may include such elements as an inventory of freight generators or consumers, descriptions of the freight network and current freight movement data. Freight modeling was defined as an operational representation of the freight network that can simulate vehicle movements or commodity flows separately from passenger movements. Freight models can be used to forecast either freight vehicle or commodity movements. Most of DOTs (95%) and majority of MPOs (63%) conduct freight studies, while much smaller numbers of these two groups (55% in DOTs; 28% in MPOs) utilize freight models. Developing freight performance measures is not yet a common activity. Only one third (32% in DOTs and 29% in MPOs) reported that they use freight performance measures (Table 1).

Table 1: DOT's and MPO's freight study/model/performance measure (Source: CQGRD)

	Freight Study		Freight Model		Performance Measures	
	Yes	**No**	**Yes**	**No**	**Yes**	**No**
DOT	21 (95%)	1 (5%)	12 (55%)	9 (41%)	7 (32%)	12 (55%)
MPO	91 (63%)	50 (35%)	42 (28%)	104 (70%)	42 (29%)	92 (64%)

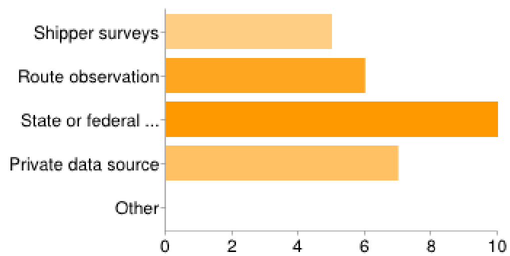
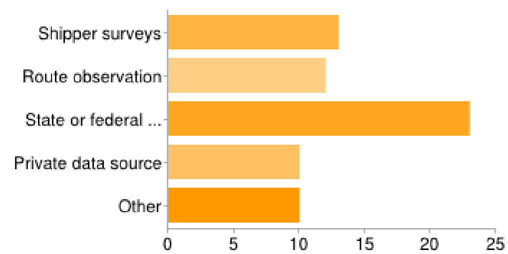
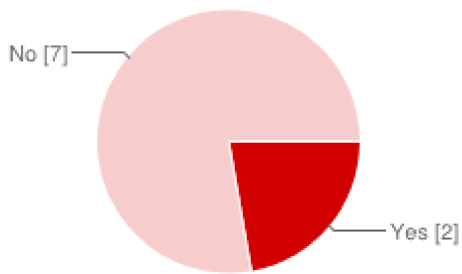
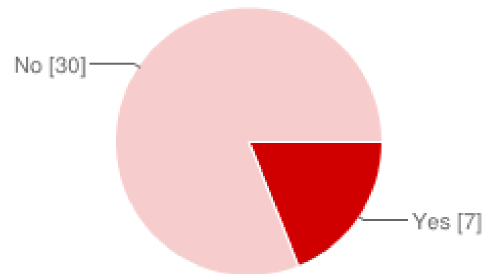
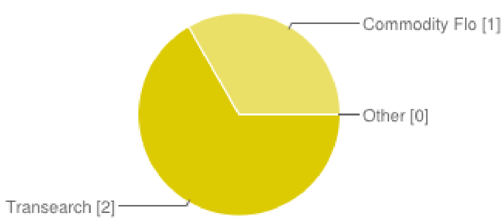
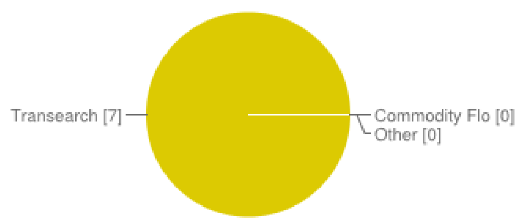
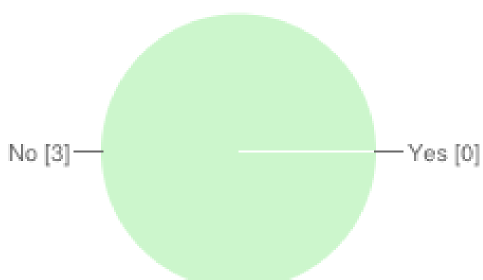
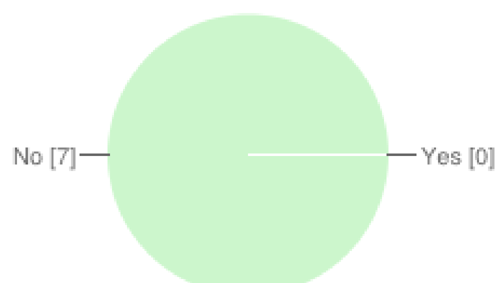
It is observed that freight demand is often forecast via the use of models. Agencies that answered the question, "How do you forecast freight demand?" also reported that their agencies operate freight models. Combining in-house models and contractor-built models, 85% of the DOT respondents and 73% of the MPO respondents utilize freight models to forecast freight demand. Vehicle-based modelling (31% of the DOT respondents and 48% of the MPO respondents) is still more common than commodity-based modelling (23% of the DOT respondents and 17% of the MPO respondents). Many DOTs (46% of the DOT respondents) are trying to develop hybrid models combining vehicle-based and commodity-based components (Table 2).

Table 2: DOT's and MPO's freight model characteristics (Source: CQGRD)

Forecasting Method	DOT	In-house model	4 (31%)
		Contractor-built model	7 (54%)
		Trend extrapolation	1 (8%)
		Other	1 (8%)
	MPO	In-house model	14 (32%)
		Contractor-built model	18 (41%)
		Trend extrapolation	1 (2%)
		Other	11 (25%)
Freight model last updated	DOT	Within the last year	6 (46%)
		Between 1 and 2 years ago	3 (23%)
		Between 2 and 5 years ago	2 (15%)
		Between 5 and 10 years ago	1 (8%)
		More than 10 years ago	1 (8%)
	MPO	Within the last year	10 (23%)
		Between 1 and 2 years ago	15 (35%)
		Between 2 and 5 years ago	9 (21%)
		Between 5 and 10 years ago	7 (16%)
		More than 10 years ago	2 (5%)
Modelling method	DOT	Vehicle-based	4 (31%)
		Commodity-based	3 (23%)
		Hybrid	6 (46%)
		Other	0 (0%)
	MPO	Vehicle-based	20 (48%)
		Commodity-based	7 (17%)
		Hybrid	8 (19%)
		Other	7 (17%)

The survey results also reveal current truck movement data sources (Table 3). Publicly available data developed by state or federal government such as the Freight Analysis Framework 3 (FAF3) is still the prevailing data source (36% of DOT respondents and 34% of MPO respondents). Other sources such as shipper surveys, route specific observations, local data, and private data sources are also often used for vehicle truck modelling activities, while GPS-based data use is limited. Only 2 DOTs and 7 MPOs reported that they have used GPS data in their freight modelling work. As for the data source for commodity-based models, Transearch is reported as the dominant source, and there was no case reported involving GPS data. One DOT and five MPOs had used GPS data in a freight model. This DOT and two MPOs said that they obtained the GPS data from the American Transportation Research Institute (ATRI).

Table 3: DOT's and MPO's data source (Source: CQGRD)

		DOT	MPO
Vehicle-based model	Data Sources		
	GPS data usage		
Commodity-based model	Data Sources		
	GPS data usage		

Many of the primary obstacles in modelling freight were well understood: insufficient funding, insufficient staffing, too many competing tasks, lack of specialized knowledge within the organization, unavailable data, and limited data collection technology.

Overall, the survey results indicate very limited use of GPS-based data and many perceived obstacles to its use within freight models. There was also great deal of interest in new and easier to obtain data sources.

Freight-Related Studies

Hunt & Stefan (2007) developed a disaggregate micro simulation freight model for Calgary, Canada. The model uses a tour-based approach to simulate the multistep nature of commercial vehicle movements. The model captures commercial vehicles as part of a larger regional travel model with three components: commercial vehicle model, person-travel model, and joint vehicle assignment (Kuzmyak, 2008). As Kuzmyak (2008) describes, the Calgary commercial vehicle model (CVM) has seven steps:

1. Tour generation: The tour generation model used survey data to establish tour generation rates for each employee for each of five industrial activities.
2. Tour purpose and vehicle allocation: The tour purpose and vehicle allocation step assigns a vehicle type and trip purpose to each tour through a Monte Carlo process.
3. Tour start time: A Monte Carlo process assigns each tour a tour start time based on survey data by activity and time period.
4. Next stop purpose: A Monte Carlo process assigns each tour to either continue to another stop or return to origin after each stop. This step chains trips together into tours.
5. Next stop location: If the last step has extended the trip, the next stop location step assigns a new destination based on the probability of the next stop being in any of the model zones (1,447 model zones). Factors considered in the probability include the next stop's possible land use type, accessibility to population categories, accessibility to employment categories, relative attractiveness, and "enclosed angle," which distinguishes among destinations heading away from or towards the tour origin.
6. Stop duration: A Monte Carlo process assigns stop duration based on observations.

7. Calibration: Results are calibrated to match observed targets in order of decreasing importance: (a) tour generation by industry and geographic area, (b) tours starting in various times of day, (c) vehicle type and tour purpose, (d) number of stops per tour, (e) total trip destinations in each geographic area by vehicle type, (f) intra-zonal proportions of trips by vehicle types, (g) total trips by vehicle type and industry

The Calgary model used a commercial vehicle survey with interviews from 3,100 business and 64,000 commercial vehicle trips (Kuzmyak, 2008). According to Hunt & Stefan (2007), among the model's strengths are its sensitivity to numerous factors, some of which are influenced by policy, including road capacity and connectivity; "truck route policy; road tolls; fuel taxes; household travel; population level and spatial distribution; and employment level, composition, and spatial distribution."

Basic Steps

Eatough et al. (1998) identify six steps of the freight transportation planning process, depicted in Figure 2 below. Freight modeling may be involved in several steps. Step 1 ("Inventory System") may include building a model of the freight transportation network, collecting data on current freight movements, and assessing their distribution and functions in the model. Step 2 ("Identify Problem") could conceivably address both existing problems foreseen in the model or made known through other data sources, and future problems revealed through freight demand projection. The demand projection can reveal transportation network inadequacies that reveal future problems (Eatough et al., 1998).

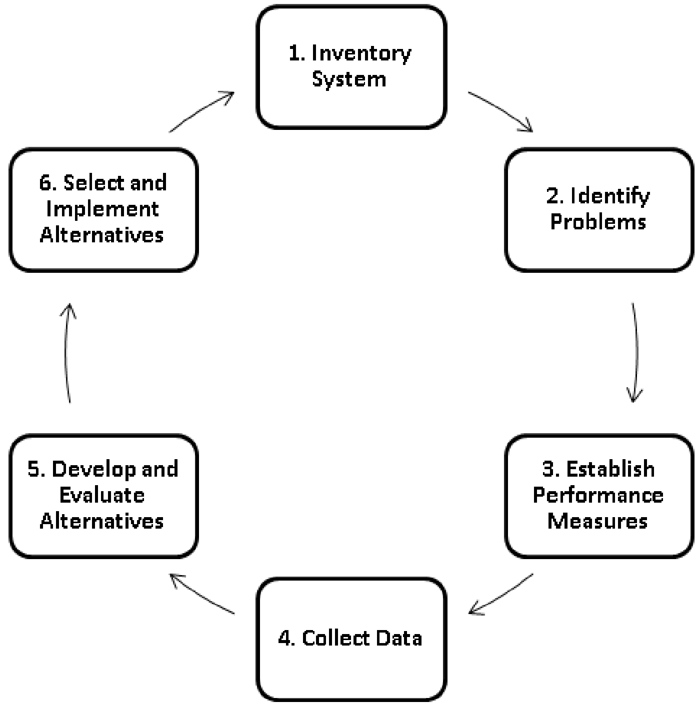


Figure 2: Steps in Freight Planning Process

(Source: Eatough et al., 1998)

Freight planning may take on different forms. Guo & Wittwer (2009) describe five different types of plans by increasing level of complexity. Each type of plan incorporates all the components of the less complex plan types, while adding additional elements. The following are plan types in order of increasing complexity.

- Descriptive: Descriptive plans inventory freight generators and estimate freight flows.
- System: In addition to descriptive steps, system plans examine freight traffic's effect on the roadway system to identify gaps and propose solutions.
- Integrated: In addition to system elements, integrated plans examine freight movements in tandem with other types of movement (e.g., passenger movement) and also possibly larger geographies (e.g., state-level).
- Strategic: In addition to integrated steps, strategic plans consider broader "policy and regulatory issues."
- Business: In addition to strategic steps, business plans set forth the steps to achieve strategic goals. They detail tasks, assign responsibility, and plan for reporting and sustaining progress (Guo & Wittwer, 2009).

Metropolitan Planning Organizations

Several surveys have assessed MPO's performing and the sophistication of freight planning at the regional scale. Vanasse Hangen Brustlin, Inc. (VHB,2006) solicited information from MPOs about their travel demand modeling methods through a web-based survey on behalf of the Transportation Research Board Committee B0090 (Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting). The survey was sent to 381 MPOs and received 228 responses from MPOs in metropolitan areas of all sizes.

In-depth interviews with 16 MPOs supplemented the survey. VHB (2006) found that freight modeling is not as advanced as passenger modeling, partially because MPOs often do not have good data about truck movements. Almost 80% of large MPOs and about half of other MPOs model truck trips, though very few model commodity flows. MPOs are reluctant to shift to a full commodity-based framework for several reasons. One of the major reasons is that data needed for commodity flow models are not readily available, which is often at a high level of aggregation or needs to be purchased from private sources (Kuzmyak, 2008). Most MPOs that model trucks use the traditional four-step approach. The survey also showed that most small MPOs (populations under 200,000) with passenger or freight travel demand models rely "on the state transportation agency or consultants for model development and application" (Transportation Research Board, 2007; VHB, 2006). Large MPOs typically reported annual forecasting budgets below $1 million (VHB, 2006).

Seventy-five percent of models in use originated within 10 years of the report. Several interviewed MPOs mentioned lack of data as an obstacle, and the interviews suggest that more MPOs might perform truck modeling if needed data were more readily available. Finally, some MPOs were considering adopting activity- or tour-based models

(20% of small and medium MPOs and 40% of large MPOs) (Transportation Research Board, 2007; VHB, 2006).

MPOs had several data sources. Many used TRANSEARCH, a commercial database including origin-destination pairs, commodities, and modes (IHS Global Insights, n.d.; VHB, 2006). For commodity flow-based models, the primary databases were the Freight Analysis Framework, Commodity Flow Survey, TRANSEARCH Database, Vehicle Inventory and Use Survey (VIUS), and Vehicle Travel Information System (VTRIS) (Kuzmyak, 2008; VHB, 2006). Some MPOs supplemented TRANSEARCH with independently collected local data (Kuzmyak, 2008; VHB, 2006).

Kuzmyak (2008) found that most MPOs do model truck movements, but that very few model other modes or underlying commodity flows. He suggests three reasons for this. First, MPOs are adapting passenger travel demand models, with which they are more familiar, to freight movement purposes. The four-step passenger travel demand model accounts for vehicle movements. Second, truck data is easier to obtain at low geographic scales than commodity movement data. Finally, trucks visibly and tangibly affect mobility.

Blonn, et al. (2007) reported a 2007 survey of small MPOs in Midwestern states. Researchers sent surveys to 56 MPOs in the states of Kansas, Missouri, Iowa, Minnesota, Wisconsin, Illinois, Kentucky, Indiana, Ohio, and Michigan. All MPOs were in cities with populations between 50,000 and 200,000 people. They received 19 valid responses for a response rate of 34%. Sixteen of the 19 respondents indicated addressing freight in their long-range plan; considering the following modes: rail (x 15), trucks (x 14), aviation (x 9), waterways (x 9). Blonn et al. (2007) also found that eight of the 19 respondents do not have a freight plan. Seven of the 9 that did have freight plans developed the plan in order to fulfill federal requirements. The majority of the MPOs that did have a specific freight plan reported that it was "primarily an inventory of freight-related facilities and generators" (Blonn et al., 2007). Table 4 lists the freight-related issues addressed by these Midwestern MPOs, with varying levels of attention given to them in their long-range plans. Numbers in the table are out of 11 MPOs surveyed that planned for freight.

Table 4: Level of Attention Given to Freight-Related Issues

	Congestion		Air Quality		Safety		Intermodal	
Level	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
None	4	36%	9	82%	2	18%	3	27%
Very little	2	18%	6	55%	3	27%	3	27%
Somewhat	11	100%	3	27%	10	91%	8	73%
A lot	0	0%	0	0%	2	18%	3	27%

Source: Blonn et al. (2007)

Of the 11 respondents who reported using freight data, five use state sources, two use regional sources, two used surveys, one uses local sources, and one uses federal sources. Commodity flow and traffic counts are the most common data elements used.

State Departments of Transportation

Several decades ago, very few states systematically planned for freight. In the early 1990s, only 4 state DOTs answered a 1993 Cambridge Systematics survey on plans for developing a statewide freight plan by saying that they did plan on developing one (Eatough et al., 1998). California, New Jersey, and Florida already included freight transportation plans as part of their overall transportation plans, with the Intermodal

Surface Transportation Efficiency Act (ISTEA) of 1991 as the impetus to create the requirement for statewide freight transportation planning (Eatough et al., 1998).

Horowitz (2006) explains in NCHRP Synthesis 358 that statewide models may overlap with MPO passenger or freight models, and that they project travel demand for areas not covered by the MPO model. States may need statewide freight models because a larger percentage of rural than urban traffic is caused by freight movements. He found a significant increase in freight modeling activity at the statewide level, with nineteen states having operational statewide models that modeled passenger and/or freight traffic. Three of these states had dormant statewide models, 5 were developing statewide models, 3 were revising them, and 1 had a partial model. Horowitz (2006) also reported that 16 of the 49 states who responded to the survey modeled freight in their statewide models, and that 12 of these 16 used commodity-based models, despite the large data requirements of such models. Just over half of freight models utilized data obtained from TRANSEARCH, three used the Commodity Flow Survey, and one performed its own shipper and carrier survey. Commodity-to-truck conversions were addressed with the following data sources: the VIUS (trucks only, x6), commercial freight data vendor (x4), rail carload waybill sample (rail only, x3), conversion factors from another state or an MPO (x2), and truck intercept surveys (x1). Trucks were the most frequently addressed mode (x15), followed by rail (x5), air freight (x5), salt water shipping (x4), fresh water shipping (x3), and less-than-truckloads/truckload movements (x1). Air pollution modeling was the most common form of post-processing (x9). Seven states also derived level of service performance measures, three performed cost-benefit analyses, and two derived economic impacts (Horowitz, 2006).

Operational Freight Demand Models (FDMs) in MPOs/DOTs

Horowitz (2006) describes the Virginia Statewide Model. It was developed in 2005 by Wilbur Smith and Associates. It includes a passenger model and a commodity-based freight model that accounts for trucks movement (Virginia Department of Transportation, 2012). Its data is primarily from TRANSEARCH supplemented by ground-based truck counts. Productions change proportionally with forecasted employment, and consumption changes proportionally to employment and population. There are no special generators (Horowitz, 2006).

The Maryland Department of Transportation was the first state in the nation to issue a statewide freight plan (Cambridge Systematics, 2009). Mainly built on the commodity flow data of TRANSEARCH by IHS Global Insight, the plan forecasts out to 2035. The forecasts (p. 30) conclude that both the Interstates and non-Interstates corridors will continue to experience increases in truck transportation. The assumed average growth rate of the economy is set between 2 and 3 percent. The Maryland Freight Plan also recognizes that the conditions of the trucking and highway systems in Maryland have implications for economic and transportation development far beyond its own boundary (Cambridge Systematics, 2009).

Shen (2005) described Florida's statewide freight demand model as it existed at the time. The model was coupled with its passenger travel demand model. Both models operated on a traditional four-step process, where each performed trip generation, trip distribution, and mode split separately before jointly assigning traffic to the road network. While it also accounted for non-freight commercial vehicles with a truck-based approach, it generated and distributed freight trucks through a commodity-based model with 14 commodity groups. Shen (2005) said that the lack of disaggregate data and accounting for international trade over the entire state were two of the main challenges.

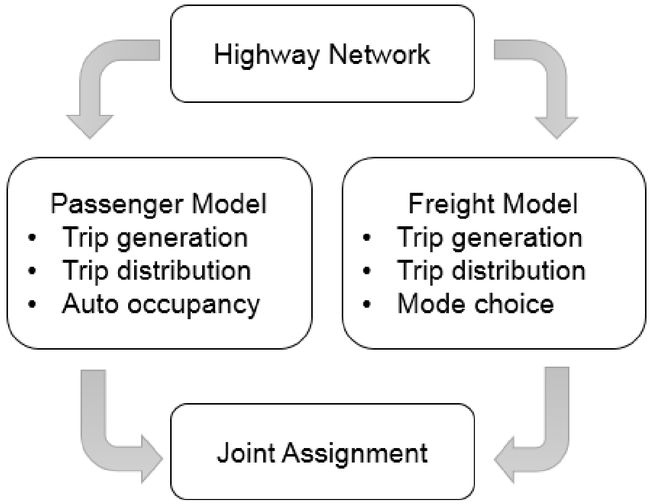


Figure 3: Florida's statewide model structure

(Source: Shen (2005))

Florida is replacing its original freight demand model with an agent-based supply chain model (Mysore, 2013; Resource Systems Group, Inc., n.d.; Smith & Shabani, 2013). The model synthesizes firms based on county business pattern data that generate supply and demand for goods to and from specific locations. The firms are aggregated at the travel analysis zone (TAZ) level. The model incorporates supply chain considerations such as inventory costs in addition to supply chain costs. The Florida model requires data on freight flows, employment, distribution centers, industry-specific economics, multimodal road networks, and costs. Figure 4 shows the data (blue), steps (green), and outputs (red) for the Florida freight model.

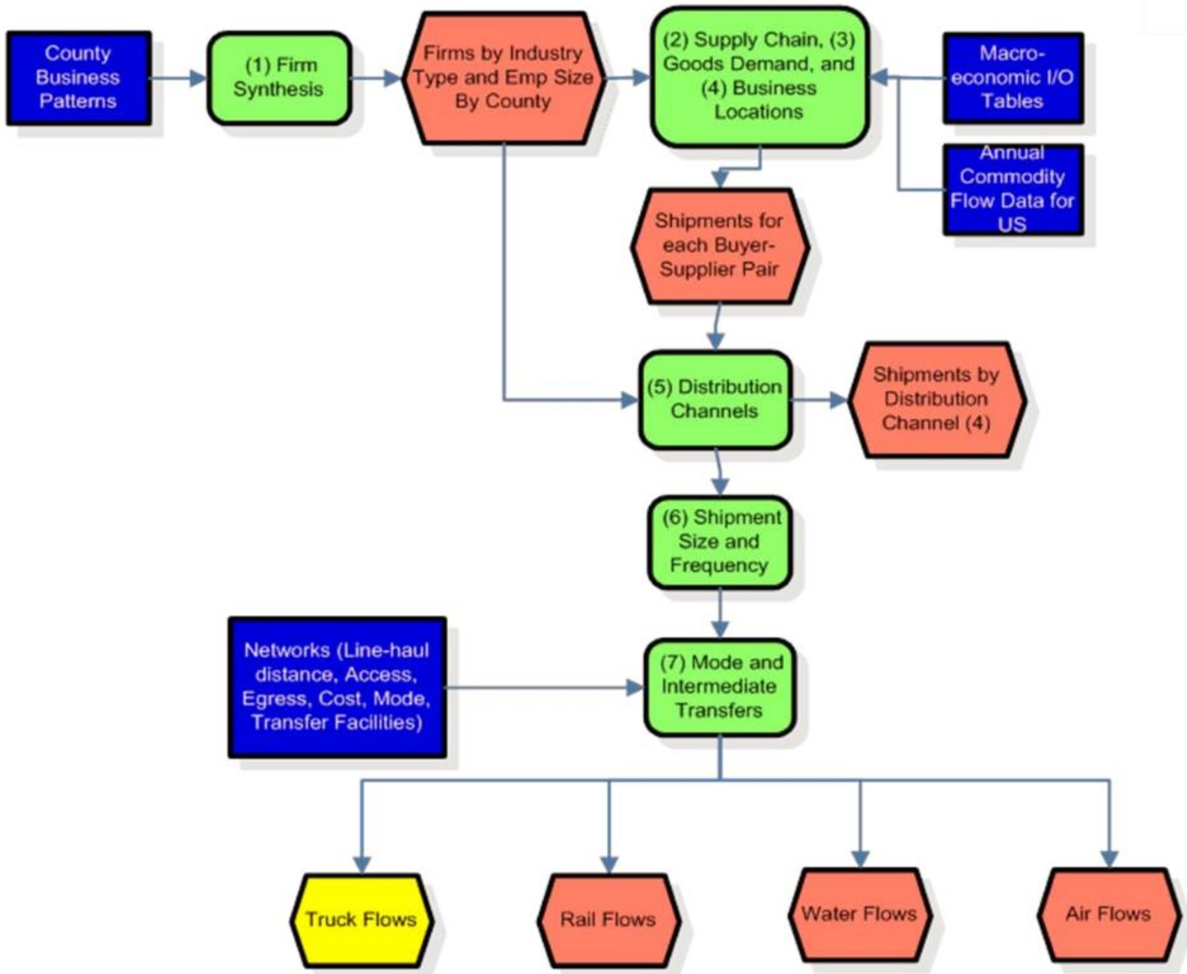


Figure 4: Florida Supply Chain Freight Model

(Source: Mysore, 2013)

Oregon's first generation Statewide (SWIM1) Integrated Model encompasses economic, land use, and travel demand models, as depicted in Figure 5 below (Hunt & Gregor, 2008). Generation 1 uses a commodity-based model that calculates freight movement as monetary flows, which it converts to tonnage and finally to trucks through fixed ratios by commodity type for both conversions. Mode split and route assignment employ a logit model. SWIM1 forecasts in five-year increments, where the outputs from one step provide inputs for the next five-year step (Hunt & Gregor, 2008). Oregon finalized a new statewide model (SWIM2) in 2009, which it used to inform its state plan under three different economic scenarios. SWIM2 uses a fundamentally similar process to SWIM1 (Knudson, Hunt, Weidner, Bettinard, & Wardell, 2011).

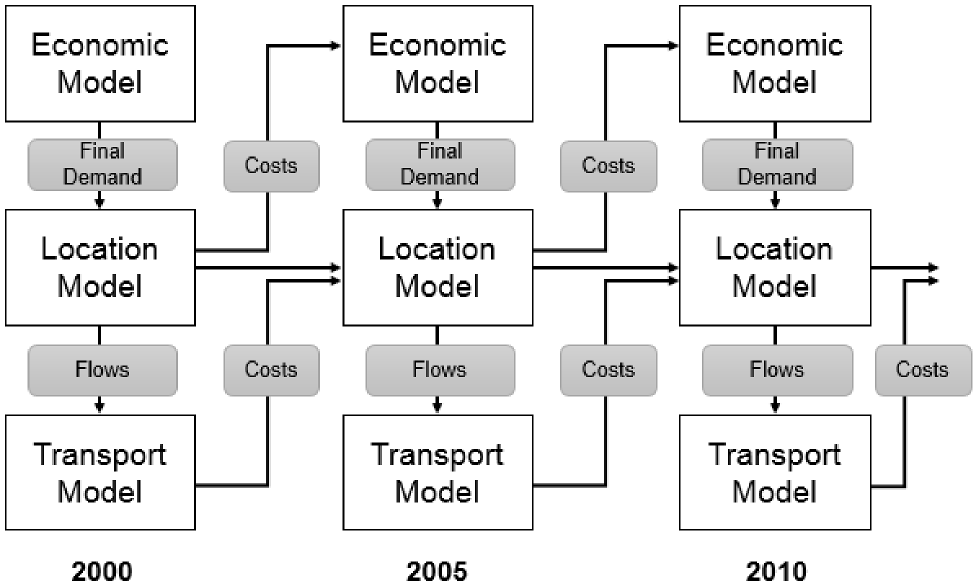


Figure 5: Oregon Statewide Integrated Model

(Source: Hunt & Gregor, 2008)

The California Department of Transportation is developing a California Statewide Freight Forecasting Model (CSFFM). CSFFM is a commodity-based trip model that contains the following six modules (CA DOT, 2013):

- Commodity Module: This module generates production/consumption and distribution based on demo-economic data and impedance information and estimates import/export freight on gateways in CA;
- Mode Split Module: This module determines mode-share for each mode in each OD pair, aggregates mode split model estimated using FAF mode data, and uses incremental logit models to evaluate impacts of mode attribute changes;
- Transshipment Module: This module derives commodity OD flows by different transportation modes;

- Data Flow of Transshipments Module: This module decomposes inter-modal trips into truck/rail/air segments and determines which transport logistic nodes are used for each freight movement;
- Seasonality and Payload Factor Module: This module applies the seasonality and payload factors to the model;
- Network Module: This module assigns truck volumes to the truck road network, assigns the corresponding tonnage of commodities to the rail network, and validate the results with ATRI's GPS data.

The CSFFM is a four-step trip-based model fundamentally and the trip generation and OD flows is built on estimating the demand for commodities and the corresponding commodity flows. It employs the GPS data mainly to validate the model results (CA DOT, 2013).

The Chicago Metropolitan Agency for Planning (CMAP), the University of Illinois at Chicago, and Resource Systems Group Inc. (RSG) created an advanced freight model that integrates two sub models. The first (called the "meso-scale model") simulates freight flows between the Chicago metro area and the rest of the United States based on the Freight Analysis Frameworks Version 3 products. The second model ("micro scale model") simulates truck movements from a tour-based approach in metropolitan Chicago. The agency is also working to develop a third sub model to supplement the meso-scale model and forecast freight flows independently of FAF3 based on national economic inputs (Chicago Metropolitan Agency for Planning, n.d.; Gliebe, Smith, & Shabani, 2013; Outwater et al., 2013a; Wies, 2012).

The meso-scale model integrates logistics components. The model accounts for truck tours and captures industry-specific economic dynamics. The meso-scale model involves several steps that are similar to those in the Florida state freight model, which involves firm-level simulation of supply chain processes that are then aggregated to produce model outputs. All of the steps below are national in scale except for the truck touring model, which is regional. Therefore, the logistics model responds to national scale economic changes, while the tour-based model responds to regional and local transportation changes (Gliebe et al., 2013; Outwater et al., 2013a).

- **Firm synthesis:** Firm synthesis generates businesses in metropolitan Chicago as well as internal and external stations. The step generates firms in different industrial sectors and size categories.
- **Supplier selection:** Supplier selection pairs suppliers and buyers by linking commodities produced by suppliers with specific suppliers requiring the commodities. Many buyers and suppliers are very near each other (i.e., fewer than 100 miles), but some are also over 2,000 miles apart.
- **Goods demand:** Goods demand distributes commodities from suppliers to buyers. The model generates demand for each consuming firm based on average consumption per employee and the firm size.
- **Distribution channels:** Distribution channel selects how commodities will travel from suppliers to buyers. The step selects between direct shipment methods and intermediate methods that pass through intermodal channels or distribution centers. The step employs a multinomial logit model that assigns either direct shipment, or 1, 2, or 3 stops to the shipment. Model variables are firm size, supplier industry, buyer industry, and distance.
- **Shipment size:** Shipment size scales commodity movements between suppliers and buyers to be annual. The step uses a multinomial logit model that assigns

weights of either less than 1,000 lbs., between 1,000 and 10,000 lbs., and more than 10,000 lbs. The majority of shipments are in the smallest category.

- **Mode and path choice:** Mode and transfers assigns a mode to each trip leg from supplier to buyer based on the shipment's total logistics cost. The total logistics cost includes costs for ordering, transportation, handling, damage risk, and inventory in-transit, as well as carrying cost and safety stock cost. The step then converts annual shipments back to daily shipments and assigns incoming freight to the buyer's warehouse location.

The propose meso-scale extension will allow CMAP to forecast future freight flows independently of FAF3 by incorporating macro-scale economic dynamics into a freight forecast sub model. This will allow the agency to produce different forecasts for different levels of foreign trade, petroleum prices, as well as infrastructure construction and changes in supply chain practice. The extension would be located between the firm synthesis step and the goods demand step, replacing the supplier selection with an agent-based pairing of buyers and suppliers (Chicago Metropolitan Agency for Planning, n.d.). Figure 6 below illustrates the extension's steps.

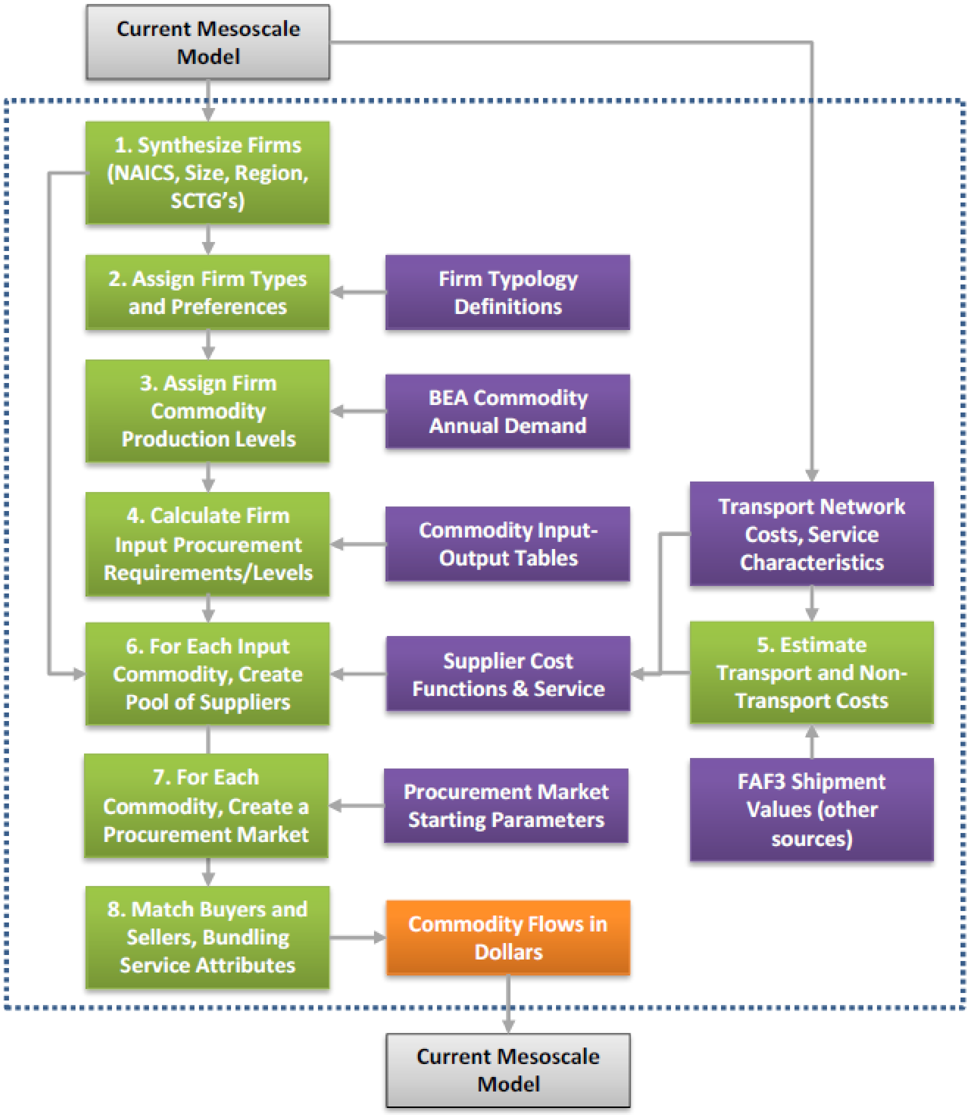


Figure 6: Components of Proposed Model Extension

(Source: Chicago Metropolitan Agency for Planning (n.d.))

The logistics model feeds into a tour-based truck model. The tour-based model is the regional-scale component of the freight model. It simulates tour-based truck movements in the Chicago metro area through a methodology that will be detailed below. The tour-based model has four components (Outwater et al., 2013a)—

- **Vehicle and tour-pattern choice:** This sub model is a joint multinomial logit model that simultaneously estimates whether or not a delivery will include stops and the vehicle size. Joint determination accounts for the fact that vehicle selection and tour composition are mutually dependent.

- **Number of tours and stop choice:** This sub model accounts for trucks that return to home base between tours. A multinomial logit model predicts whether a truck will return to home base after a stop to complete the tour. Next, hierarchical clustering selects stops based on proximity that can be reached in a single tour.
- **Stop sequence and duration:** This sub model orders stops into a reasonable delivery order. Next, the model predicts stop duration based on commodities and shipment size.
- **Delivery time of day:** This sub model uses a multinomial logit model to predict tour start time. Trip times of day feed into the route assignment module.

In Canada, Ferguson et al. (2012) applied the framework in the Calgary commercial vehicle model (Hunt & Stefan, 2007) to the Greater Toronto and Hamilton area (GTHA) in Ontario, Canada. Tour-based trips are one of the three commercial vehicle flows that they addressed. They obtained data from three sources. Company level data for 185,790 establishments came from InfoCanada. Data included establishment address, the number of employees, and the Standard Industrial Classification to designate the industry sector. A survey of 597 firms in Peel County, Ontario provided establishment-level trip and tour generation data. The Ministry of Transportation of Ontario Commercial Vehicle Survey and hourly count data from the Data Management Group supplemented observed movement data. The model follows the same steps as the Calgary commercial vehicle model (Hunt & Stefan, 2007). Trip generation rates were based on industrial sector and number of employees. While trip generation rates were not validated with manual observations, traffic flows were validated and deemed reasonable (Ferguson, Maoh, Ryan, Kanaroglou, & Rashidi, 2012).

Other Regional Travel Demand Modeling (TDM) Activities with Freight components in the South-Eastern United States

The Southwest Georgia Interstate Study (2010) has incorporated a section for truck trip table development, which estimates truck trips independently from passenger trips in the travel demand modeling process (PBSJ, et al., 2009). The development of the truck trip table is built on FAF2 dataset and is consisted of the three following steps (PBSJ, et al., 2009):

- Construction of the commodity OD flows for 67 Georgia Freight Analysis (GFA) zones: The commodity flows across 138 FAF regions were extracted by transportation mode and by SCTG commodity type and are aggregated into the 67 GFA zones;
- Conversion from tonnage of commodities to truck volumes: This step aggregated the 43 types of commodities by the SCTG code into 12 types of commodities and converted the tonnage of each of the 12 types of commodities into number of trucks;
- Disaggregation of truck trips across 67 GFA zones into 1569 TAZs: This step employs socioeconomic data to estimate the shares of the truck volumes by the 1569 TAZs in southwestern Georgia, so that the truck OD flows between the 67 GFA zones were disaggregated into the TAZs and can be assigned to the transportation network.

This truck trip table development component is mainly based on commodity flows, which is built on the FAF dataset, and converted commodity flows to truck trips using conversion table between tonnage and trucks by different commodities. This method is more applicable at the regional level when it is used to estimate the total truck flows into or out of the region, but is not very accurate when the truck flows were broken down to the TAZ level.

The Chattanooga Regional Planning Agency (RPA) developed a travel demand model with freight components in 2008 and 2009. Cambridge Systematics headed model development and validation while RPA gathered the necessary socioeconomic data. The TRANSCAD-based model used 2007 as a base year and forecasted travel demand as far as 2035 for that year's long range transportation plan (Regional Planning Association & Cambridge Systematics, 2010).

The model is a traditional four-step model consisting of trip generation, trip distribution, mode split, and route assignment. It covers all or part of four counties in Georgia (parts of two counties and one complete county) and Tennessee (one complete county). It has 590 internal travel analysis zones (TAZ) and 38 external TAZs (Regional Planning Association & Cambridge Systematics, 2010).

The trip generation component generated passenger trips and commercial vehicles in three categories: light-, medium-, and heavy-duty trucks. Socioeconomic data informing trip generation included various forms of household data, employment data, school enrollment, and hotel-motel units. Trip distribution employed a gravity model. Mode split considered automobiles and transit for passenger, but was omitted for freight as trip generation only accounted for trucks. Vehicle counts validated route assignment. However, among the improvements planned for the 2014 model are to validate truck trips separately from passenger trips (Regional Planning Association & Cambridge Systematics, 2010).

The Memphis Area MPO developed the Memphis Travel Demand Model in 2007 in association with Kimley-Horn and Associates, Cambridge Systematics, and HNTB. Originally conceived with a horizon year of 2030, the current model under development has a horizon year of 2040 for that year's long-range transportation plan. The TransCAD-based model follows the traditional four-step approach for modeling private cars (Memphis Area MPO, n.d.).

The Memphis Travel Demand Model models three classes of commercial vehicles: light trucks ("four-tire trucks"), medium trucks ("single unit trucks"), and heavy trucks ("combination trucks"). The truck components follow a three-step model that omits mode split since trucks are the only mode considered. The trip generation step generates light, medium, and heavy trucks according to employment by economic sector. Trip distribution uses a gravity model to match trip generations and trip attractions. Route Assignment matches trips with routes concurrently with automobiles through a "multi-class highway assignment procedure" (Memphis Area MPO, n.d.).

Challenges in implementing MPOs/DOTs Freight Demand Modelling (FDM)

Turnquist (2006) addresses four important characteristics that should be considered for effective modeling: First, an effective model should produce useful outputs and allows users to know how to use; second, an effective model should involve significant variables and represent interactions among those variables; third, an effective model should operate in a way that is verifiable and understandable; and fourth, an effective model should use data that can be obtained, calibrated, and tested. In this section, challenges in implementing freight demand modeling at MPO and DOT level are reviewed.

Limited Available Data

Models typically require complex data that is not available from a single source (Pendyala, Shankar, & McCullough, 2000). For example, traditional four-step models might require demographic and socio-economic characteristics for its trip generation step, freight origin-destination tables for its following steps, and a series of data on delays, costs, fleet constraints, and labor constraints to calculate impedance. Lindsey (2008) finds that the limited availability of data is one of the large challenges to effective freight modeling that metropolitan planning organizations face. Likewise, the Transportation Research Board (2007) determined the lack of truck data within and beyond MPO boundaries to be a major obstacle in MPO freight modeling. Generally, meager data are available for modeling because most of the data needed for freight modeling are proprietary information of individual companies who are hesitant to relinquish it for fear of competitive disadvantage. Furthermore, private companies are reticent to provide data when the activity removes staff from other revenue-generating tasks (Gray, 2005). Data limitations have furthermore constrained the model types available, with the primary models in use being time-series forecasts, and aggregate and disaggregate flow models. Limited geographic specificity in commodity flows has also been a challenge in developing commodity-based models (Spear, 2005). To advance, Lindsey (2008) suggests regional-level data collection and standardizing data format.

Figliozzi, et al. (2007) found that few transportation planners in major developing countries use “analytical urban truck tour models” largely because disaggregate truck data is rarely available to planners” (Ambrosini & Routhier, 2004; Figliozzi et al., 2007). When disaggregate truck data is available, it is possible to use the disaggregate data to analyze freight movement, revealing the relationship between trip length and empty trips, trip speed, and movement (Figliozzi et al., 2007). Potential new data sources include technologies grouped under the heading of intelligent transportation systems (ITS) and a series of truck and containers trackers implemented by carriers through radio frequency identification (RFID) and GPS devices (Bronzini, 2006).

Feedback between Freight and Passenger Demand

Freight demand and passenger demand both affect each other in a cycle, where road capacity or congestion caused by both sectors causes these same sectors to adapt their behavior accordingly. For instance, if passenger travel is low on a given road relative to capacity, freight might increasingly use the route instead of other more congested routes. Regan & Garrido (2001) reviewed several different freight models, finding that most do not sufficiently explain the interrelation between freight and passenger travel demand, which is particularly important in urban environments, with effects of either demand feeding to decision makers on both sides. For example, air travel has heavy interactions between freight and travel demand, with the supply of both services linked. Moreover, models should better consider not just the shipper and the carrier, but also the intervening actors, such as freight forwarders, brokers, agents, and facilitators (Regan & Garrido, 2001).

Fundamentally Different Characteristics for Freight and Passenger Travel

Freight models encounter several challenges as a group. Most freight models are derived from passenger demand models. Therefore, as a group they assume that freight and passenger movement respond similarly (Holguin-Veras & Thorson, 2000). Regan & Garrido (2001) reported that few freight models had addressed the means by which decision makers in the freight transportation system made their choices. Instead, freight models focused on the number of trucks moving, not on the decision making behind the truck movements. Regan & Garrido (2001) recognized that freight decisions are made not only by shippers and carriers, but also by third party logistics, and the choice between private and commercial transport becomes one of the most important decisions that companies make. The researchers examined the need for developing freight demand models which incorporate shipper or carrier behavior to represent urban goods movements accurately considering international freight flows. The situation becomes more complex for freight when the globalization of production and logistics are accounted for, as well as logistics considerations such as location and size of distribution centers, shipment sizes, and batch sizes. Tavasszy, Ruijgrok, & Davydenko (2012) review how this requires complex, multifaceted logistics networks to manage freight transport from produce to consumer.

Finally, Holguín-Veras & Thorson (2000) review one of the final challenges in modeling freight travel compared with passenger travel behavior, which is freight's diverging time values. Most passengers have roughly similar values of time (VOT), while some freight items (such as medical supplies) may have much more sensitivity to time than others (like bulk raw materials). De Jong, Gunn, & Walker (2004) highlight how different characteristics of time value, size, and bulk make different commodities flow through logistics systems very differently. Fresh flowers or microchips move very differently than wheat or industrial machinery.

Holguín-Veras & Thorson (2000) and De Jong et al. (2004) explain how more decision makers are involved in freight movement patterns than in passenger movement. They include shippers, carriers, brokers (including third part logistics or 3PL agents, warehouses, and receivers, as well as households as final customers). These decision makers can fragment decision making for a single trip over several areas of specialization.

There are also other differences in the way that freight and passengers move around. While passengers usually anchor their daily tours around a primary purpose, such as work or school, freight tours often do not have a single, primary destination, but are organized so as to minimize vehicle miles in the process of making several customer-specific deliveries (Kuzmyak, 2008).

Unique Sector Characteristics

The Transportation Research Board (2007) also found that MPOs encounter difficulties modeling freight because of a wide gap in institutional knowledge between logistics operators and many transportation planners. It found that it is uncommon for transportation planners or modelers to know "how businesses make decisions on freight logistics," making it difficult to assess the factors driving freight movement, which is particularly relevant in logistics models, or to understand the impacts on shippers and carriers of policy measures (Transportation Research Board, 2007).

Challenges Unique to Urban Freight Models

Urban freight modeling faces several obstacles to accurate modeling that are not encountered in regional freight modeling. They include "land use patterns, barriers (physical and operational) to moving goods into and through a central business district of a city, and the presence of traffic congestion" (Regan & Garrido, 2001). Urban trucking involves daily multi-stop tours that are not as common in regional (e.g. intercity) flows. What is picked up and dropped at each site is hard to identify. Urban truck movements also often pass near or through residential areas using surface streets, creating locally concentrated environmental and safety issues. Urban areas are where a good deal of intermodal transfer activity occurs between large truck-rail and truck-water terminals: notably around large and congested seaports. Urban freight movements include lots of commercial or "service" trips that are much less common between cities.

Other Challenges

In addition to general challenges, each family of freight demand modeling approaches has its own challenges. As already mentioned, commodity-based models require commodity movement data that is often expensive and hard to obtain. Moreover, it omits empty trips, and most methods of accounting for empty trips in a commodity-based model neglect "the interrelationship among empty trips, commodity flows, and the logistics of freight movements" (Holguín-Veras & Thorson, 2000). However, commodity-based models do include mode choice in the model, and recognize that freight movement derives from the demand for goods. Trip-based approaches account neither for mode choice nor for the underlying economic and behavioral characteristics of commodity movement, though they do account for empty trips, which usually fall between 15% and 50% of total trips and the truck movement data required is usually more easily available (Holguín-Veras & Thorson, 2000).

Local Trips (Commodity-Based Models)

The United States Department of Transportation et al. (2010) identified one limitation with current commodity-based freight models: many of the local truck activities are not accounted for, e.g. they miss many short-distance urban area movements (mostly commercial "service" trips), which lead to the underestimation of truck trip volumes within the urban area.

Modelling Methodology

Trend and Time Series Analysis

Trend and time series analysis extrapolates data on past freight movement to estimate future freight movement. Time series analysis can offer a parsimonious data requirement if past trends in freight movement activity are easily tied to just one or two explanatory variables. This may be the case where short to medium term (up to 5 year) forecasts are concerned, Past studies offer a variety of methods to choose from, including simple growth factor methods, multiple regressions, exponential smoothing, artificial neural networks, multivariate autoregressive, Box-Jenkins autoregressive and moving average, space time autoregressive moving average and space-time multinomial probit models (Southworth, 2011).

Elasticities may be derived to show some sensitivity to external factors. Advantages of such models include ease of implementation and low data requirements (Pendyala et al., 2000). However, data sources have to date been limited to either freight moving through a limited number of high volume facilities (e.g., seaports) or to very a limited set of O-D flows.

Four-Step Models

Four-step models are the traditional approach to modeling travel demand. They originated to model passenger (commuter) movements, and in subsequent years they have been adapted to address freight. They may be either commodity-based or truck-based depending on the type of data that their early steps generate. They involve the following four steps:

Trip generation

Trip generation estimates the goods produced in and attracted to each TAZ (for commodity-based models) or the number of trucks that the activity in each TAZ produces (for truck-based models). As previously discussed, modelers use observed data from surveys, GPS recordings, or other sources to derive standard generation rates based on certain attributes, which are normally at the TAZ level. When there are activities whose generation rates diverge substantially from the standard rates, they may be treated as special generators. Common examples are ports and intermodal (Beagan et al., 2007; De Jong et al., 2004). The output from the generation step is either tons of goods or dollar value of goods (for commodity-based models) or number of trucks (for truck-based model) that are produced in and attracted to each zone. At this step, producing and attracting TAZs are not yet paired.

Distribution

The distribution step spatially matches trip or commodity productions and attractions between origins and destinations. Depending on the output of the generation step, it allocates either commodity flows or vehicles based on commodity flow data or vehicle movement data collected from surveys or another source (Beagan et al., 2007). Output is in tons of commodities or number of vehicles that move between two different zones. Gravity distribution is the most common form (De Jong et al., 2004; Kuzmyak, 2008; Southworth, 2002).

Mode Split

The mode split step occurs only in commodity flow models as truck-based models preselect the mode. De Jong et al. (2004) lists different model types for addressing mode split: elasticity-based, aggregate, disaggregate, neoclassical, economic direct demand, micro simulation, and multimodal network based.

Route Assignment

Models that include a mode split step first convert commodity movements among origins and destinations by mode to a number of vehicles based on tonnage-to-vehicle ratios, using data sources such as the U.S. Census Bureau's Vehicle Inventory Use Survey (VIUS). Logistics models might also be used to convert commodity flow tons to vehicles by explicitly modeling supply chain decisions (De Jong et al., 2004). The route assignment step places vehicles onto the transportation network. Beagan et al. (2007) explain how the model needs to address time of day, road capacity, and truck prohibitions. Routes may be assigned according to fixed paths connecting TAZs, or routed dynamically to account for congestion (Beagan et al., 2007; De Jong et al., 2004).

The model may load trucks onto the road network before or after automobiles, or it may simultaneously load trucks and automobiles, using multi-class assignment routines.

Commodity-based models account for commodity movements among producers and consumers in space. The fact that commodity-based freight deals directly with the goods movements that drive vehicle flows causes some researchers to recommend them over vehicle-based models (Kuzmyak, 2008; Southworth, 2002). While their level of complexity may change according to the variables incorporated (Spear, 2005), commodity-based models often follow a "four-step" method based on passenger demand model's four-step method (Cambridge Systematics et al., 2008). Holguín-Veras & Thorson (2000) explain the commodity-based model steps in Table 5 below. The model breaks the geographic area into discrete zones for which certain characteristics of commodity producers and consumers are known.

Table 5: Model components of commodity-based "Four Steps" approach

Step	Approach
1. Commodity Generation	Commodity generation rates or zonal regression models
2. Commodity Distribution	Gravity models (simply or doubly constrained) or intervening opportunities
3. Commodity Mode Split	Logit models based on panel data. Rarely done in urban area
4. Vehicle Loading	Loading rates based on previous surveys
5. Traffic Assignment	Standard traffic assignment techniques

Source: Holguín-Veras & Thorson (2000)

The first step, commodity generation, uses population, employment, and trip generation rates by commodity to estimate commodity productions and attractions in each zone

(Cambridge Systematics, National Cooperative Highway Research Program, & Transportation Officials, 2008). Commodities are usually measured in dollars or tons (Spear, 2005). Furthermore, available data may capture annual flows, prompting the need to convert from annual flows to daily flows (Spear, 2005). Commodity distribution links productions in one zone to attractions in another, with assumptions about the decrease in attraction due to distance (Holguín-Veras & Thorson, 2000). Common means of distributing commodities include the Fratar (or Furness) method, gravity models, or maximum utility-based logit models (Horowitz, 2006). Generation and distribution outputs are often calibrated. TRANSEARCH data is a common calibration dataset for statewide freight models (Horowitz, 2006). Mode split estimates the amount of traffic that will use each mode with a discrete choice model. As mode split models are very complex, so the utilization of existing mode split parameters are common (Cambridge Systematics et al., 2008). Mode split may also follow a different fixed percentage or variable expression (Horowitz, 2006). Vehicle loading is an intermediate step for freight travel demand that estimates the amount of freight that each vehicle will contain (Holguín-Veras & Thorson, 2000). Finally, trip assignment gives each shipment a route on transportation infrastructure, typically through a freight truck only or multiclass assignment model (Cambridge Systematics et al., 2008).

The four-step model is versatile in that it may use aggregate and/or disaggregate data (with suitable aggregation) to forecast freight or passenger travel demand. It can also include trucks that do not carry freight, including safety vehicles, utility vehicles, public service vehicles, and business and personal service vehicles (Beagan et al., 2007) .

Truck Modelling

Truck models often follow a modified version of the four-step approach that omits mode choice (Cambridge Systematics et al., 2008; Chow, Yang, & Regan, 2010). Trucks are the only mode considered in this model, and therefore the model does not have a modal choice/shift component. Trucks are generally classified into light, medium, and heavy trucks. In the truck model, the trip distribution step typically utilizes a gravity model, in which the coefficients will be developed based on local surveys or from other sources, e.g. the Quick Response Freight Manual (Cambridge Systematics et al., 2008). Most of these truck models use aggregate data to generate aggregate truck trips (Chow et al., 2010).

Chow et al. (2010) address the state of the practice in freight demand modeling, beginning with an extensive review by the National Cooperative Highway Research Program (Cambridge Systematics et al., 2008), which addresses the state of five freight demand model classes: Direct facility flow factoring methods, origin-destination factoring methods, truck models, four-step commodity flow models, and economic activity models. Each of these model classes has tended in practice to rely on aggregate data, which makes them "insensitive to economic behavior at the level of the firms that act as the decision-makers" (Holguín-Veras & Thorson, 2000). In response to this sort of criticism, much recent research has focused on developing disaggregate models (Chow et al., 2010; Southworth, 2011).

In detail, the direct facility flow factoring method is a simple, relatively easy method of estimating future origin-destination-based truck movement that is most useful for short-term projections. The origin-destination factor method is similar to the previous method. However, it additionally considers mode split and assignment. The four-step commodity model is derived from passenger models, and it has been used in states including Iowa, Florida, Texas, Pennsylvania, and Wisconsin (Cambridge Systematics et al., 2008; Iowa Department of Transportation & Iowa State University Center for Transportation Research and Education, 2008; Pennsylvania Department of Transportation, 2007; Proussaloglou, et al., 2007). The economic activity model has been used in Oregon to model freight based on land use and economic cost (Cambridge Systematics et al., 2008; J. Y. Chow et al., 2010; Hunt et al., 2001).

In the end, the most appropriate model depends on the area being modeled, including the size of the state, the data available, the organizational structure, and the economic activity. For example, a large state like California seeking to model freight in the entire state would use a regional commodity-based model because of its size, the existence of several large MPOs, and the presence of a large port (Los Angeles-Long Beach), requiring a vehicle-based truck touring model (see (Ritchie, 2013)).

Finely grained socio-economic data is necessary to produce and attract freight movements in freight travel demand models. However, models have employed different levels of geographic detail and different attributes to generate truck-generation and attraction rates for different activities. The goal is to isolate the activity attributes that best determine the number of trips generated so that truck trip generation rates can be estimated for any activity with given attributes.

The most common level of geographic detail is the transportation analysis zone (TAZ) (Beagan et al. 2007; Hunt & Stefan, 2007; Kuzmyak, 2008) where urban area modeling is concerned. However, there have also been attempts to use more geographically precise attributes to generate trips, including major land uses (Bassok, et al., 2011), more precise land uses (Fischer & Han, 2001), and locations of individual establishments (Kawamura, et al., 2005; Ortuzar & Willumsen, 1994), though establishment-level truck generation rates were not part of a specific modeling process.

Population and employment characteristics are the most common datasets used to determine truck generation rates. (Kuzmyak, 2008) reports that Atlanta and Baltimore both use TAZ-level data on the number of households and employment in land-use characterizes office, retail, and industrial. Calgary's commercial vehicle model also generates tours from TAZ employment by establishment category, which are industrial, wholesale, retail, service, and transportation Hunt & Stefan, 2007). Zone land uses are low density, residential, retail and commercial, industrial, and employment node (Hunt & Stefan, 2007). Pendyala et al. (2000) reports that demographic, socio-economic, and factors capturing "levels of economic activity in different industry sectors" are used. Fischer & Han (2001) describe trip generation rates that rely on measures of land use intensity, including land acreage, building floor area, and number of employees. However, Fischer & Han (2001) also cite other economic indicators that may be used when data is available, including the number of container lifts. The problem is that productivity varies significantly by industry, so aggregating land uses may cause inaccurate truck generation estimates. Fischer & Han (2001) believe that land use analysis may need to be very disaggregate to capture meaningful differences in productions per employee. This has caused several researchers to examine trip generation rates at the establishment level. Bassok et al. (2011) used GPS truck movement data in the Puget Sound region to create trip generation rates for grocery stores, though the rates under-represented observed movements. Ortuzar & Willumsen (1994) found "turnover, floor area and location/site area occupied by the firm, and the number of employees" to influence truck generation, though others (Kawamura et al., 2005) found weak links with employees and floor area. Southworth (2014) provides a review and listing of past efforts to disaggregate FAF and CFS regional commodity flows to the county and sub-county levels for statewide and multi-county MPO modeling of, in particular, truck freight movements (e.g. by using zip code areas as TAZs).

Tour-Based Modelling

Tour-based models are also referred to as trip-chaining models. They account for the occurrence of back-to-back trips without returning to a home base, which might be a warehouse where loading and unloading occur. A trip is a single movement between two endpoint origins and destinations. Figliozzi et al. (2007) defines a tour "as the path that a commercial vehicle follows when it leaves its depot or distribution center (DC) and visits different destinations (two or more destination or stops) in a sequence before returning to the depot or DC during a single driver shift."

According to Kuzmyak (2008), private-sector logistics firms have for some time now modeled trip chains through dispatch algorithms to inform planning decisions. Logistics firms benefit from proprietary movement data that makes it easier to model trip chains. Ruan, Lin, & Kawamura (2012) explain how freight operators often chain trips to form tours in order to minimize operating expenses while providing the best service to clients. Because commercial vehicles are more likely to chain trips than passenger vehicles, many traditional four-step models do not account for them (Holguin-Veras & Wang, 2008). Tour-based approaches to freight demand modeling address this particular behavior of trip chaining that is common among freight operators.

There are greater data requirements for tour-based models than for truck-based models. According to Guo & Wittwer (2009), tour-based models require "vehicle travel diary data by type of establishments." The models predict vehicle types, tour purpose, number and location of stops for each tour.

Ruan et al. (2012) assert that tour-based approaches account for behavior and decision making processes better than those that do not overtly consider tours. They apply the concept of tour chaining to data from the Texas Commercial Vehicle Surveys (Prozzi, et al., 2006; Prozzi, et al., 2004) covering five Texas cities or regions to identify tour chaining behavior. Tour chaining occurs when a vehicle completes multiple tours within a day from the same or different base. The authors find that tour chains offer the possibility of better modeling carriers' delivery strategy than do tour-based approaches alone. Moreover, "the tour-chain-based model provides more details in distribution strategy, distribution channel, and why and how the individual tours are bundled, which are not well understood in the freight and logistics modeling literature" (Ruan et al., 2012).

While much freight traffic covers long-distances, urban commercial traffic can affect congestion, pollution, and roadway maintenance costs in a significant way (Hunt & Stefan, 2007). Furthermore, while transportation demand models often derive urban commercial traffic in a manner similar to urban passenger traffic, the two operate under different decision making, expense, and value of time dynamics (Hunt & Stefan, 2007). Hunt & Stefan (2007) examine Calgary's commercial vehicle tour-based micro simulation model. They identify three main characteristics of urban commercial traffic, saying that it has—

- A large number of stops
- No natural drop-off order
- An almost exclusive use of roads (as opposed to waterways, rail, or air infrastructure)

Hunt & Stefan (2007) assert that tour-based models best reflect the behavior of much urban commercial traffic, as opposed to traditional four-step models and their derivatives. Their tour-based micro simulation model for Calgary uses the following steps in Figure 7:

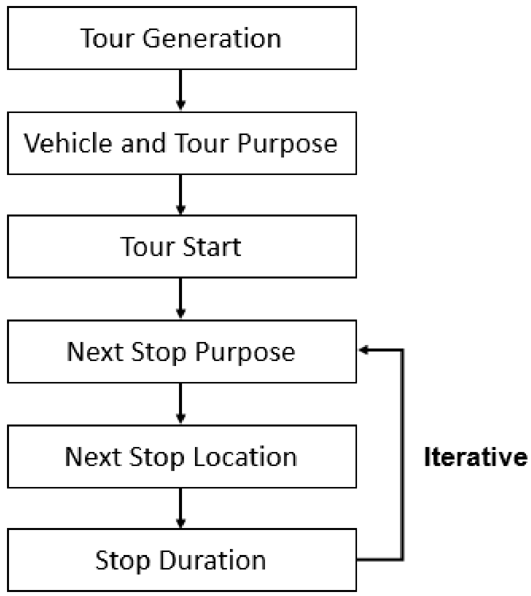


Figure 7: Microsimulation Tour-Based Model

(Source: Hunt & Stefan (2007))

Figliozzi et al. (2007) collected disaggregate information about truck tours in Sydney Australia to analyze tour characteristics. Their analysis used eight months of truck activity sheets for a freight forwarder in Sydney. They found an average of 6.8 trips per tour in Sydney. This aligns with past studies that found an average of 6 trips per tour in Calgary (Hunt & Stefan, 2007), 5.6 trips per tour in Denver (Holguin-Veras & Patil, 2007), and 6.2 in Amsterdam (Vleugel & Janic, 2004).

Wang & Holguin-Veras (2010) developed an aggregate entropy-maximization tour-based freight model. It comprises two components: a tour choice model and a tour flow distribution model. The tour choice model creates a tour set aligned with observed average tour length. The tour flow distribution model uses productions, attractions, and an impedance function to distribute trips, similar to a gravity model. They applied the model to 1998 and 1999 truck data for the Denver area. The estimated tour flows closely match the observed values with a mean absolute percentage error of 6.71%. They determined model results to be relatively accurate and demonstrated the tour-based model's potential for commercial vehicle movements in urban areas.

Gliebe, et al. (2007) created an intra-urban commercial vehicle movement model for the state of Ohio. It is a disaggregate model that will function in tandem with an aggregate commercial model, a person-travel—long-distance model (PT-LD), and a household-based person transport model to form the four-part Ohio statewide model. Table 6 below depicts each sub model's area of applicability. Gliebe et al's (2007) disaggregate commercial model (DCM) addresses commercial trips under 50 miles long. It is commodity-based with a structure similar to that of Calgary model.

Table 6: Ohio statewide model's sub models and area of application

Parts of Ohio statewide model	Application
Disaggregate commercial model (DCM)	Commodity-based commercial trips under 50 miles
Aggregate commercial model (ACM)	Commercial trips over 50 miles
Person-travel—long-distance model (PT-LD)	"Service of professionally oriented business trips" over 50 miles
Household-based person transport	Home-to-work trips and personal work-based trips (E.g., lunch from work)

Source: CQGRD, modified from Gliebe et al. (2007)

Micro-Simulation Models

There are other variations of the traditional four-step model. Wisetjindawat, et al. (2007) proposed a commodity-based microsimulation model, which could be defined as a model using “the behavior of each freight agent individually…to determine the characteristics of each freight movement”. It generates commodity demand for each individual consumer business or establishment according to production and consumption of commodities based on micro-level characteristics of businesses and establishments in the modeling area. They introduce the microsimulation model that incorporates elements from logistics science such as vehicle inventory, vehicle routing, and scheduling which have to date been largely absent from commodity-based models. Applied to Tokyo, Wisetjindawat et al. (2007) assessed ways to improve the model by including additional variables. According to Kuzmyak (2008) such microsimulation models are an efficient way for “representing sequential events,” such as in urban truck models.

Economic Activity Models

Beagan et al. (2007); Federal Highway Administration (2007); and Pendyala et al. (2000) include description of economic activity models. Economic activity models consist of economic/land use models and freight transportation demand models in interaction. They seek to capture commodity movements driven by the conversion of economic inputs to economic outputs (Pendyala et al., 2000). Economic activity models require several types of data: socio-economic data for the economic/land use model, input-output economic data for spatial modeling, land use data, and transportation network data (Beagan et al., 2007).

Supply-Chain/Logistics Models

Several researchers describe logistics models (J. Y. Chow et al., 2010; Guo & Wittwer, 2009; Kuzmyak, 2008; Pendyala et al., 2000). Logistics models fundamentally model decisions as products moving through the supply chain. They incorporate commodity flow movements in response to decision making by logistics agents (e.g., shippers, carriers, freight forwarders) in search of low-cost channels and ultimately convert the commodity flows into vehicle movements to load onto the transportation network. Because of the complex decisions and multiple actors, logistics models may require further development for freight modeling (Pendyala et al., 2000). According to (J. Y. Chow et al., 2010), logistics models may resemble tour-based models except that they model commodity flows whereas tour-based models analyze vehicle movements that result from commodity supply-demand considerations.

Hybrid

Beagan et al. (2007) explains the existence of hybrid approaches, which "blend commodity flow modeling techniques with freight truck modeling techniques," (p. 6-1) while economic activity models combine an economic-land use model and a freight transportation demand model (p. 7-1). Hybrid models combined a long-haul four-step commodity-based model with a short-haul three-step truck model to benefit from both commodity-based models' effectiveness for modeling long-distance movements with truck-based models' advantage in data availability for short-range movements. It is important here that the two models not double-count movements. A number of studies assign inter-county movements using a commodity-based model and intra-county movements using a truck-based model (Beagan et al., 2007).

Other Methods for Freight Demand Projection

MPOs and state transportation agencies may perform freight demand forecasts according to one of several methods, of which formal freight models are not the only options. First, they may not forecast it at all, instead assuming that changes in flows will remain minimal or relying on informed expert opinions to project flows into the future. Some small eastern states do not develop model forecasts of statewide freight movements either because of lack of funding and because their size and homogeneity may allow the assumption that freight and passenger traffic behave similarly (Spear, 2005). They may also extrapolate from past trends, projecting freight volume into the future based on equations fitted to past data (Pendyala et al., 2000). Finally, elasticity methods adjust freight flows according to changes in specific variables, though they are limited in accounting for changes in multiple variables (Pendyala et al., 2000).

Strengths and Limitations of Current Freight Forecasting Models

NCHRP Report 606 reviews the state of the practice of freight activity models and discusses five major classes of freight models and the data they need, including (NCHRP, 2008):

- Direct facility flow factoring method (regression methods, etc.);
- Origin-Destination factoring method (Transearch OD data, FAF OD data);
- Three-step truck model (generation, distribution, assignment);
- Four-step commodity model (generation, distribution, mode split, assignment); and
- Economic activity model (integrated economic/land use forecasts and multimodal commodity demand including generation, distribution, mode split, and assignment).

Chow et al. (2010) added another two important classes of freight models to the list above, which include “Logistic Models” and “Vehicle Touring Models”. As Fischer et al. (2005) concluded and Chow et al.(2010) reiterated, these two categories result from the need to improve the sensitivity of models to economics of commodities for policymaking (logistic models) and more realistically capture the movements of vehicles for impact assessment (vehicle touring models). Chow et al. (2010) also summarized the major data needed for the two classes of freight models, including commodity flow data, truck load data, make/use and I-O tables, intermodal facilities, logistics costs, firm shipment sizes and distributions, and truck activity diaries (Chow et al., 2010). They also noted that the unavailability of data is the major reason for the few applications of these two classes of freight models.

Table 7 summarizes the strengths and limitations of the seven classes of existing freight models.

Table 7. Freight Model Comparisons

Model	Strengths	Limitations
Direct facility factoring	Multi-variable; "All-in-one" format; Corridor and mode specific.	Not network based; No supply/demand, capacity.
OD factoring (FAF)	Available national data; Convertible to state & local scales from national scale; Course spatial data can be refined by local counts and optimal methods; Available future forecasts; Multimodal commodity flows; Multimodal vehicle flows; Regularly improved; Relatively low cost.	Local and state data are proprietary; or estimated; Course spatial structure (CFS districts & counties); Static "snap shorts" of the future; Not directly integrated with economic census; Not predictive; Not seasonal or by hour of day.
Three-step truck models	Predictive model; Detailed level of analysis; Multimodal commodity flows.	Data intensive; High data collection or purchase cost; Expensive to develop; Long development time.
Four-step method	Same as three-step; Explicit modal split; Connects commodities to modes.	Same as 3-step method; Requires advanced user skills.
Economic activity model	Economic & land use data & forecasts integrated with the three- or four-step methods; Multi-modal & multi-commodity method; Simple factor methods based on historic traffic& freight trends & forecasts of economic activity; Applicable to special generator intermodal facilities, corridors, regional, & statewide scales; Easy sensitivity of assumed factors; Straight forward policy analysis of alternative modal operations & restrictions; Uses data from local, state & national sources.	Linear relationships between economic activity & freight flow; Does not recognize differences in: values of freight output per ton, production per employee, transportation requirements per ton, or competition among facilities & modes.
Logistic models	Improves the sensitivity to economics of commodities for policymaking; Incorporate multiple intermediate stops to represent distribution channels; Equipped with behavioral distinctions which apply to the many decision-makers within the chain; Involves details on the movements of raw goods and finished products and focus on units of commodities.	Requires a lot of data from different sources which are difficult to acquire, such as the data of make/use and I-O tables and logistics costs.
Vehicle touring models	Similar to the merits of logistic models, but the unit of analysis is vehicle instead of commodities; Most powerful to capture the movements of vehicles and decisions of carriers realistically for more accurate evaluation; May employ space-time multinomial probit model to forecast the distribution of freight flows over space and time; May allow truck tour-based microsimulation to more accurately forecast truck movements at local level;	Also require a log of data which might be difficult to acquire, such as truck load data, intermodal facilities, firm shipment sizes and distributions, and truck activity diaries; It is often hard to validate the results.

Source: Edited from NCDOT (2009) and Chow et al. (2010)

GPS-based data uses in Freight Planning/Modelling

GPS data Uses in Passenger Modeling Cases

Wolf & Lee (2008) explain that researchers have frequently used trip diaries to collect individual travel behavior data, though underreporting has been a recurring issue that has been difficult to quantify (Richardson, 2000). Many researchers have attempted to extrapolate the missing data from the reported trips using data expansion techniques, some even accounting for underlying socio-economic patterns in reported travel data (Armoogum & Madre, 1997; Polak & Han, 1997; Richardson, Ampt, & Meyburg, 1995; Wolf, et al., 2003; Zmud & Arce, 2000).

Global positioning system information offers the possibility of assessing the size of underreporting and creating corresponding corrective factors in travel demand models. It allows a different approach to accounting for trips that are not reported, as opposed to using expansion techniques on reported data since it uses observations instead of reported trips (Wolf et al., 2003): although GPS reporting of truck trips is currently limited in its ability to be representative due to sample size limitations.

Bricka & Bhat (2006) list U.S. passenger travel demand surveys with GPS components prior to 2006 (Table 8).

Table 8: Passenger travel demand surveys with GPS components

Study	Year Conducted	No. of Households	No. of Households with GPS & CATI	% of CATI Surveyed Households Participating in GPS Survey	Level of Trip Under-reporting
Lexington	1996	100	84	84.0%	NA
Austin	1997	2000	200	10.0%	31%
California	2001	16990	292	1.7%	23%
Los Angeles	2001/2	23302	293	1.3%	35%
Pittsburgh	2001/2	2553	46	1.8%	31%
St. Louis	2002	5094	150	2.9%	11%
Ohio	2002	6338	230	3.6%	30%
Laredo	2002	1971	87	4.4%	81%
Tyler-Longview	2003	2336	249	10.7%	NA
Kansas City	2004	3049	228	7.5%	10%

Source: Bricka & Bhat (2006)

Several surveys have employed GPS devices before, including in Lexington, KY (by the FHWA); Austin, TX; and Atlanta, GA. The Federal Highway Administration's study in Lexington, KY used GPS devices to record trips in vehicles for six days, though the GPS data differed substantially from what participants reported (Wagner, 1997; Wolf et al., 2003). A 1997 study in Austin, TX matching GPS devices with travel surveys allowed a clearer quantification of the differences between GPS records and individual reports (Pearson, 2001). The Commute Atlanta program, which aimed to assess the effects of converting automotive fuel tax, registration fee, and insurance costs into variable driving costs and was funded by the FHWA and GDOT, utilized GPS device to collected year-long vehicle activity data in 2004 (Guensler, Li, Ogle, Axhausen, & Schönfelder, 2006). The second-by-second longitudinal vehicle activity data, allows comprehensive analysis of individual trip and activity demand, though it requires heavy automatic data processing (Guensler et al., 2006).

Wolf et al. (2003) review the functioning of the California Statewide Travel Survey in 2001, which supplemented travel diaries with in-vehicle, self-installed GPS devices with a rooftop antenna and powered by a cigarette lighter. The survey used initial sample of 500 households with the expectation that between 100 and 200 households would drop out without completing all steps of the one-weekday survey. The 500 households were chosen among the 16,500 households participating in the self-reporting survey (Wolf et al., 2003).

GPS data Uses in Freight Modeling Cases

M6 Corridor Freight Performance Measures

Hudson & Rhys-Tyler (2004) outlined the use of GPS to develop an early example of freight performance measurement for the M6 highway corridor in the United Kingdom. The M6 runs north-south from the northwest of England into southern Scotland (Marshall, 2013). The Freight Transportation Association commissioned a study in 2002 to provide performance measures for the highway based on GPS devices installed in trucks. The GPS devices were already present in the survey vehicles to manage operations (Hudson & Rhys-Tyler, 2004). The pilot survey occurred between April 22 and May 5, 2002. It gathered the location of trucks in a wide area with latitude and longitude readings that could be on the M6 corridor, and it then compared the observed locations with a series of vectors defining the M6 corridor (between junctions1 and 21). Researchers made 153,085 observations of 15,184 trips. Observations were taken every 21 minutes. Each observation also included location, heading, speed, and observation time. Observations from the same vehicle were linked into trips made of multiple observations. The observations were analyzed to produce minimum, maximum, and median speeds for different times of day and different M6 segments (Hudson &

Rhys-Tyler, 2004). They calculated average, space-mean speeds by dividing the distance traveled by the time elapsed.

Researchers encountered several challenges. The road was represented by a series of vectors, leading the distance and speed over the segment to be slightly underestimated. There were also segments when the apparent time to traverse a segment was unreasonably high due to trucks stopping for reasons unrelated to congestion, such as at a service station. Performance measures will need to account for non-traffic-related stops (Hudson & Rhys-Tyler, 2004). Researchers recommended using more frequent observations to improve speed accuracy. Finally, GPS devices could often not distinguish between trucks on the highway or at an adjacent rest area. Researchers had to exclude non-moving vehicles in rest areas.

FHWA Freight Performance Measures

The Federal Highway Administration measured the performance of five highways corridors (I-5, I-10, I-45, I-65, and I-70) that handle approximately 25% of loaded truck vehicle miles. The American Transportation Research Institute (ATRI) gathered truck location and speed information for approximately 250,000 trucks in 2005 though GPS devices installed in each vehicle. ATRI matched the truck locations to one of the five corridors when possible, allowing the Federal Highway Administration to assess average speeds on each segment. The Federal Highway Administration handled privacy concerns by assigning each vehicle a randomly generated number for use in analysis (Federal Highway Administration, 2006).

Melbourne, Australia

Greaves & Figliozzi (2008) review the use of passive GPS sensors to gather freight movement data in Melbourne, Australia in June 2006. The survey used vehicle-installed passive GPS devices that were installed for this purpose. GPS devices can encounter several challenges, including lack of proper installation. Therefore, Gestate sent a trained employee to install and remove each device. A roof-mounted antenna enhanced signal, and the device tapped into the vehicles electricity via the cigarette lighter. Similar devices have served in several passenger travel surveys (Greaves & Figliozzi, 2008).

The pilot survey included 30 trucks with two or three axles based in the Melbourne area operating for several freight companies. The survey lasted for one week, producing 210 truck days of data. The goals were to assess the willingness of freight shipping companies to participate in GPS surveys, gather and analyze disaggregate freight movement data, and explore the use of GPS data in performance measures which might incentivize shipper participation (Greaves & Figliozzi, 2008).

To improve data accuracy, researchers eliminated identifiable errors by, for example, scrubbing out locations that implied a speed above 150 kilometers per hour. Researchers used algorithms to identify trip ends, defined as locations where the truck was stationary within 30 meter diameter for 240 seconds. The 30 meter diameter accounts for apparent fluctuation in the location due to GPS imprecision. Researchers found that 240 seconds balanced the risk of falsely identifying trip ends when the vehicle was actually immobile for other reasons and missing real trip ends. This still over-identified trip ends in some cases, so a researcher manually checked short trips afterwards. Algorithms would also use previous data to extrapolate a truck's starting position when the GPS device did not have a signal at the start of a trip (Greaves & Figliozzi, 2008).

Corridor Travel Time Benchmarking in Washington State

McCormack & Hallenbeck (2006) describe a corridor travel time benchmarking study that occurred in Washington State to compare corridor performance before and after roadway improvements. Researchers used two techniques to gather truck information:

Commercial Vehicle Information System and Networks (CVISN) and GPS. CVISN are electronic tags installed on 30,000 trucks in Washington that register at state weight stations and at some ports. Researchers deduced travel time from sequential CVISN device detections. Secondly, researchers installed 25 GPS devices onto trucks. The devices were powered by truck cigarette lighters and recorded location every five seconds. Researchers downloaded the data every three weeks and identified stops over three minutes as trip ends. A specially coded C++ program assigned GPS measures to road segments.

Puget Sound Region

The Washington State Department of Transportation (WSDOT) used truck GPS data to develop performance measures for freight transport in the Puget Sound region, focusing on a three-week construction project on the I-90 bridge and utilizing spot speeds of GPS data to analyze roadway system's reliability (McCormack, et al., 2010). Ma et al. (2011) describe how WSDOT acquired commercially available GPS truck movement data from three GPS device vendors able to provide movement data for over 2,500 trucks per day and geocoded it to fit both onto the road network and into traffic analysis zones. WSDOT worked in collaboration with Transportation Northwest (TransNow) at the University of Washington and the Washington Trucking Associations (McCormack et al., 2010). WSDOT processed the data into reduced datasets for each company that only included the same relevant data columns to speed the analysis process. Then the researchers processed the data using algorithms to eliminate false readings, detect trip starts and ends, and correct for signal loss. Trip start and end identification is important to correctly build origin-destination pairings. Finally, they developed performance measures related to traffic flow, speed, distance, and variability, which they integrated into a web-based performance measurement tool for state transportation employees (Ma et al., 2011).

Gauteng, South Africa

Joubert & Axhausen (2011) used existing GPS devices in 31,053 vehicles in Gauteng province, South Africa to develop provincial productivity metrics. The data was gathered over the first six months of 2008. The GPS devices maintained by DigiCore Fleet Management transmit data every five minutes including location and vehicle ignition status. Researchers identified trip ends in function of speed and vehicle ignition.

Osaka GPS Route Identification

Yokota & Tamagawa (2012) sought to overcome a challenge with using GPS devices: assigning vehicles to the correct road when roads are near each other or even above one another. Researchers used GPS data collected from trucks in the Osaka, Japan region in 2009. Osaka features some highways on bridges running directly above and parallel to local roads. Thus, determining which road the truck is on based purely on present location is impossible. Therefore, the researchers developed an algorithm to assign GPS readings to roads based on past, present, and future movements and based on road network connections. For example, future readings would reveal the road that the truck had occupied in the past based on where it goes if the raised highway and local road separate at some point. Researchers validated the algorithm, which correctly assigned all 100 entrance and exit ramp movements.

Georgia Truck Freight Corridor Measures of Performance

Southworth & Gillette (2011) provided a review of the latest information on truck freight performance metrics. They also developed a truck freight performance template and applied it using a multi-source dataset to the I-75 corridor between Macon and Valdosta, the latter city located at the Georgia/Florida border. By combining ATRI GPS data on truck speeds with Georgia DOT and FAF truck class specific traffic count data, they derive average corridor transit times, fuel consumption, accident and emissions estimates; as well as a travel time reliability measures which they combine these measures with the results of truck cost modeling to estimate the dollar cost of delays to truck transport.

Opportunities

Provide Disaggregate Data

Greaves & Figliozzi (2008) noted several opportunities for GPS-based freight movement data, one of which is to provide disaggregate information for trip-based freight demand models.

Develop Performance Measures

GPS data can help to develop performance measures, which Greaves & Figliozzi (2008) say might incentivize truck companies' participation in similar surveys. It might also be able to be combined with truck weight to inform pavement management techniques, or emissions or fuel consumption models might be able to use the truck speeds from freight GPS surveys.

Since 2002, the American Transportation Research Institute (ATRI) has been working with the Federal Highway Administration to explore methods and approaches for measuring freight performance (Jones, Murray, & Short, 2005). McCormack et al. (2010) conclude that GPS data can be used in a confidential way to provide average travel rates along major interstate corridors. Currently, ATRI's FPM database contains billions of truck data points from several hundred thousand vehicles spanning more than 7 years, and the data includes periodic time, location, speed and anonymous unique identification information (American Transportation Research Institute, 2012; McCormack et al., 2010).

To support performance measures in the Puget Sound Region, WSDOT assigned all trips to one of three trip types based on trip distance, time at trip end, and path traveled (Ma et al., 2011). The performance measures are based on travel analysis zone origin-destination pairs rather than specific roadways to "monitor network performance between economically important areas even when truck drivers choose multiple connecting routes" (Ma et al., 2011). Actual performance measures include measures of speed, travel time, distance, and variability (Ma et al., 2011; Southworth & Gilette, 2011).

Logendran, Peterson, & Northwest (2006) installed GPS units on 14 trucks from two different companies in the Portland, Oregon area to gain information about commodity flows and the potential impacts on highways managed by the Oregon Department of Transportation. The research team analyzed truck movement data, measuring the average number of stops per vehicle, travel time between stops, road usage per truck per day, and drivers' response to congestion in terms of route changing. Results suggested that truck drivers persisted in their routing during peak hours, though at lower volume.

Feliu, et al. (2013) and Pluvinet, et al. (2012) used a GPS-equipped smartphone application to collect and analyze GPS data on urban truck movements in Bilbao, Spain (G. Feliu et al., 2013) and Lyons, France (Pluvinet et al., 2012). The research teams distributed smartphones to truck drivers equipped with applications that tracked the truck location at two-second intervals. The research team used recorded GPS data to estimate fuel consumption and carbon dioxide emissions.

Wheeler & Figliozzi (2011) collected GPS data, loop sensor data, and incident data from an Oregon Department of Transportation's transportation management system to develop highway performance measures for heavily trafficked freight corridors. Freight-specific performance measures included congestion, travel time, cost, and emissions.

Challenges

Identifying Trip Ends

Automatically identifying trip ends has proven to be a recurring problem in many case studies, with most authors concluding that there is an inherent trade-off between missing real stops of short duration and falsely identifying trip ends when the vehicle was really stopped for another reason. Most adjusted their working definitions of a trip end and examined data portions manually to minimize the falsely identified or missed trip ends.

In the Puget Sound region, properly identifying trip ends based on the length of time for which a truck is immobile missed many real trip ends. An immobility threshold time of three minutes excluded certain trip ends that were found manually. WSDOT overcome the challenge by including whether the engine was off or the vehicle was in park in the algorithms that identified trip ends (Ma et al., 2011). In each case, it appears that adjusting the identification algorithms and checking manually for accuracy can help insure that as many trip ends are accurately identified and as few omitted as possible (Greaves & Figliozzi, 2008).

Du & Aultman-Hall (2007) compared passenger travel diaries and corresponding GPS data from Lexington, KY between March 2002 and July 2003 to create a trip identification algorithm. The length of time stopped did not capture all trip ends and it omitted others. Du & Aultman-Hall (2007) found that the most accurate algorithms for identifying passenger trips ends accounted for heading changes and departures from the road network (e.g., to enter a parking lot) in addition to minimum time stopped.

Sharman & Roorda (2011) used clustering to assess repeated visits to the same site by freight trucks. They also compared truck travel diaries and corresponding GPS data for six Toronto-area trucks over three months in 2007. Additionally, they had access to fleet management GPS data for 818 trucks with 40 companies over one month in 2006. They found that Ward's method is the most accurate method for clustering trip ends around a site. The method has three steps: (1) Create a matrix showing the distance between all points. Each point is a unique cluster. (2) Merge closest two clusters and recalculate the matrix. Continue until all points are in one cluster. (3) Process can be stopped at different points to form different numbers of clusters. The researchers confirmed Ward's method's accuracy by comparing results with other indices.

Obtaining Proprietary Movement Data

In the Puget Sound region, researchers faced difficulty acquiring data (Ma et al., 2011). While most truck companies contacted agreed to share their GPS data, the technical difficulties of integrating the information into a single usable format proved insurmountable. GPS device vendors were a more practical data source. Ma et al. (2011) outlined several advantages and disadvantages of obtaining truck movement data from GPS device vendors. Among the advantages, the vendors had consolidated data for several truck companies, they more consistently had technical expertise, and they were able to strengthen the provider relationship through a legal contract. Among the disadvantages that (Ma et al., 2011) cited are the privacy concerns that complicated contract negotiations, the fact that vendors organized data in ways more suited to industry than research, and that the researchers continued to pay for data throughout the project.

Similarly, in Melbourne, Greaves & Figliozzi (2008) outlined challenges that the survey encountered in collecting and analyzing GPS data for freight models. Fear of losing proprietary information or being placed in a competitive disadvantage compared with companies that do not participate makes freight companies hesitant to participate in GPS-based freight movement surveys, and drivers also have privacy concerns.

NCFRP Report 08 offers the following criteria for selecting a GPS vendor: 1) provides national service coverage area to make sure the consistency of data and data formatting; 2) provides the necessary truck movement data, e.g. data, time, location; and 3) providing to some degree of archived historical data (Cambridge Systematics, 2010).

Network Modeling

Researchers on the M6 Corridor found that accurate network modeling affected performance measure accuracy (Hudson & Rhys-Tyler, 2004). The road was represented by a series of vectors, leading the distance and speed over the segment to be slightly underestimated. There were also segments when the apparent time to traverse a segment was unreasonably high due to trucks stopping for reasons unrelated to congestion, such as at a service station. Performance measures will need to account for non-traffic-related stops (Hudson & Rhys-Tyler, 2004).

Data Accuracy and Lost Data

In the California Statewide Travel Survey, researchers noted a few difficulties with the GPS data collection process. For example, these difficulties included delayed GPS recording due to cold-engine starts. Since the GPS devices received power through the vehicles' cigarette lighter, they did experience "acquisition delays…when left unpowered for more than 30 minutes," causing them to omit trip origin. The GPS also recorded gaps in trips that were reported as one by the driver, due likely either to trip chaining "since the gaps between consecutively recorded GPS trip end and start signals are 3 to 13 minutes." They could also have been due to signal obstructions, such as tunnels (Wolf et al., 2003).

In Melbourne, researchers found that gathering accurate GPS data was another challenge for the following reasons: there are limits imposed by the US-military on the devices' ability to precisely determine location, loss of signal due to obstructions like trees, tunnels, or tall buildings, and finally because of "cold starts" (Greaves & Figliozzi, 2008). In cold starts, the beginning of a trip is absent from the data because of the time it takes to acquire satellite connections, which can be as high as 15 minutes when the vehicle is moving. When there are previous data points, it is possible to extrapolate the trip start location based on the previous locations. Still, manual examination of some short trips may be needed (Greaves & Figliozzi, 2008). Researchers in the Puget Sound area encountered similar challenges (Ma et al., 2011). The researchers therefore excluded trips from certain performance calculations which were likely due to GPS location misreads, including trips with extremely fast speeds, trips with very short time or distance, and trips outside the study area. Finally, algorithms addressed signal loss and signal "jiggle," which is where the location wobbles around a certain point due to inaccuracies in the GPS system. To address signal loss, algorithms extrapolated from the last recorded positions and the first position when the signal is reacquired, while algorithms also marked detected trips possibly resulting from signal jiggle for manual inspection (Ma et al., 2011).

SECTION III. TOUR-BASED FREIGHT DEMAND MODEL

Framework of the Tour-Based Truck Demand Model

Prior to 1990 urban travel rarely modeled truck trips separately. Typically in these models, trucks were implicitly included in the non-home-based (NHB) trip category and are rarely given much thought. Since the 1990's, however, trucking's increasingly important role in air quality conformance, traffic congestion, and economic growth have all an increased attention has been paid to estimating truck movement separately. Initially, and still today, nearly all of these truck trip models use the conventional aggregate four-step methodology: paying limited attention to the links between commodity flows, truck types, trip patterns, trip lengths, or to data rich comparisons needed to link truck origin-destination flows and truck counts.

Research over the past decade (see Section II above) indicates, however, that a true *goods movement* (a.k.a. freight demand) model would cover all modes of freight and would provide a very detailed representation of how material is transported throughout its useful life. Such a model would cover shipping of raw materials to factories, transfer of partially finished goods between factories, delivery of finished goods to wholesalers and retail distribution centers, distribution of products to stores, and transfer of recycled goods from consumers to processing centers. It would also address intermodal cooperation and competition, which is critical in the freight business. Finally, such a model would be usable for goods movement policy analyses on a regional or larger scale, as well as be able to provide data on truck trip movements for regional travel models. A good deal of effort is currently being devoted to the development of such models and the data bases needed to develop and support them. However, the state of the art in true goods movement modelling is not yet sufficiently developed to the point where it is easily adoptable by most urban travel forecasters. And since the need for truck volumes at the link level is immediate, that tends to be where much of the practical effort is currently focused.

But even within the context of a truck trip model, researchers have begun to question whether a different modelling approach is warranted. In recent years, a new form of personal travel model has begun to be adopted: the *activity-based* model (often referred to as "ABM"). Instead of estimating zonal aggregate travel statistics, the new approach is completely disaggregate. Each person's travel is estimated, in terms of round-trip tours that begin and end either at home or the workplace. Usually, traffic analysis zones are still used to describe and organize demographic data and the transportation system, but all travel is described in terms of tours by individuals. Many of these tours have intermediate stops for various purposes. This is recognized to be more representative of the way in which people actually travel. Typically, these new models require new home-interview surveys and lengthy and expensive calibration efforts. Since a standard framework of such models does not yet exist, each one is highly customized, which also increases the development effort.

Some analysts have developed simplified procedures to apply disaggregate tour-based models. These efforts do not attempt to represent travel in as much detail as a true ABM and they may be based on survey data borrowed from other cities. However, a simplified approach has been shown to provide many of the benefits of a true ABM at a small fraction of the development time and cost, complexity, and model run time. A good example is a model developed in 2010 for Glynn County, GA (Brunswick). This model was developed in six months for less than $50,000 and used the same inputs as the state DOT's four-step model for that region. It uses standard travel forecasting software (Cube), operates on a conventional computer, and runs very quickly. For the model user, it looks virtually the same as any other travel model.

Some analysts have theorized that this disaggregate tour-based approach could be used to model truck trips as well. Efforts to do so date back to the early 1980s (Southworth, 1982a, 1982b), but were hampered for years by lack of suitable data and insufficient interest in spending money to collect it (and this was before GPS and other vehicle tracking options were available). In fact, this approach might well be particularly suited to estimating truck travel, since many truck trips do make two or more stops daily between origin and destination. Also, truck travel is considerably more diverse in nature than personal travel, which would seem to make it suited to a disaggregate approach. For example, a truck hauling goods from a factory to a warehouse might stop at one location for the driver to eat lunch and at another location to take on fuel. Most current models ignore those stops, focusing on the main tour origin (factory) and destination (warehouse). However, a tour-based model would capture the intermediate stops and reflect the implications of those stops on VMT.

A literature review suggests that until recently, most of the work on truck tour models was conducted in a research setting. A major problem has been obtaining the kind of detailed data necessary to develop such models. Cohen (2007) used an establishment survey to develop a commercial tour model as part of the Ohio statewide travel model. Ruan, Lin, & Kawamura (2011) used similar data to develop a truck trip chaining model for Texas. Russo & Carteni (2004) and Wang & Holguin-Veras (2010) described research approaches to address this problem. Samimi, Mohammadian, & Kawamura (2010) have authored several papers that describe the state of the art, provide reasons to consider tour modelling, and outline a methodology for estimating truck tours on a nationwide basis. Outwater et al. (2013b) describe a proof-of-concept study for a tour-based and logistics supply chain model for the Chicago area.

Perhaps the most directly relevant prior research was documented by Kuppam et al. (2013) in a presentation at the May 2013 TRB Planning Applications Conference. He described a tour-based truck model developed for the Phoenix area that was based on truck GPS data. That model includes components for tour generation, stop generation, tour completion, stop purpose, stop location, and stop time period. Building upon previous work, the model is a series of connected logit models leading to a set of trips that can be assigned to a network in the conventional manner. This reference was used as a principal source in developing the modeling framework used in the present project.

The proposed new framework for this model builds upon the work of Kuppam et al. (2013) and the innovative model for Brunswick, GA, by Allen (2011). Truck movements are modelled as individual tours, which may or may not return to the starting point on a daily basis and which may or may not have intermediate stops. A series of logit models are applied and Monte Carlo simulation is used to identify the tour's main destination zone, the number of intermediate stops, the stop locations, and the time period of the tour's start. Some of these steps are identical to the work of Kuppam et al. (2013), but some simplifying assumptions are made (as in (Allen, 2011)) that make the problem more tractable within the limited budget available. In addition, the process needs to be somewhat generic in that it is being developed in two different sized cities (Atlanta, Birmingham) and is intended to be transferable to other cities. Also, this is not purely a research tool, but provides a "real world" model that is being applied using commercially available software, validated to traffic counts, and integrated with the region's existing model set.

As with the model in Kuppam et al. (2013) and as described below, this project uses truck GPS data provided by the American Transportation Research Institute (ATRI) for the two regions. Although this data provides excellent information on origin, destination, and stop locations, it must be used with caution, as it represents an unknown sample of the universe of truck trips. Due to data confidentiality requirements, nothing is known about the type of vehicle or type of ownership (company vs. owner/operator). It is virtually impossible to calculate any reasonable expansion factor so that each record can represent a known fraction of the universe. Nor can the purpose of each stop (or of the whole tour) be determined.

Figure 8 illustrates the components of the proposed model structure. Each component is described in more detail below.

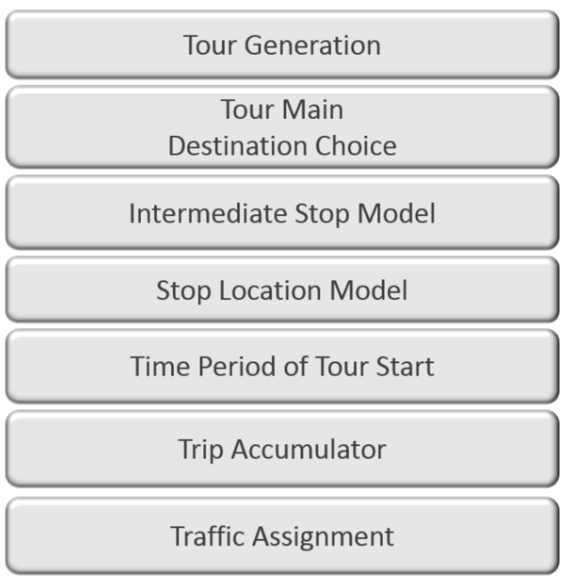


Figure 8: Model Structure

The study model is a tour-based truck model with input and calibrating data from truck-mounted GPS units. As such, the model estimates truck movements rather than commodity flow or movements of non-road-based freight vehicles. Tour-based models promise improved modeling accuracy because they account for more fundamental dynamics than models for individual truck trips. Tour-based models recognize that movement and routing decisions do not view each segment of a multi-segment trip chain separately, but rather make decisions that maximize the utility of the entire tour (i.e., trip chain) rather than any given segment. Each tour is assumed to have a “home” zone where the truck starts and ends the trips, a primary destination, and intermediate stops. Model output is in units of truck tours rather than commodity flows.

The model uses truck-mounted GPS data as model inputs and calibrators. Data consists of records containing the truck ID, start date/time, start zone, end date/time, end zone, and travel distance (calculated from latitude/longitude). Early data analysis converts raw GPS data into truck tour records that can serve as model inputs.

Tour Generation: The tour generation submodel produces truck tours in each travel analysis zone based on zonal characteristics. Travel analysis zone productions were based on the following socio-economic variables used by the Atlanta Regional Commission.

- Employment in eight categories
- Population
- Households
- University enrollment
- Land area
- Zone type: a categorical variable ranging from 1 (central business district) to 7 (rural) on the basis of the population and employment density in the subject zone

- "Truck zone flag," which is a binary variable that takes the value of 1 for zones that have been designated as a "truck zone" based on the generation of above average truck trips per employee. Examples include industrial parks, warehousing areas, truck stops, quarries, intermodal terminals, etc.

Output from the truck generation model was used to scale ATRI GPS truck data by using expansion factors. Expansion factors for each county are shown in the later section.

Next, the tour records were summarized by the zone of the tour main origin. Then, a Cube script was written to calculate these ARC and derived variables described above. This produced a file with one record per zone with the observed data and several candidate explanatory variables.

Finally, the model was validated by applying it to zone-level data and comparing the outputs to the observed tours. The model team made several adjustments to check for inconsistencies, spatial mismatch, external trips, or other factors distorting submodel outcome.

Main Destination Choice: The tour main destination choice submodel identifies a primary destination zone for each tour produced in the tour generation submodel. The tour destination choice submodel calculates the probability of each zone being a primary destination for tours originating in every other zone. The probabilities are based on each potential destination's utility. The submodel applies to internal-to-internal and external-to-internal trips. Internal-to-external trips are treated differently (a description can be found in a later section). The destination choice submodel uses a logit form to calculate the probability of each destination, using the following equation.

$$p_{ij} = \frac{e^{U_j}}{\sum_x e^{U_x}} \tag{5}$$

where ‘p’ is the probability of going from zone i to zone j, ‘x’ is the range of candidate destination zones, and ‘U’ is a linear function of various attributes of the origin zone i and destination zone j.

Intermediate Stops: The intermediate stop submodel identifies if each tour contains intermediate stops, and if so how many. The first submodel step estimates the number of intermediate stops on the way from the tour origin zone to the tour main destination zone, and from the main destination zone back to the origin. The step uses a multinomial logit model with choices from zero intermediate stops to a maximum number of intermediate stops. The maximum number in the Atlanta model is six stops because analysis of GPS data revealed that 91.3% of tours made six or fewer stops.

The second step uses zone attractions to identify destination zones for each intermediate stop. This submodel identifies each intermediate stop independently of those that precede or follow it. This is different from some models which predicate later stop locations based on earlier stops. Treating each stop independently greatly simplified stop identification processing requirements and makes the model easier and faster to run. Otherwise, the intermediate stops model resembles the main destination choice submodel.

Time of Day: The time of day submodel splits tours into different time of day categories based on observed trip times in the GPS data and a fixed set of factors derived for each trip purpose. The submodel applies calculated probabilities to each generated truck tour. The entire tour is assigned to a period, based on the start time.

In the Atlanta truck tour model, the time of day submodel uses the four time periods currently used by the Atlanta Regional Commission: AM peak = 6 – 10 am, Midday = 10a – 3 p, PM peak = 3 – 7 pm, Night = 7p – 6am.

Trip Accumulator: The trip accumulator submodel takes the output tour records from the previous submodels and breaks them into individual trips (origin – stop, stop – stop, stop – destination), in preparation for assignment. Separate trip tables by period are then built. These are aggregated to daily trips for the purpose of computing an estimated daily trip length frequency distribution.

Traffic Assignment: The traffic assignment submodel assigns each tour segment to a route on the road network. As the freight model is intended for use in tandem with existing passenger travel demand models, the traffic assignment submodel integrates into existing traffic assignment models for the Atlanta Regional Commission and the Birmingham Metropolitan Planning Organization.

Background and Study Areas

The research team built tour-based truck models for two southern metropolitan areas: Atlanta and Birmingham. The Atlanta model was built in coordination with the modeling team at the Atlanta Regional Commission (ARC). It covers the 20-county area for which the ARC models travel demand and derives air pollution emissions. The counties include Barrow, Bartow, Carroll, Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Hall, Henry, Newton, Paulding, Rockdale, Spalding, and Walton counties. While the Regional Transportation Planning Commission of Greater Birmingham covers the six counties of Jefferson, Shelby, Blount, Chilton, St.

Clair, and Walker, the travel demand model covers the two core counties of Jefferson and Shelby only.

The Atlanta Regional Commission maintains the regional travel model for the Atlanta area. This is a 20-county area covering most of north Georgia (see Figure 9).

Figure 9: Twenty-county area modeled by the Atlanta Regional Commission

In 2005, a new trip-based truck model was developed for ARC, calibrated to 2000 traffic counts. This model included three sub-purposes: Commercial, Medium Truck, and Heavy Truck. *Commercial* represents a new type of light-duty trip that is non-personal in nature. Examples include cars, light trucks, and vans used for deliveries, tradesmen, service vehicles, and government vehicles. Medium trucks represent buses, vehicles with two axles and six tires, and single-unit vehicle with three or four axles (FHWA classes 5-7). Heavy trucks are either a single or multiple trailer combination (FHWA classes 8-13). In 2010, the truck model was updated and recalibrated to match 2005 counts.

A significant development in Atlanta travel forecasting is the culmination of a nearly ten year effort to develop a detailed, state of the art activity-based model (ABM) for personal travel. For some time now, this process has been in its final development stages and has been applied in parallel with the older four-step trip-based model. Sometime in the near future, the ABM should be formally adopted as ARC's principal travel forecasting tool. (However, some components of the ABM, such as commercial/truck and external travel, will remain as four-step aggregate trip-based models.)

For many years, ARC has used a traffic analysis zone system consisting of 2,027 internal zones and 91 external stations, for a total of 2,118 zones. ARC recently embarked on a major effort to expand its zone system to 5,873 internal zones and 108 external stations, for a total of 5,981 zones. This will provide greatly increased spatial detail.

The Regional Planning Commission of Greater Birmingham maintains the regional travel model for the two-county core Birmingham area (see Figure 10). RPCGB is responsible for 6 counties, but the travel demand model only covers the Metropolitan Planning Area, which is the census defined urbanized area + areas that will likely become urbanized in the next 20 years.

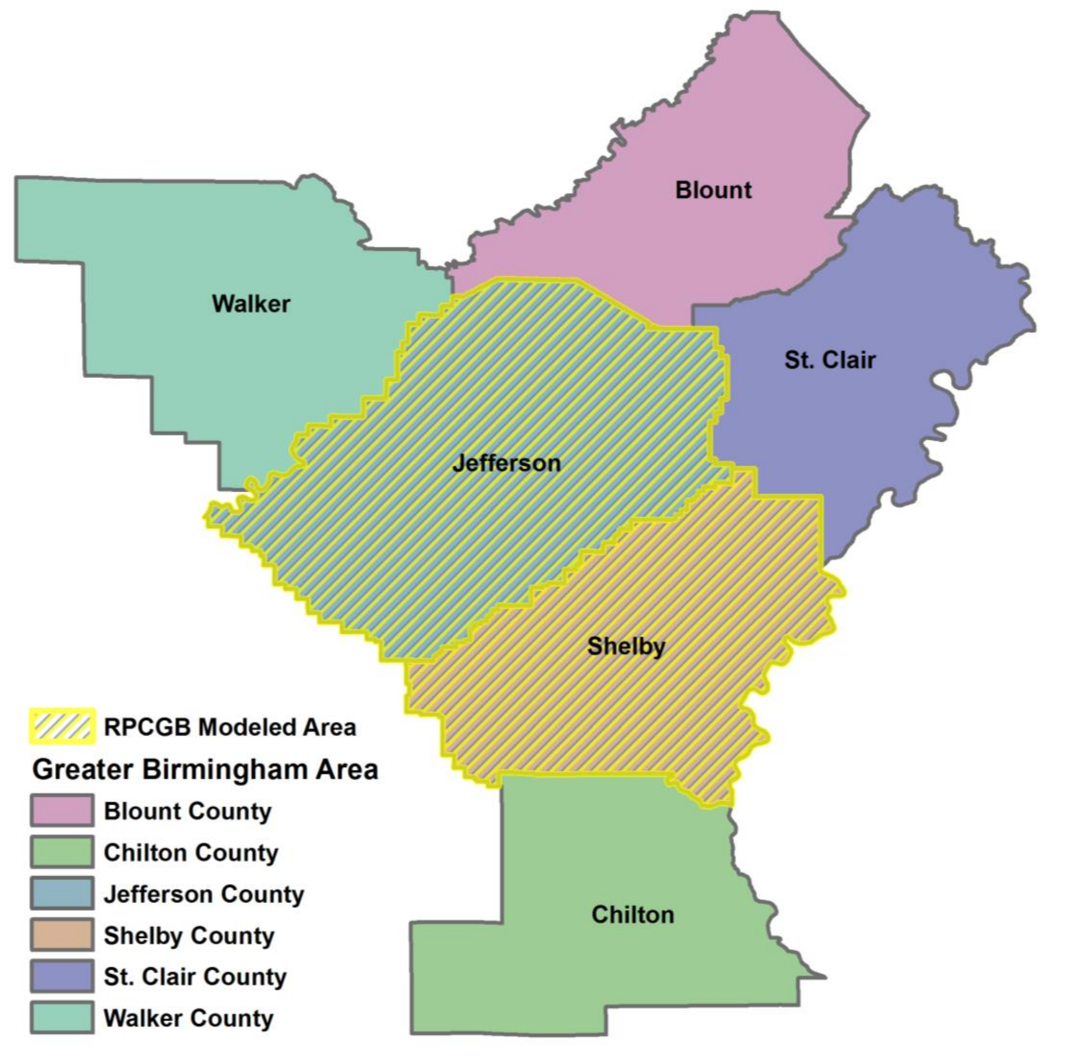


Figure 10: Regional Planning Commission of Greater Birmingham Modelled Area

The existing (999 zone) RPCGB model includes a truck component. This process creates a combined truck and taxi table, using parameters borrowed from the literature. No information was provided on the definition of "truck" in the model, or the calibration or validation of truck trips in the existing model.

Data Collection

Truck Definition

In developing truck models, there is an issue with regard to truck definition. The Federal Highway Administration (FHWA) classification system recognizes 10 types of trucks. FHWA Classes 4 through 7 are medium-duty trucks; Classes 8 through 13 are heavy-duty trucks. The current ARC truck model is based on this FHWA's vehicle classification: Medium Truck (single unit, 2-3 axles) and Heavy Truck (semi-trailer, 4+ axles) (Figure 11).

However, the ATRI's national database is based on the maximum loaded weight of the truck using the gross vehicle weight rating (GVWR). Gross weight is defined by FHWA as follows: "Gross vehicle weight means empty vehicle weight plus cargo weight". ATRI's GVW database suggests that 89% of the population is Class 8 and the remaining 11% have GVW putting them in the Class 7 or smaller. Additionally, ATRI estimates the following: (1) 72% Very Large or Large Fleet; 28% Small or Medium Fleet, (2) 83% Truckload; 17% Less-than-truckload, and (3) 83% For-hire; 14% Private; 3% other (Figure 12).

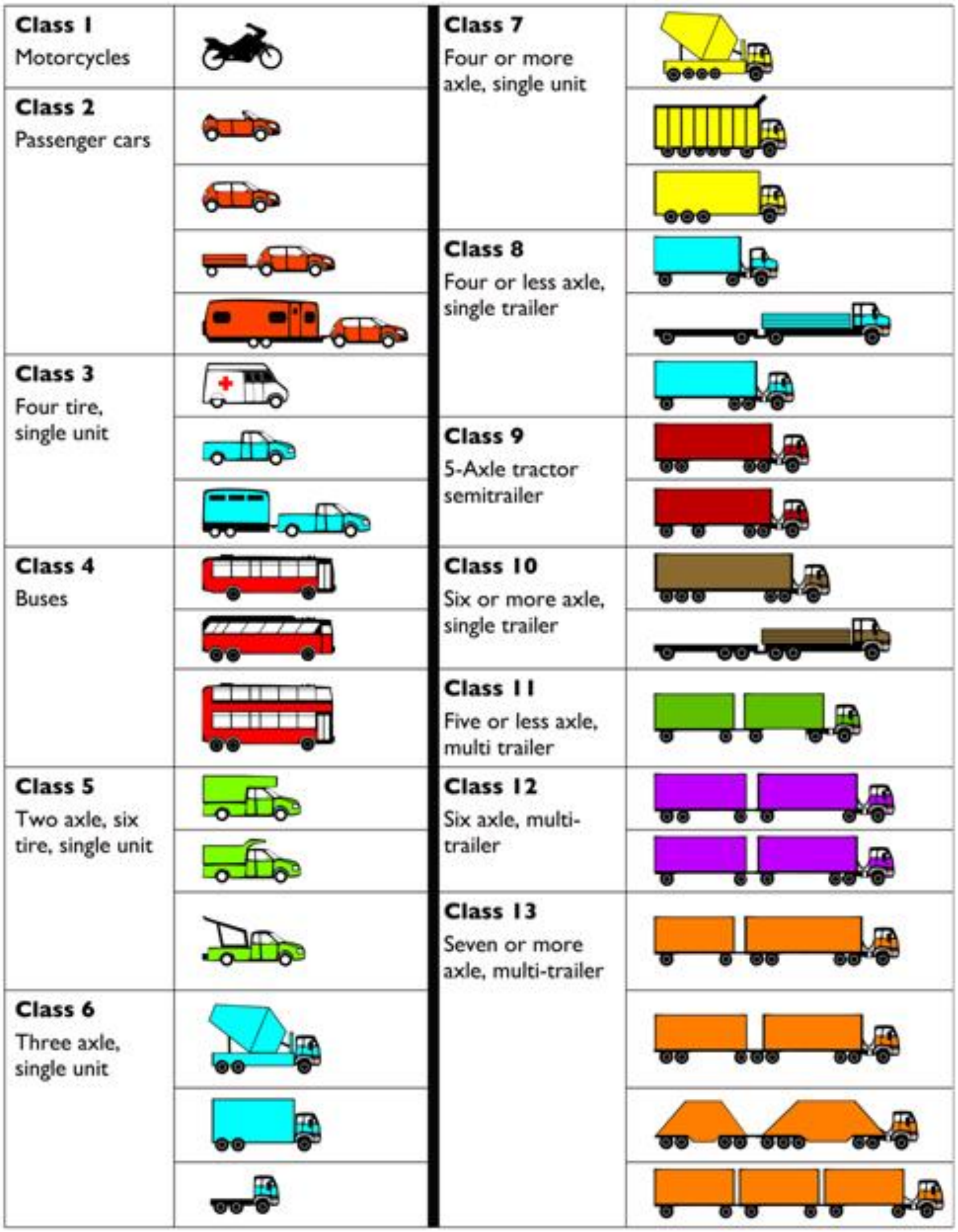


Figure 11: FHWA's 13 Vehicle Category Classification

(Source: Federal Highway Administration)

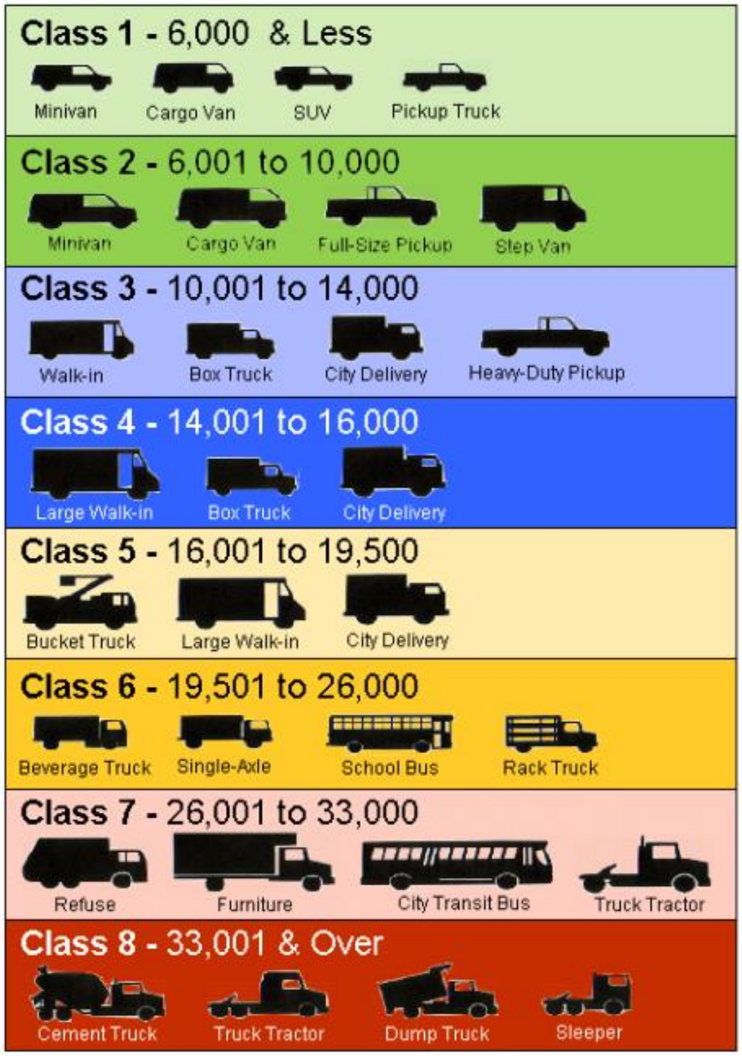


Figure 12: GVW based Truck Classification

(Source: Oak Ridge National Laboratory, Center for Transportation Analysis, Oak Ridge, TN. Weight category definitions from 49CFR565.6 (2000))

The research team assumes that the ATRI's truck GPS data provides an equivalent of the sum of MTK + HTK trucks used in ARC's model. This is a caveat and suggests that comparing the model outputs should be conducted with great care to make analyses meaningful due to the lack of truck classification in the collected GPS truck data.

GPS data processing

The American Transportation Research Institute (ATRI) provided truck movement data for the Atlanta and Birmingham metro areas. Trucks traveling through these areas have GPS units that record the truck's location, the date, and the time of day at regular intervals. These location points and times provide a record of the truck's movement.

ATRI maintains a database of truck locations based on in-truck GPS units. ATRI extracted a sample of truck "pings" from a sample of trucks in and around the Atlanta and Birmingham areas: February, May, July, and October of 2011.

A "ping" is a signal that transmits a record of the time, date, and vehicle location (latitude/longitude). These records are stored on a device on-board the truck and later downloaded. Truck operators provide the data to ATRI, who remove the identifying information and repackages the data for sale.

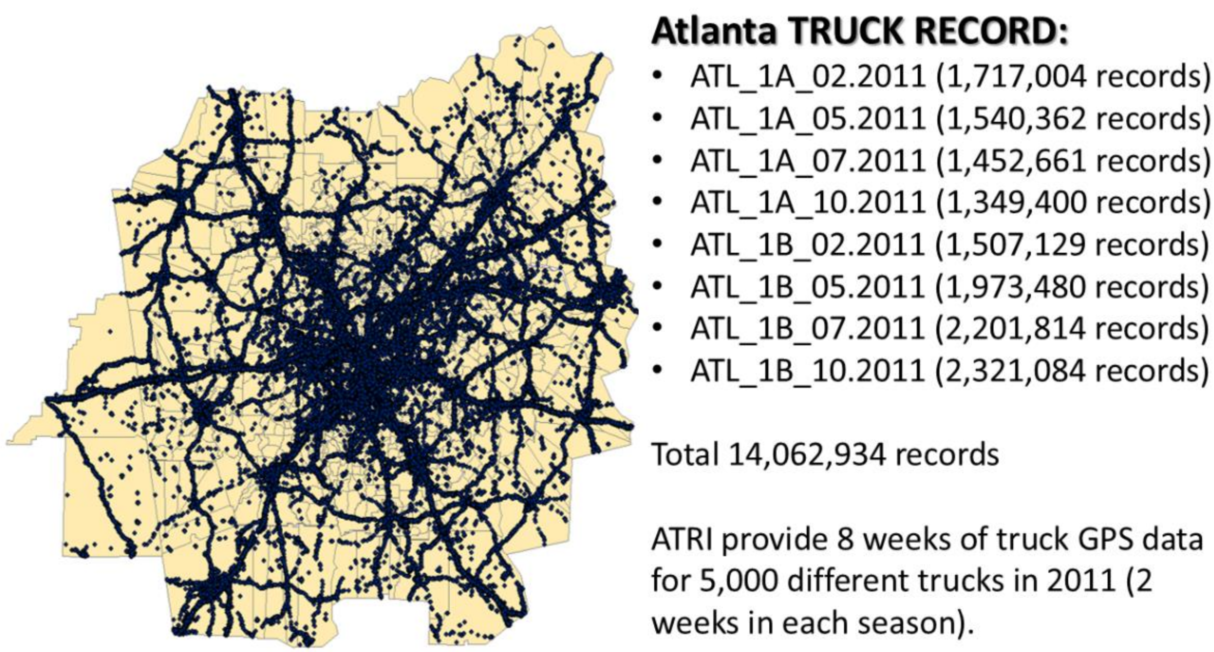
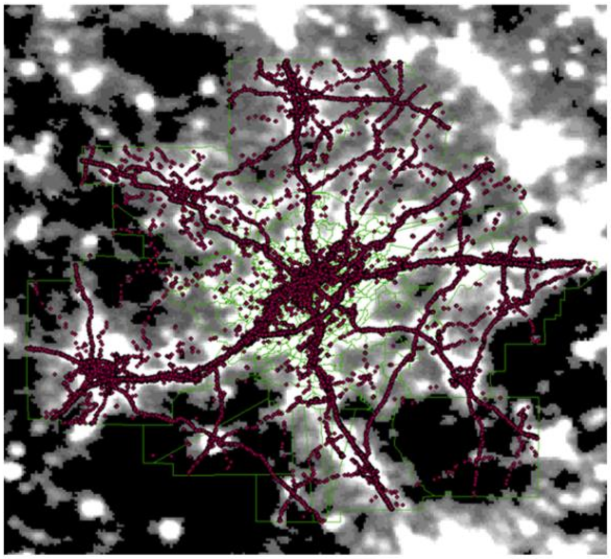


Figure 13: Atlanta Truck GPS Data



Birmingham TRUCK RECORD:

- BMH_1A_02.2011 (497,762 records)
- BMH_1A_05.2011 (465,937 records)
- BMH_1A_07.2011 (387,992 records)
- BMH_1A_10.2011 (400,817 records)
- BMH_1B_02.2011 (570,629 records)
- BMH_1B_05.2011 (688,292 records)
- BMH_1B_07.2011 (721,516 records)
- BMH_1B_10.2011 (755,895 records)

Total 4,488,840 records

ATRI provide 8 weeks of truck GPS data for 5,000 different trucks in 2011 (2 weeks in each season).

Figure 14: Birmingham Truck GPS Data

The data consists of 14,062,934 records for the Atlanta area and 4,488,840 records for the Birmingham area, each identifying the date/time at two separate locations, along with the traffic analysis zone ("zone") at each location (the original data included the latitude/longitude at those locations, but ATRI geocoded those to ARC zones). Considerable processing was required to convert this information into tours. The following steps were used:

- Delete records on weekends and holidays.
- Remove records with improper geocoding.
- If the Start and End times on a record are on different days, delete the record because we don't know what happened to the truck during that period (exception: if the Start/End time closely span midnight over two consecutive days, keep the record). These steps resulted in 9,934,191 records for Atlanta.
- For each truck, examine the current record and the next record to determine if it is stopped, just starting to move, in motion, or coming to a stop. This was

complicated by the fact that the GPS pings did not occur on a consistent time schedule, but apparently at random times.

- Very short movements that didn't leave a zone were considered to be either local drayage or bad data and were ignored.
- Many inconsistencies were noted between the Start/End locations and the time stamps (e.g., a truck moved from one zone to another, but no time elapsed). These were handled by examining preceding and following records to establish a reasonable sequence of events.
- The Start/End times were compared to the distances to get a speed for each record. Generally, if the speed was less than 3 mph, the truck was considered stopped. Records with extremely high speeds were also dropped since these probably reflect incorrect geocoding.
- A "tour" was considered to consist of all of the movements from a Start location (zone) until the truck returned to that same location (zone), or midnight of that day, whichever occurred first. (Multi-day tours were not considered.)
- The study team provided ATRI with a set of polygons that approximately represented each external station, to permit the geocoding of external locations
- Some trucks were represented only once in the entire file; others appeared on several different days. Some trucks were represented in more than one month's data. All correct observations were used; no attempt was made to prevent a truck from appearing more than once. An effort was made to factor the entire database to represent one "average" day, but this did not prove to be productive.

Table 9 and Table 10 presents the basic total tour statistics.

Table 9: Tour Statistics for Atlanta

	Tours	Stops	Stops/Tour
I/I	111,424	333,899	3.00
I/X	25,751	39,990	1.55
X/I	50,845	69,858	1.37
X/X	32,732	48,802	1.49
Total	**220,752**	**492,549**	**2.23**

Table 10: Tour Statistics for Birmingham

	Tours	Stops	Stops/Tour
I/I	26,606	60,069	2.26
I/X	11,662	11,584	0.99
X/I	22,629	21,343	0.94
X/X	25,936	26,177	1.01
Total	86,833	119,173	1.37

It seems logical that internal tours would have more stops than external tours. There are almost exactly twice as many X/I tours as I/X tours, which seems reasonable given the economic strength of the Atlanta and Birmingham areas and the fact that each has the largest concentration of economic activity in its State. The overall share of X/X trips at the cordon is 46% (X/X trips cross the cordon twice) for Atlanta and 43.1% for Birmingham, which are not too different from the 56% share found by PBQ&D in a 2008 analysis of heavy truck travel (Donnelly et al., 2008). Note that the definition of X/X travel here is different from the usual definition. Here, a trip is considered X/X if it starts and ends outside the region, even if it made a stop within the region.

GPS truck data provided by ATRI includes the following attributes:

- Truckid: This is a unique truck ID.
- Parking_from: This indicates if the vehicle is in a known truck stop at the first point: 1 = at a truck stop, 0 = not at a truck stop
- Readdate_from: This is the first date/time stamp in a series
- TAZ_2000_from: This is the TAZ ID for the first position read in a series.
- To_readdate: This is the second time stamp in a series
- To_TAZ_2000: This is the second TAZ ID in a series
- To_Parking: This indicates if the vehicle is in a known truck stop at the second point: 1 = at a truck stop, 0 = not at a truck stop
- Distance traveled: This is distance traveled in miles from point A to point B. It uses the great circle distance equation (i.e. it is not snapped to a roadway).

In order to illustrate how truck records have been processed to turn into trip and tour records, one unique truck (Truck ID: 0014827042235482023992) was selected. A part of the cleaned truck records of the selected truck is shown in Figure 15. Full records are placed in Appendix. After clean up processing, there remained 224 cleaned truck records.

A FoxPro program was used to process truck GPS data. The ATRI data comes from 4 months in 2011: February, May, July, and October. Only the dates in each month that were weekdays were identified only, and weekends and national holidays were deleted: Presidents Day (2/21), Memorial Day (5/30), Independence Day (7/4), and Columbus Day (10/10). All 8 sets of input files were concatenated for processing. Some GPS records span a multi-day period. If the records closely span midnight over 2 consecutive days, those were included, otherwise deleted, because we do not know what really happened to the truck during the time period. From given distance and calculated time between origin and destination in each record, speed was calculated in mph.

In order to convert truck records into trip records, four STATUS categories were defined as truck's activity: F = first record, D = trip departure, A = trip arrival, L = last record. We are trying here to figure out when the truck is stopped and when it is moving. We also need to know where it is when it starts moving (from the origin) and when it stops moving (at the destination). If the record is the first record for this truck and the speed < 2 mph, we set a logical variable 'STOPPED' to True and the value for the column 'STATUS' is replaced with 'F'. When the truck is starting to move, this was considered as a Departure record (STATUS = 'D'). If the truck is not "stopped" and the speed is larger than 3 mph, it was considered as moving. Arrival (STATUS = 'A') and last records (STATUS = 'L') were also identified by observing truck movements.

1	TRUCKID	DATEFROM	TAZFROM	PARKFROM	DATETO	TAZTO	PARKTO	DISTANCE	HRFROM	HRTO	TIME	SPEED	DAY	WEIGHT	STATUS
1770	001482704223548202392	02-16-11 04:09:36	1440	0	02-16-11 04:10:16	1440	0	0.000000000	4.1600	4.1711	0.0111	0.0	16	0.0526	
1771	001482704223548202392	02-16-11 04:11:27	1440	0	02-16-11 05:19:35	1440	0	0.000000000	4.1908	5.3264	1.1356	0.0	16	0.0526	
1772	001482704223548202392	02-16-11 05:19:35	1440	0	02-16-11 06:28:00	1440	0	0.000000000	5.3264	6.4667	1.1403	0.0	16	0.0526	
1773	001482704223548202392	02-16-11 06:28:00	1440	0	02-16-11 07:36:25	1440	0	0.000000000	6.4667	7.6069	1.1403	0.0	16	0.0526	
1774	001482704223548202392	02-16-11 07:36:59	1440	0	02-16-11 08:10:59	1440	0	0.230731253	7.6164	8.1831	0.5667	0.4	16	0.0526	
1775	001482704223548202392	02-16-11 08:10:59	1440	0	02-16-11 08:15:20	1440	0	1.058156708	8.1831	8.2556	0.0725	14.6	16	0.0526	D
1776	001482704223548202392	02-16-11 08:15:20	1440	0	02-16-11 08:32:09	840	0	8.268395127	8.2556	8.5358	0.2803	29.5	16	0.0526	
1777	001482704223548202392	02-16-11 08:32:09	840	0	02-16-11 08:38:21	841	0	0.475977923	8.5358	8.6392	0.1033	4.6	16	0.0526	
1778	001482704223548202392	02-16-11 08:38:21	841	0	02-16-11 08:41:01	841	0	1.272169127	8.6392	8.6836	0.0444	28.7	16	0.0526	
1779	001482704223548202392	02-16-11 08:41:01	841	0	02-16-11 08:55:54	139	0	3.233089901	8.6836	8.9317	0.2481	13.0	16	0.0526	
1780	001482704223548202392	02-16-11 08:55:54	139	0	02-16-11 09:05:34	139	0	0.077771064	8.9317	9.0928	0.1611	0.5	16	0.0526	A
1781	001482704223548202392	02-16-11 09:05:34	139	0	02-16-11 09:05:54	139	0	0.083963224	9.0928	9.0983	0.0056	15.0	16	0.0526	D
1782	001482704223548202392	02-16-11 09:05:54	139	0	02-16-11 09:08:34	139	0	0.091833785	9.0983	9.1428	0.0444	2.1	16	0.0526	A
1783	001482704223548202392	02-16-11 09:08:34	139	0	02-16-11 09:11:28	143	0	0.250102859	9.1428	9.1911	0.0483	5.2	16	0.0526	D
1784	001482704223548202392	02-16-11 09:11:45	139	0	02-16-11 09:28:53	143	0	0.172724998	9.1958	9.4814	0.2856	0.6	16	0.0526	A
1785	001482704223548202392	02-16-11 09:28:53	143	0	02-16-11 09:55:37	143	0	0.100710025	9.4814	9.9269	0.4456	0.2	16	0.0526	
1786	001482704223548202392	02-16-11 09:55:37	143	0	02-16-11 10:04:41	143	0	0.276205890	9.9269	10.0781	0.1511	1.8	16	0.0526	

Figure 15: A Part of Truck Records of Truck ID 001482704223548202392

Based on the STATUS variable, the cleaned truck records were turned into trip records which must have legitimate origin and destination zone information. The example above shows an example of the trip records for the selected truck (Truck ID: 001482704223548202392) containing 23 truck trips generated out of 224 truck records.

TRUCKID	TRIP	ORIG	DEST	STARTTIM	ENDTIM	STARTDAY	ENDDAY	TTIME	WEIGHT
00148270422354820239992	1	401	1440	0.1511	0.8281	16	16	0.6770	0.0526
00148270422354820239992	2	1440	139	8.1831	8.9317	16	16	0.7486	0.0526
00148270422354820239992	4	139	143	9.1428	9.1958	16	16	0.0530	0.0526
00148270422354820239992	5	143	2057	10.2092	11.5389	16	16	1.3297	0.0526
00148270422354820239992	6	2057	2077	12.7664	16.0878	16	16	3.3214	0.0526
00148270422354820239992	7	2077	143	16.5136	18.1831	16	16	1.6695	0.0526
00148270422354820239992	8	143	881	18.7583	19.4053	16	16	0.6470	0.0526
00148270422354820239992	9	881	1440	19.6050	19.8092	16	16	0.2042	0.0526
00148270422354820239992	10	1440	434	13.7839	14.4539	17	17	0.6700	0.0526
00148270422354820239992	11	434	1678	14.5969	15.2872	17	17	0.6903	0.0526
00148270422354820239992	12	1678	1085	15.4139	15.8242	17	17	0.4103	0.0526
00148270422354820239992	13	1085	1891	16.6300	17.2433	17	17	0.6133	0.0526
00148270422354820239992	14	1891	143	20.1175	21.3272	17	17	1.2097	0.0526
00148270422354820239992	15	143	139	21.5153	21.8633	17	17	0.3480	0.0526
00148270422354820239992	16	139	432	22.1658	23.1906	17	17	1.0248	0.0526
00148270422354820239992	17	432	410	23.3414	23.3761	17	17	0.0347	0.0526
00148270422354820239992	18	143	1440	0.4756	1.3042	18	18	0.8286	0.0526
00148270422354820239992	20	1440	344	11.5547	11.9069	18	18	0.3522	0.0526
00148270422354820239992	21	344	2034	12.4506	13.9633	18	18	1.5127	0.0526
00148270422354820239992	22	2034	2033	17.8239	18.1881	18	18	0.3642	0.0526
00148270422354820239992	23	2033	882	18.9717	21.4567	18	18	2.4850	0.0526
00148270422354820239992	24	882	1440	21.7108	21.8264	18	18	0.1156	0.0526
00148270422354820239992	25	1440	143	23.3469	23.9867	18	18	0.6398	0.0526

Figure 16: Trip Records of Truck ID 00148270422354820239992

A second FoxPro program was used to convert the trip records into tours. This program reads records until it finds one that is a different truck or a different day, or the origin is not equal to the previous destination and stores the location of each stop.

Figure 17 show an example of the selected truck's tours. Tour 1 starts from zone 401 and ends at zone 1440 taking seven intermediate stops during the tour at zones 1440, 139, 143, 2057, 2077, 143, and 881 on Feb. 16, 2011 (Figure 18 (A)). Tour 2 starts from zone 1440 and ends at zone 410 taking seven intermediate stops during the tour at zones 434, 1678, 1085, 1891, 143, 139, and 432 on Feb. 17, 2011 (Figure 18 (B)). Tour 3 starts from zone 143 and returns to the same zone after taking six intermediate stops during the tour at zones 1440, 344, 2034, 2033, 882, and 1440 on Feb. 18, 2011 (Figure 18 (C)). Overall, this GPS sample shows that the selected truck contained 224 cleaned truck records and those records were turned into 23 trips making up three tours (determined through this study) during the period of Feb. 16~18, 2011 (Figure 18 (D)).

TRUCKID	TORIG	TDEST	TSTART	TEND	TDAY	TRIPS	WEIGHT	STOP01	STOP02	STOP03	STOP04	STOP05	STOP06	STOP07	STOP08
0014570242191033477538	2055	1329	19.6200	20.9797	8	3	0.0526	410	434	0	0	0	0	0	0
0014570242191033477538	2061	1329	18.4717	20.1506	9	2	0.0526	434	0	0	0	0	0	0	0
0014570242191033477538	1329	434	9.5656	10.1239	10	3	0.0526	434	2057	0	0	0	0	0	0
0014570242191033477538	2057	1329	18.9950	20.1333	11	3	0.0526	434	432	0	0	0	0	0	0
00147704916385437	2100	1348	21.0561	22.9272	16	1	0.0526	0	0	0	0	0	0	0	0
0014827042235482023992	401	1440	0.1511	0.8281	16	8	0.0526	1440	139	143	2057	2077	143	881	0
0014827042235482023992	1440	410	13.7839	14.4539	17	8	0.0526	434	1678	1085	1891	143	139	432	0
0014827042235482023992	143	143	0.4756	1.3042	18	7	0.0526	1440	344	2034	2033	882	1440	0	0
00150423475485122051	969	361	0.9625	1.6681	7	2	0.0526	2057	0	0	0	0	0	0	0
0015187328240287071808264058	614	2077	4.0828	4.1133	14	1	0.0526	0	0	0	0	0	0	0	0
0015187328240287071808264058	2077	1741	0.2478	2.2569	15	1	0.0526	0	0	0	0	0	0	0	0
00155700409164502427	1695	2100	20.5694	20.9350	16	2	0.0526	1687	0	0	0	0	0	0	0
001561246644499641161493682	343	2090	12.6658	13.3475	10	3	0.0526	428	1351	0	0	0	0	0	0
001561246644499641161493682	2077	1687	12.3353	15.1522	11	3	0.0526	1904	1704	0	0	0	0	0	0

Figure 17: Tour Records of Truck ID 0014827042235482023992

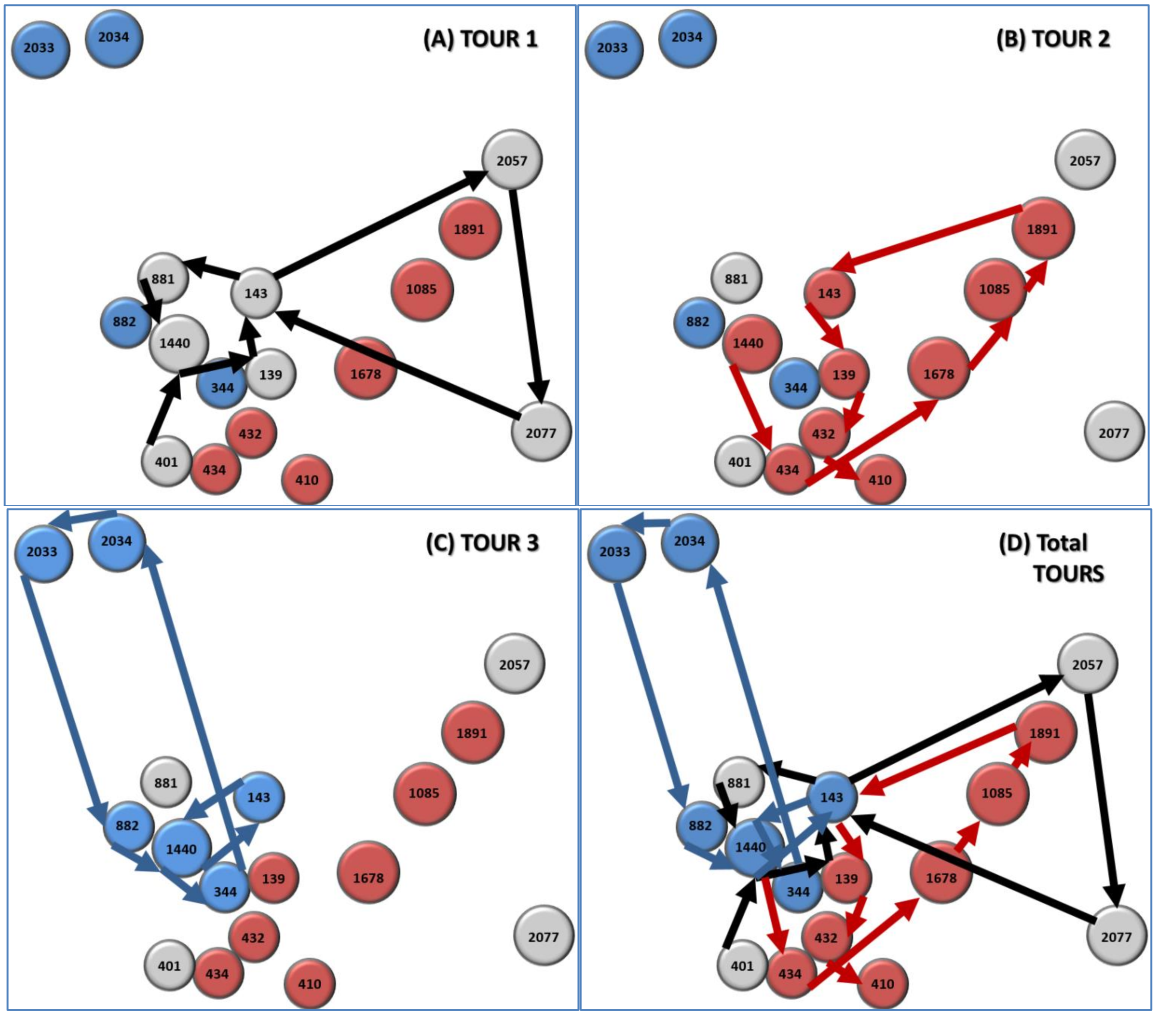


Figure 18: Tours of Truck ID 0014827042235482023992 during Feb. 16~18, 2011

Tour Statistics: Atlanta

Some of the tour statistics for the Atlanta metropolitan area are summarized here and those for the Birmingham area are included in the Appendix.

Number of Tour Starts by TAZ

Figure 19 shows the number of tours starting from the Atlanta TAZs and external stations, showing where the truck tours are mostly generated. There is a clear pattern of external truck tours being generated in the TAZs and external stations along the interstate highway, which is also consistent WITH the locations of the region's distribution centers. There are some TAZs that have an extremely high number of truck tours. These TAZs are identified as “truck zones” in the model due to their high truck tour generation rate, related employment, and abundant distribution center facilities.

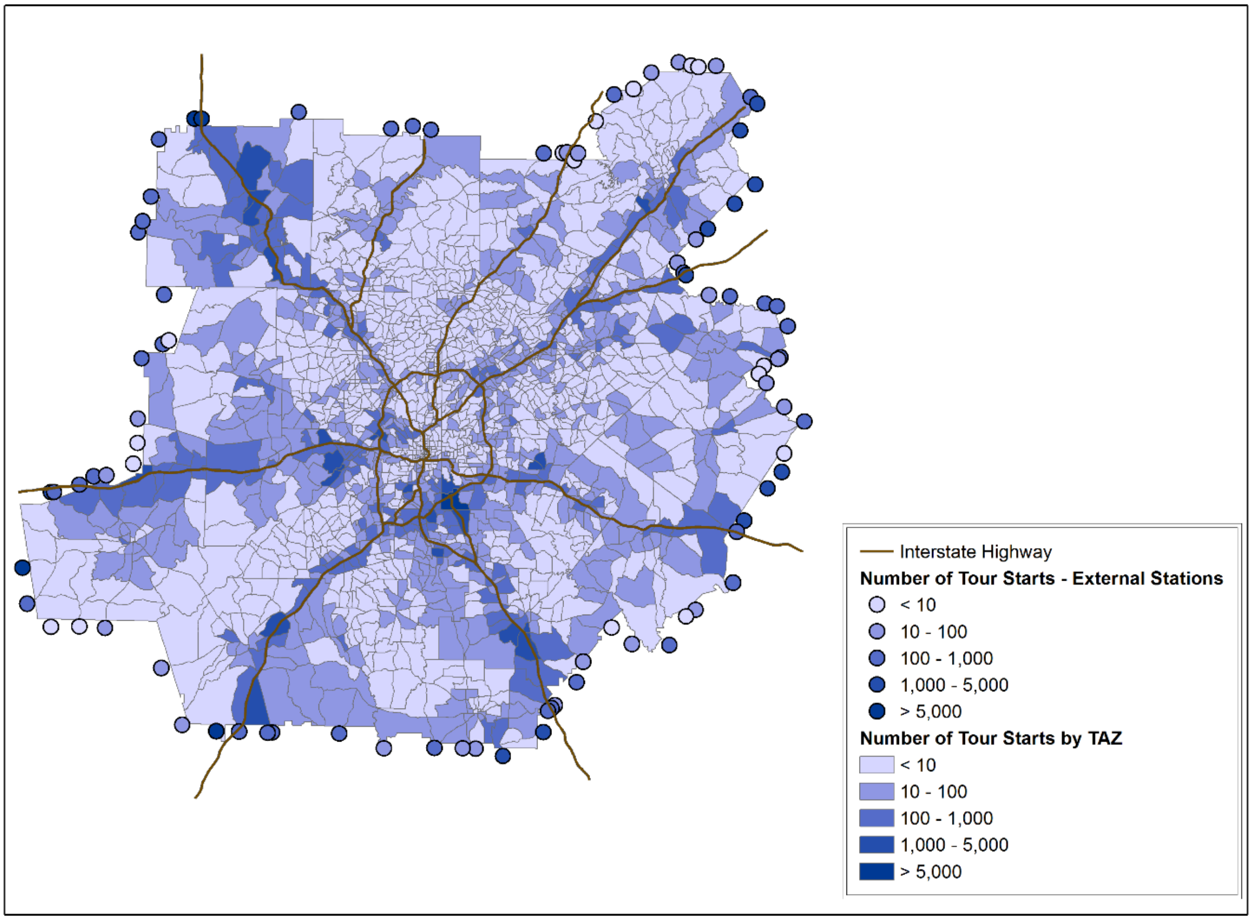


Figure 19. Number of Truck Tours Starting from the TAZs and External Stations - Atlanta

Number of Tour Ends by TAZ

As a comparison, Figure 20 shows the number of truck tours ending in all the TAZs and external stations, showing those locations that attract most of the truck tours. Similarly, the TAZs and external stations that attract most of the truck tours also fall close to the interstate highways and truck zones that often have both high numbers of tour starts and tour ends.

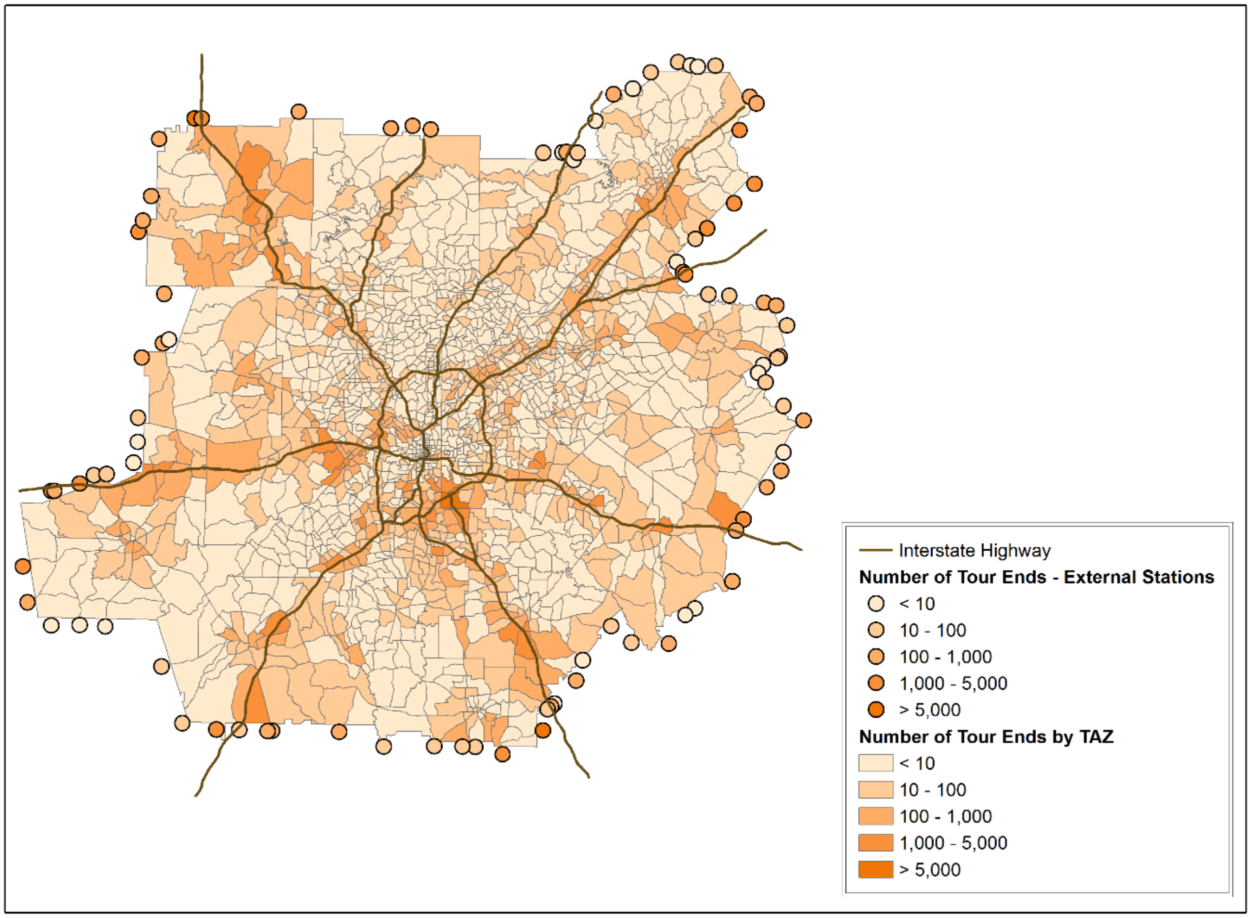


Figure 20. Number of Truck Tours Ending in the TAZs and External Stations - Atlanta

Number of Intermediate Stops by TAZ

Figure 21 shows the number of intermediate stops made in the TAZs and external stations. Compared with the number of tour starts and number of tour ends in the TAZs, the number of intermediate stops are more distributed across the TAZs. The intermediate stops reflect the distribution channels that are used by the truck tours, which is a significant characteristic of tour-based freight modeling compared to trip-based modeling. A truck tour, going from the origin TAZ to the destination TAZ, may not follow the shortest path between the two, but will likely cover specific intermediate stops in between. This reflects the trip-chaining nature of truck tours. It is also plausible that most of the external stations do not have many intermediate stops, as shown in the figure.

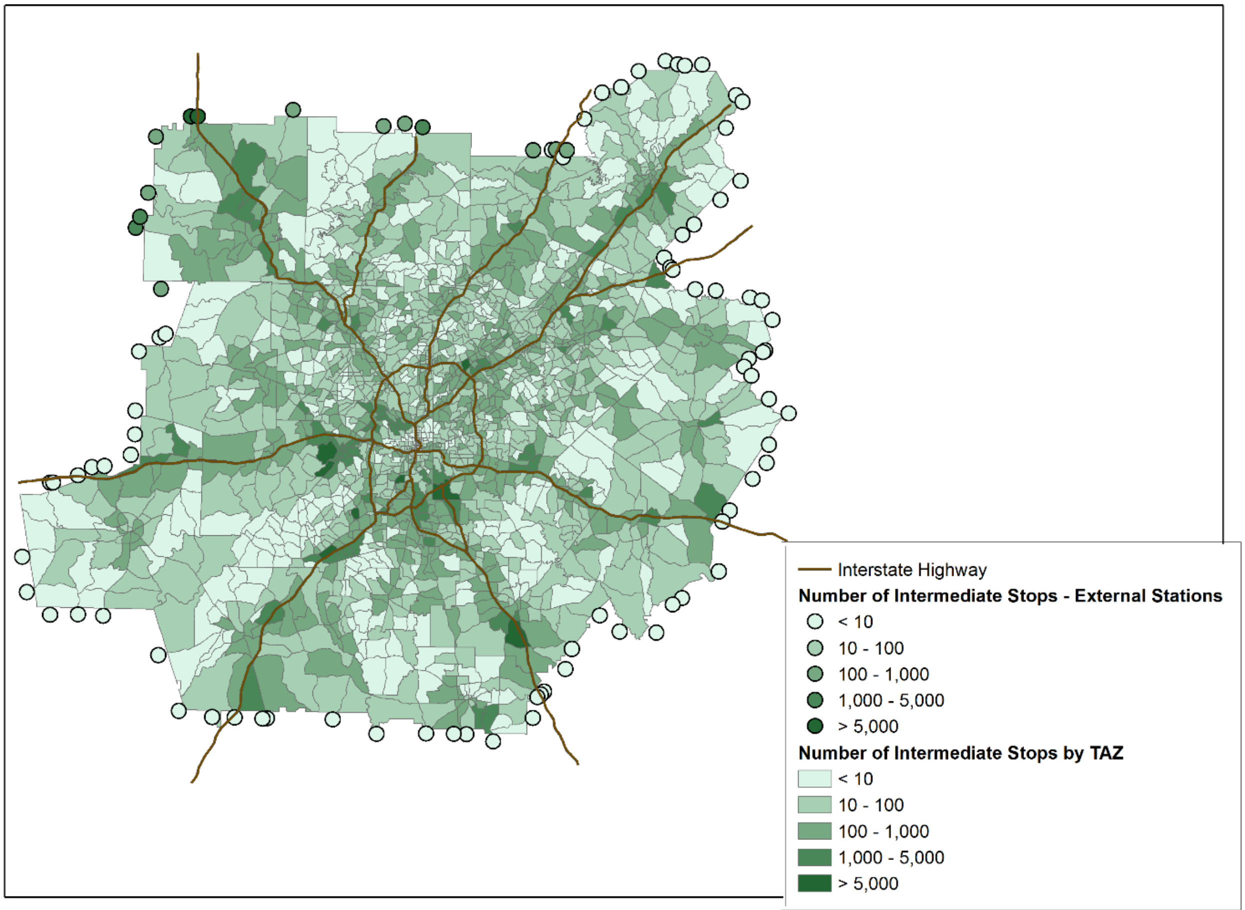


Figure 21. Number of Intermediate Stops made in all the TAZs and External Stations - Atlanta

Start Time Distribution

As mentioned previously, modeling the time of day when the truck tours start is an important feature of this model, because truck trips do not follow the same distribution of start time as passenger trips. Figure 22 shows the distribution of the start time of truck tours in the Atlanta metropolitan area in a 24 hour time scheme. The peak period for truck tour starts is between 9am to 12am, which is about 3 hour behind the traditional morning commute-dominated “peak hour”, which is often defined as 6am to 9am. There is also a noticeable peak around midnight, which might be caused by the way that a “tour” is defined in the model (since a “tour” was considered to end when the truck returns to the start location, or midnight of that day, whichever occurs first). It means that any tour passing midnight will be considered as a new tour, which may result in the greater number of tours generated during midnight, as shown in the following figure. However, even if the actual number of tour generations during midnight is only half of the number shown in the figure, it still forms a peak, indicating the relative importance of truck movements during night time. The difference between the peak of truck tours and normal passenger trips is quite obvious, which is another reason why freight demand modeling is in need.

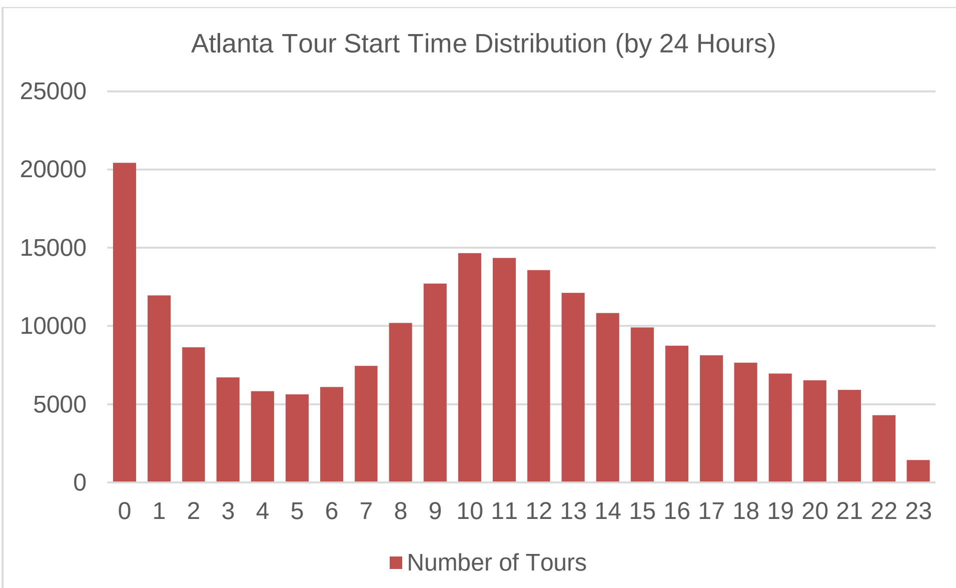


Figure 22. The Distribution of the Start Time of Truck Tours in Atlanta Metro Area

End Time Distribution

As with as the distribution of truck tour start times, the distribution of truck tour end times also follow two peaks, one in the midday around 10am to 1pm and the other around midnight, as shown in Figure 23. These peaks occur about one hour after the start time peaks.

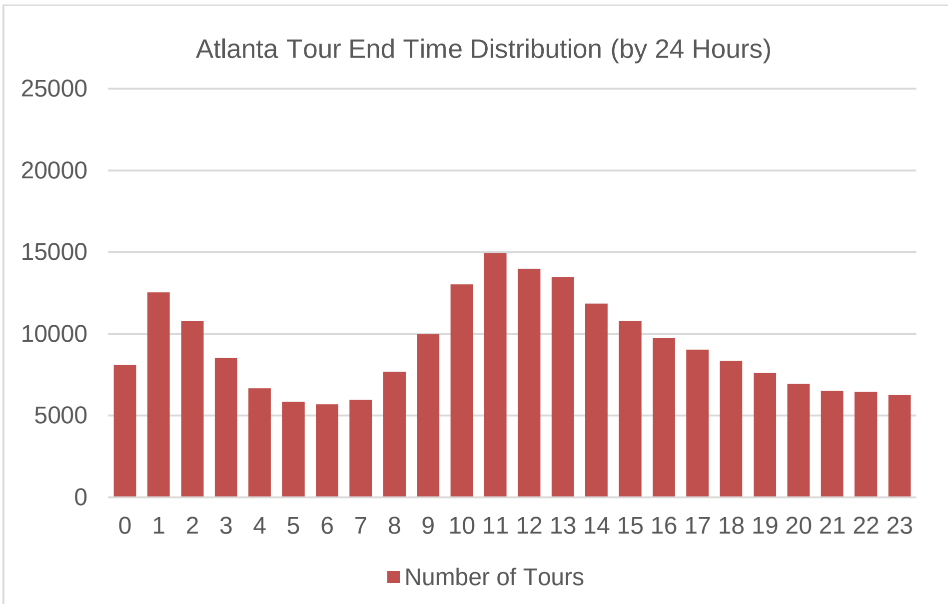


Figure 23. The Distribution of the End Time of Truck Tours in Atlanta Metro Are

Socio-economic data from MPOs

Each metropolitan planning organization provided a series of data for variables that it uses in its travel demand model. These socio-economic variables were available at the level of the traffic analysis zone (TAZ). They include variables such as employment size and type, population size, and land areas.

Review MPO employment breakdown by TAZ

The tour-based model requires socio-economic data at the traffic analysis zone (TAZ). However, most data sources conform to U.S. Census Bureau geographic boundaries, such as the census tract, rather than TAZs. Therefore, the research team converted data from the census tract level to TAZs with the following steps.

1) **Gather census tract level data**. The research team downloaded data variables from the Longitudinal Employer–Household Dynamics data through the U.S. Census Bureau website and at the block level. The research team aggregated all block groups in each census tract for Residence Area Characteristic (RAC) and Workplace Area Characteristic (WAC) data.
2) **Prepare the Census Tract Shapefile.** The research team downloaded the census tract shapefile from Tiger Product (http://www.census.gov/geo/maps-data/data/tiger.html). Then the team joined the socio-economic data to the census tract shapefile in ArcGIS according to the census tract ID, and calculated the census tract area with the "calculate geometry" tool in ArcGIS. This allowed the team to determine the proportion of the TAZ composed of each census tract. Then, the research team used the intersect tool on the census tract and TAZ shapefiles. This breaks each area belonging to a unique census tract and TAZ into an individual shape. The team created a new column in the shapefile table attributes and used the "calculate geometry" function to calculate each polygon's area.
3) **Scale the Variables.** The team created one more column and calculated its values to be the ratio of the polygons' area over the census tract's total area. This ratio would scale the census tract-level values to a lower scale. The team multiplied the census tract-level values by the ratio.
4) **Aggregate Variables at the TAZ Level.** The research team used the ArcGIS "dissolve" function to aggregate the variables for each polygon for each TAZ. These TAZ-level variables served as model inputs

Vehicle Classification Counts

The traffic counts that are collected from the permanent and portable traffic collection devices (Automatic Traffic Recorders: ATRs which are installed under the surface of the roadway to count traffic 24/7, 365 days a year) are used in the calculation of the Annual Average Daily Traffic (AADT) estimates. Figure 24 shows the locations of ATRs in the Atlanta modeling area. In order to adjust short-term traffic counts collected from ATRs, traffic factors are used in the calculation of Average Annual Daily Traffic (AADT).

> **AADT** = 24-hour Short Term Volume * Daily Adjustment Factor * Monthly Adjustment Factor * Axle Adjustment Factor

GDOT's Office of Transportation Data provided vehicle classification count datasets which takes into account the 16 vehicle classification definitions used by the Federal Highway Administration. These datasets are available online under the following location:

http://www.dot.ga.gov/informationcenter/statistics/TrafficData/Pages/default.aspx

An example of vehicle classification count is illustrated in Table 11.

Table 11: Vehicle Classification Count Data

Column Heading	Description	County	
CTYNAME	Name of County	APPLING	APPLING
CTY	Ignore or delete this field	1	1
CTYFIPS	3-digit FIPS code for GA Counties	001	001
TC	Traffic Counter #	0183	0183
RT	Route Type	1	1
FC	Functional Class	06	06
BEGDATE	Date of Collection	1/3/2012	1/3/2012
DoW	Day of Week	Tue	Tue
DIR	Direction	N	S
Cycles	Class 1	0	1
Cars	Class 2	235	217
SUV/Pkups	Class 3	113	123
Bus	Class 4	3	3
2-Axle	Class 5	20	21
3-Axle	Class 6	3	8
4-Axle	Class 7	0	0
3/4-Single	Class 8	5	10
5-Single	Class 9	48	44
6-Single	Class 10	0	2
5-Multi	Class 11	0	0
6-Multi	Class 12	0	0
7-Multi	Class 13	0	2
8-Multi	Class 14	0	0
UnClass	Class 15 (Cannot be Classified)	0	0
TOTVOL	Total # of Vehicles	427	431
TRUCKS	Total # of Trucks	79	90

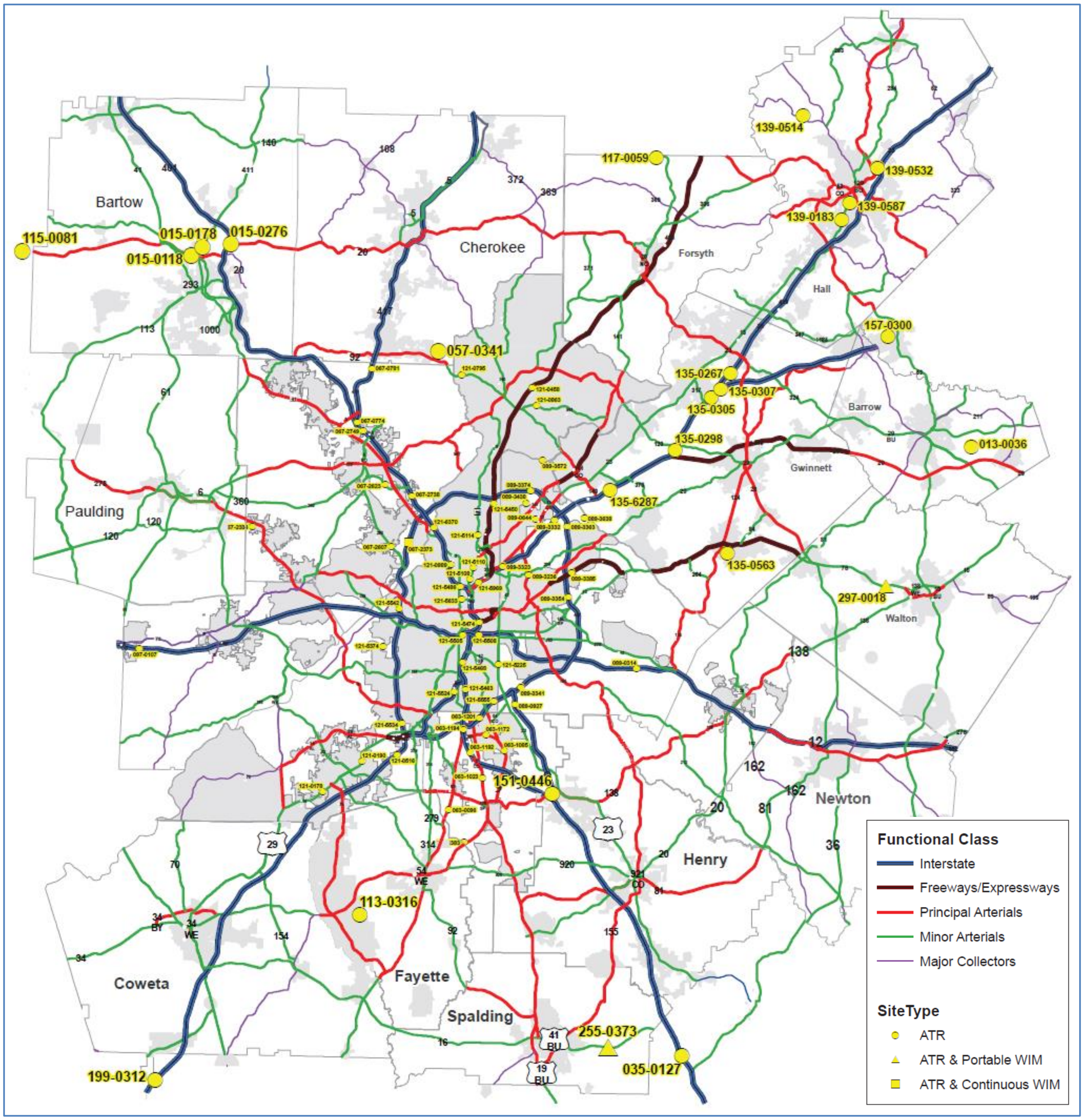


Figure 24: Automatic Traffic Recorders Locations within Atlanta Modeling Area

It is useful for models to distinguish among as many relevant categories of vehicles as possible to account for the fact that different commercial vehicle categories may have different trip-making characteristics. However, it was not possible to incorporate different commercial vehicle categories because the GPS location data does not distinguish among vehicle types. Due to this, 2010 truck percentages by location (Table

12) was used instead of vehicle classification by functional class for truck volume assignment validation purposes, as described later in this report.

Table 12: Automatic Traffic Recorders Locations and Truck Percentages & Volumes

County	TC	Estimated AWDT	Truck Volume	Truck Percent	LOCATION
BARROW	0036	9284	530	0.057	CR415:2.3 mi East of SR8/53
BARTOW	0118	47619	3380	0.071	SR3/US41, Cartersville: bn Grassdale Rd. & SR 61
BARTOW	0178	10593	1050	0.099	SR61:bn SR20 (Canton Hwy) & I-75
BARTOW	0276	74789	21690	0.290	I-75:just above SR20
CHEROKEE	0341	3652	130	0.035	CR398/Wiley Bridge Rd:N of SR92
CLAYTON	0005	43648	2010	0.046	SR3/Tara Blvd:bn McDonough/SR92 & Cardinal/CR798
CLAYTON	0096	36212	1340	0.037	SR85:bn Flint River Rd/CR449 & SR138
CLAYTON	0383	6402	190	0.030	CR501/Thomas Rd:bn Flint River & SR54
CLAYTON	1023	73029	2780	0.038	SR3/Tara Blvd:@Sherwood Forest cemetery SB
CLAYTON	1032	19822	1210	0.061	Old Dixie Hwy/SR3:bn Morrow Rd & Forest Pkwy
CLAYTON	1085	22594	860	0.038	Jonesboro Rd/SR54:1st light S of F.Pkwy on SR54
CLAYTON	1172	19657	1260	0.064	Forest Pkwy:in front of City Hall
CLAYTON	1192	190267	18460	0.097	I-75:bn 19/41 & Forest Pkwy/Farmer Market exit
CLAYTON	1194	224169	22640	0.101	I-75:bn Forest Pkwy SR331 & I-285
CLAYTON	1201	141108	22580	0.160	I-285:bn Clayton/Fulton Co. Line & I-75
COBB	0774	79948	4800	0.060	I-575/SR417:bn I75 & SR5/Cnctr Ernest Barrett Pkwy
COBB	0781	91982	4780	0.052	I-575/SR417:bn .8 miles S of SR92
COBB	2141	38434	1420	0.037	Cobb Pkwy/Sr-3/US41:S of Franklin Rd
COBB	2334	3949	120	0.030	CR4516/Powder Sprngs Dallas:bn Finch & Warren Farm
COBB	2373	157575	23640	0.150	I-285:@Orchard Rd
COBB	2607	30943	1140	0.037	SR280:bn Cooper Lake/CR1892 & King Spring/CR1891
COBB	2623	30030	1290	0.043	S. Cobb Dr/SR280:@Dobbins AFB, S of Ridenour Rd
COBB	2738	309078	33070	0.107	SR401(I-75): btwn Windy Hill and Delk Rd
DEKALB	0314	144463	15460	0.107	I-20 EB @ Fairington Rd Overpass
DEKALB	0644	18018	670	0.037	Chamblee Tucker Rd/CS075705:near SR13
DEKALB	0927	82291	12100	0.147	DEKALB 0927 I-675:bn Clayton/Dekalb Co line & I-285
DEKALB	3047	38258	1110	0.029	DEKALB 3047 SR10:bn Rockbridge Rd & Rays Rd

County	TC	Estimated AWDT	Truck Volume	Truck Percent	LOCATION
DEKALB	3236	26400	530	0.020	DEKALB 3236 SR155:bn N. Druid Hills & Lavista Rd
DEKALB	3323	232881	9780	0.042	DEKALB 3323 I-85:@North Druid Hills Rd
DEKALB	3332	237028	11140	0.047	DEKALB 3332 SR403 (I-85): btwn Chamblee Tucker and SR407 (I-285)
DEKALB	3341	163075	24460	0.150	DEKALB 3341 I-285/SR407:bn Bouldercrest Rd & I-675
DEKALB	3363	217866	22440	0.103	DEKALB 3363 I-285: NB @Henderson Mill Rd.
DEKALB	3374	231814	22950	0.099	DEKALB 3374 I-285:@Shallowford Rd
DEKALB	3385	118855	5350	0.045	DEKALB 3385 SR410/Stone Mtn Freeway:bn I-285 & Brocket Rd CR5152
DEKALB	3438	12540	410	0.033	DEKALB 3438 Chamblee/Dunwoody Rd/CR5156:@Colt Dr
DEKALB	3572	6655	180	0.027	DEKALB 3572 Dunwoody Club Rd/CR5178:Mt Vernon & Winters Chapel
DEKALB	3638	24937	820	0.033	DEKALB 3638 Pleasantdale Rd/CR5182:bn Lynray & Pleasant Shade
DOUGLAS	0107	75592	14820	0.196	DOUGLAS 0107 I-20 between SR 939 (Liberty Road) and Post Road
FAYETTE	0316	6798	140	0.020	FAYETTE 0316 CS 30407:Robinson Rd S of Wingate
FORSYTH	0059	5368	300	0.055	FORSYTH 0059 CR741/Bannister Rd:S of SR9 Dahlonega Hwy
FULTON	0178	11220	1500	0.134	FULTON 0178 SR14:S of Fairburn City Limits
FULTON	0190	17622	920	0.052	FULTON 0190 SR14/US29:@Lumber yard
FULTON	0458	147532	5900	0.040	FULTON 0458 SR 400 N of Mansell Rd
FULTON	0516	152570	18310	0.120	FULTON 0516 I-85:bn Flat Shoals Rd & I-285 MP 66.95
FULTON	0795	53460	1500	0.028	FULTON 0795 SR92/Wdstock Rd:W of Mt Park/Bowen Rd near Cobb CL, Fulton Co.
FULTON	0863	18183	380	0.021	FULTON 0863 SR961/Old AL Rd:bn SR140/Holcomb Brdg & Old AL Rd
FULTON	0989	5720	150	0.026	FULTON 0989 W Wesley Rd/CS000603:bn Moores Mill & Dawn View Ln
FULTON	5016	26554	740	0.028	FULTON 5016 SR3/Northside Dr: bn Marietta St & 14 St
FULTON	5108	40293	1090	0.027	FULTON 5108 Peachtree Rd/SR9:bn Collier Rd & Terrace Dr

County	TC	Estimated AWDT	Truck Volume	Truck Percent	LOCATION
FULTON	5110	36333	840	0.023	FULTON 5110 SR9/Roswell Rd:bn Peachtree Rd & Lakeview Dr
FULTON	5114	31471	690	0.022	FULTON 5114 Roswell Rd/SR9:bn Piedmont Rd & Long Island Dr
FULTON	5225	24882	1490	0.060	FULTON 5225 Moreland Av/SR42:bn McDonough Rd & Custer
FULTON	5374	11583	360	0.031	FULTON 5374 Cascade Rd/CR4176:bn New Hope Rd & Danforth Rd
FULTON	5450	125345	2260	0.018	FULTON 5450 SR400:South of Johnson Ferry overpass
FULTON	5452	201696	7060	0.035	FULTON 5452 SR400:N of Johnson Ferry bn Abernathy & I-285
FULTON	5463	170819	11620	0.068	FULTON 5463 I-75:bn Fulton Co Line & Cleveland Av
FULTON	5474	318065	16220	0.051	FULTON 5474 I-75/I-85 at Grady Curve
FULTON	5486	218240	10040	0.046	FULTON 5486 I-75:@Northside Dr
FULTON	5505	172326	9480	0.055	FULTON 5505 I-20:bn McDaniel St & Windsor St
FULTON	5508	193919	9500	0.049	FULTON 5508 I-20:@Capitol Av
FULTON	5524	143561	5020	0.035	FULTON 5524 I-85:bn Sylvan Rd & Cleveland Av
FULTON	5534	147653	27320	0.185	FULTON 5534 I-285:bn I-85 & Washington Rd CR1389
FULTON	5542	166452	26470	0.159	FULTON 5542 I-285:bn I-20 & SR8
FULTON	5555	138468	22710	0.164	FULTON 5555 I-285:@Forest Park Rd
FULTON	5633	12628	480	0.038	FULTON 5633 SR9/US19/14th St:1 block N of N-side Dr @Macmillan
FULTON	5969	255717	9720	0.038	FULTON 5969 I-85:bn Northbound & SR400 Northbound
FULTON	6370	192280	7690	0.040	I-75:@Chattahoochee River
GWINNETT	0241	96646	7250	0.075	SR 316: 1.1 Mile W of Sugarloaf Pkwy
GWINNETT	0267	62755	6650	0.106	SR419/I-985:bn I-85 & SR20 Buford Dr
GWINNETT	0298	165550	23180	0.140	I-85 BTWN SR316 & SR120
GWINNETT	0305	160336	23090	0.144	I-85NB:btwn Lawrenceville-Suwanee Rd and I-85/I985 split
GWINNETT	0307	102630	16630	0.162	I-85:btwn I-85/I-985 and Suwanee-SR20 (N of split)
GWINNETT	0563	17633	620	0.035	Lenora Church Rd:bn E.Park & Dorian Rd
HALL	0183	14388	940	0.065	SR13:@Southern Railroad
HALL	0514	2706	120	0.046	CR186/Elrod Rd:E of SR136

County	TC	Estimated AWDT	Truck Volume	Truck Percent	LOCATION
HALL	0532	4719	240	0.051	White Sulphur Rd:bn Jesse Jewel Pkwy & Beverly
HALL	0587	5962	290	0.048	Industrial Blvd:bn Hall & Mtn Crest
HENRY	0412	159676	24110	0.151	I-75:bn I-675 & Hudson Bridge Rd
HENRY	0446	49445	8410	0.170	I-675:bn I-75 & Clayton Co Line
NEWTON	0218	47707	9730	0.204	I-20:1 mi West of Social Cir Exit
SPALDING	0373	12133	1580	0.130	SR-16 btwn S. McDonough Rd & High Falls Rd
WALTON	0018	21384	1560	0.073	SR10:bn Youth Monroe Rd & SR10BU Alcovy River

Model Development: Atlanta, GA and Birmingham, AL

Framework Transfer

The Birmingham model was to be developed in almost exactly the same way as the Atlanta model. The same truck GPS data was obtained from ATRI and processed in a manner that was parallel to the Atlanta approach. The key differences include:

- In Atlanta, the GPS data was assumed to represent medium and heavy trucks. ARC previously had validated MTK and HTK models, and these were consulted to provide target values. After the Atlanta model was completed, ATRI clarified that its GPS data actually represents mostly heavy trucks – 89% are class 8 and above. Birmingham did not have existing models for both MTK and HTK. Although two sets of truck count data were available, there was no documentation on which count represented which type of vehicle. The research team assumed that one of the count types represented HTK. Also, it was not clear that the Birmingham region required separate estimates of MTK trips. Thus, the decision was made to model only HTK in Birmingham.

- Since the Atlanta model was completed first, the Birmingham model was able to benefit from that experience. Certain assumptions regarding model structure and parameter values were changed from the Atlanta version, as a result of increased knowledge gained from that work.

- The nature of truck traffic is different in Birmingham. A key difference is that the share of external and through trucks (as a proportion of total truck traffic) is much higher in Birmingham than in Atlanta, probably due to the different size of the manufacturing base of the two areas.

- Alabama DOT provided a sufficient number of daily truck counts. The consulting team also requested truck counts by hour or time period, but those were not provided. Although a time of day model was calibrated, it could not be validated.

As the truck tour model was being developed, the Regional Planning Commission of Greater Birmingham (RPCGB) was in the process of changing its traffic analysis zone (TAZ) system. The old system had 999 internal TAZs and external stations, while the new one has 1,986. Since the ATRI GPS data was geocoded to the old TAZs, that system was used for model calibration.

Tour Generation

i. Model Structure

Conventional trip-based models measure travel in terms of independent trips between pairs of zones. This approach ignores the relationship between trips that may be segments of a tour. Analyses of personal travel indicate that multi-stop tours make up fewer than 20% of all tours. But for commercial travel, it seems likely that multi-stop tours are a higher share of total travel. While some truck tours are obviously “simple” tours (pick up something one place, drop it another), many trucks make multiple stops to deliver goods (e.g., UPS/FedEx, “route” drivers, such as those who deliver foodstuffs to grocery stores and restaurants). So it seems probable that modelling tours is more important and complex for trucks than for personal travel.

The original specification for a tour-based truck model included a true disaggregate tour generation step. The model considers each individual truck and models the probability of it making 0, 1, 2, tours per day. However, in order to apply this kind of model, this approach requires an inventory of all trucks in the region. This was investigated and found to be infeasible, at least within the resources available to the present project. Therefore, a true disaggregate tour generation model could not be developed.

Instead, a zonal aggregate model of the number of tour starts was developed. This includes all tours: those that stay within the region (I/I), those that start in the region and leave it (I/X), and those that start outside the region and end inside (X/I).

ii. Available Model Data

ARC has developed a considerable amount of data to support application of its travel models. The principal file is the socioeconomic and land use data by zone. This includes the following variables for each zone: employment by 8 categories (construction, manufacturing, transportation/communications/ utilities [TCU], wholesale, retail, finance/insurance/real estate [FIRE], service, government), population, households, university enrollment, acres. In addition, the ARC model includes a submodel that computes the area type for each zone. This is a zonal variable that ranges from 1 (CBD) to 7 (rural) on the basis of the population and employment density in the subject zone and all other zones whose centroids are within 1 mile (straight line distance) of the subject zone. This so-called “floating zone method” provides a smoother transition between area types. The model is shown in Table 13.

Table 13: Atlanta Area Type Model

Pop Density	Employment Density (jobs/acre)						
(persons/acre)	<0.05	0.06-0.32	0.33-6.65	6.66-12.44	12.45-25.10	25.11-57.97	> 57.97
< 0.43	7	7	6	4	4	3	2
0.44-0.78	7	6	6	4	3	3	2
0.79-2.38	7	6	5	4	3	2	2
2.39-3.48	6	5	5	4	3	2	2
3.49-5.40	6	5	5	4	3	2	1
5.41-8.07	5	5	5	3	3	2	1
> 8.07	5	5	5	3	2	2	1

RPCGB also has developed a considerable amount of data to support application of its travel models. The principal file is the socioeconomic and land use data by zone. This includes the following variables for each zone: housing units, population, total employment, retail employment, and school enrollment. Generally, a two-way split of employment (retail/non-retail) is not sufficiently detailed to identify truck travel patterns. A more robust truck model requires greater differentiation of employment at the zone level. The minimum disaggregation is: industrial, retail, office, and other. This data was not available from RPCGB.

Fortunately, the Census Bureau has a program called Longitudinal Employer-Household Dynamics (LEHD) which provides a breakdown of existing employment by 20 NAICS groups at the census block level. The research team obtained this data and converted it to the RPC's (old) zone system. The different categories of employment were then aggregated to produce industrial, retail, office, and other breakdowns. Table 14 shows the equivalency.

Table 14: Employment Category Equivalency

Model Category	NAICS Code	NAICS Category
Industrial	11	agriculture
	21	mining
	22	utilities
	23	construction
	31-33	manufacturing
	42	wholesale
	48-49	transportation, warehousing
Retail	44	retail
Office (service)	51	information
	52	finance/insurance
	53	real estate
	54	professional/technical/scientific
	55	management
	56	administrative
	92	government
Other	61	educational
	62	health care
	71	entertainment/recreation
	72	hotel/food
	81	other services

The current LEHD data provided TAZ-level percentages which were then used to disaggregate the RPCGB non-retail employment by industrial, office, and other categories. The information will not be forecast– for the present project the LEHD's percentages are assumed to apply in the future as well.

In addition, the RPCGB model includes a sub-model that calculates the area type for each zone. This is a zonal variable that ranges from 1 (CBD) to 9 (rural), computed on the basis of the combined population and employment density in the subject zone and all other zones whose centroids are within 1 mile (straight line distance) of the subject zone. This so-called "floating zone method" provides a smoother transition between area types. The model is shown in Table 15.

Table 15: Birmingham Area Type Model

Combined Density (pop+emp/acre)	Area Type
> 20	1
15 – 20	2
12 – 15	3
8 – 12	4
5 – 8	5
1 – 5	6
0.5 – 1	7
0.25 – 0.50	8
< 0.25	9

The final zonal variable is a “truck zone flag”. This is a binary (0/1) variable that takes the value of 1 for zones that have been designated as a “truck zone”. These are zones that contain land uses that are likely to generate a higher than average number of truck trips per employee. Examples include industrial parks, warehousing areas, truck stops, quarries, intermodal terminals, etc. These were identified by examining satellite photos and checked by ARC staff and members of the ARC Freight Committee. About 46 such zones were identified throughout the region, as shown in Figure 25.

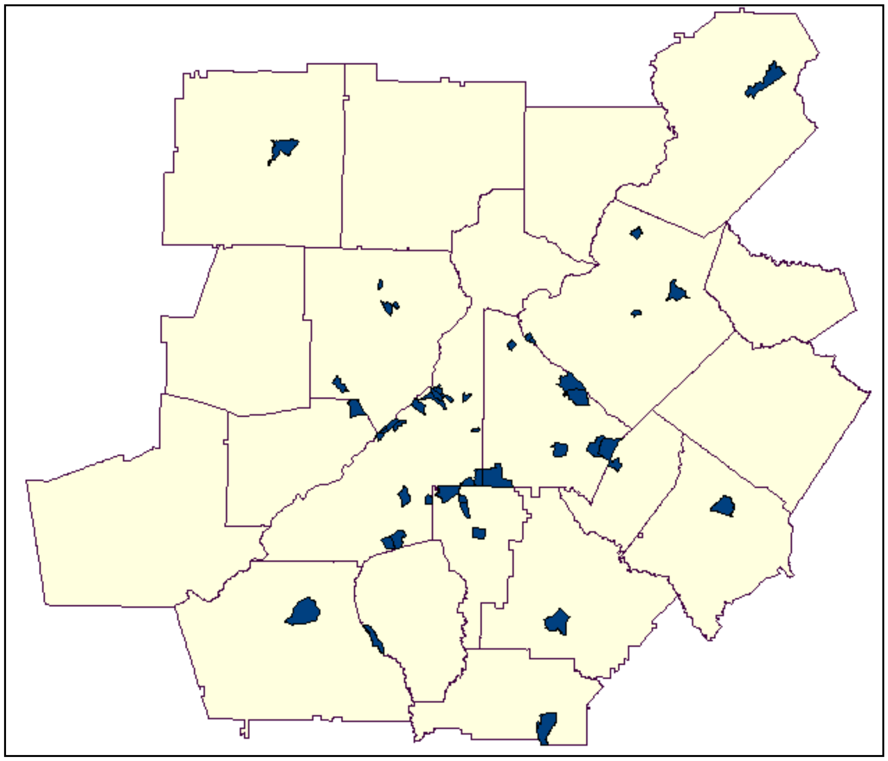


Figure 25: Atlanta Truck Zones

(Source: The Travel Forecasting Set for the Atlanta Region, 2008 Documentation, PBS&J, October 2010.)

Birmingham truck zones were also identified by examining satellite photos that were also reviewed by local staff. Some zones that might seem like good candidates for truck zones were not included, since they contained a relatively large number of employees, which would be expected to generate a commensurate number of truck trips. The initially proposed list of truck zones was reduced slightly as part of the assignment validation process, as it was discovered that some zones did not need the extra boost in trips. The final list is shown in Table 16.

Table 16: Birmingham Truck Zones

Truck Zone ID	Land Use
161	industrial
163	intermodal terminal
176	airport
202	manufacturing
207	manufacturing
395	manufacturing
396	warehousing, US Steel
478	warehousing
498	industrial
623	intermodal
627	warehousing
628	manufacturing
664	quarry
667	intermodal, warehousing
740	manufacturing
750	industrial park
774	airport, manufacturing

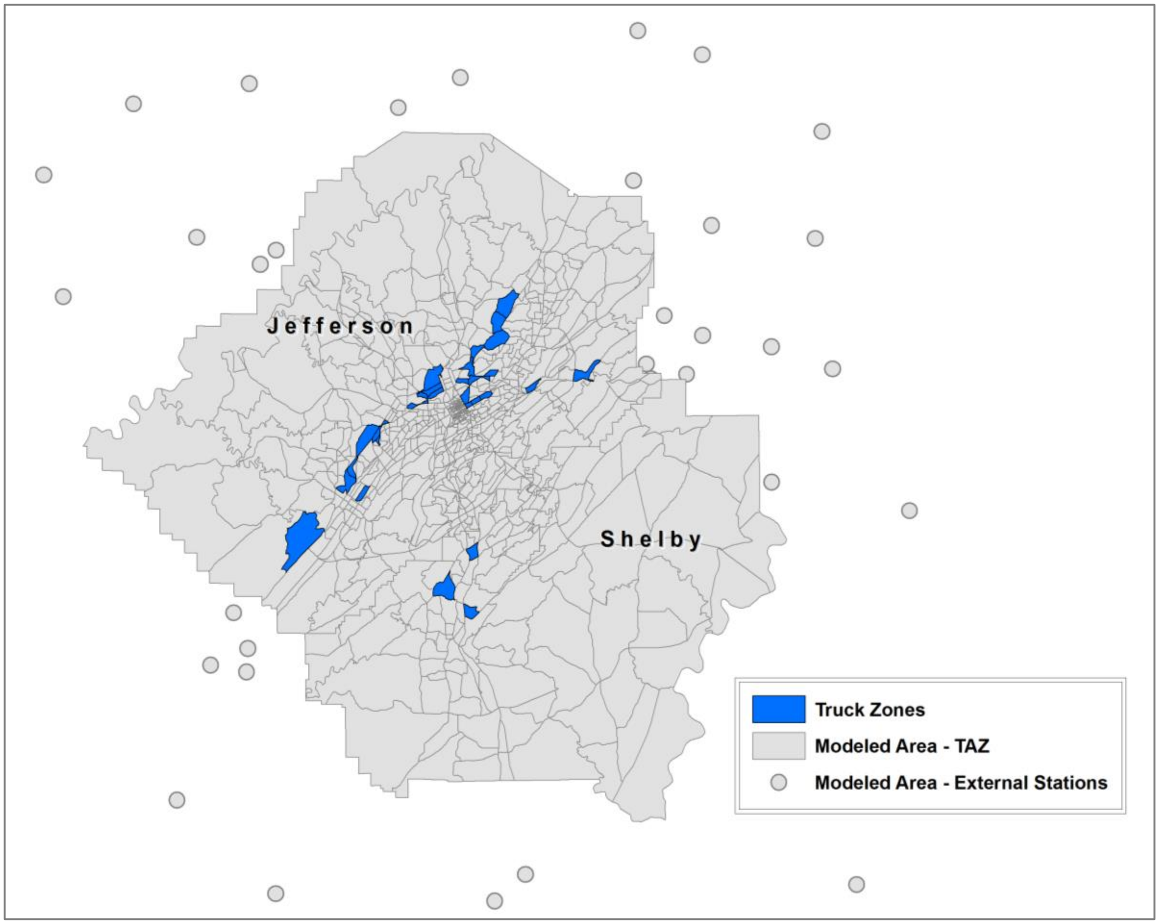


Figure 26: Birmingham Truck Zones

iii. Generated Data

The input data already available for the ARC model can be used to calculate a number of other statistics that might be relevant to the generation of truck tours, based on other such models and common sense. Variables that could not be readily forecast were not included in the model. ARC and RPCGB provide forecasts of the model data listed above. Other variables can also be generated from that data, which can also be easily forecast from the basic ARC and RPCGB data. These variables are as follows:

- **Accessibility**

  This refers to the ability of people in a zone to get to jobs and houses. It reflects both development density and the proximity of the roadway network. Typically, it is computed for each zone. There are many ways to measure accessibility and several candidate measures were developed for possible use in model calibration:

- ACCH15: the number of households that can be reached within 15 minutes' travel time (over the road network) from this zone (off-peak network)
- ACCH30: the number of households that can be reached within 30 minutes
- ACCE15: the number of jobs that can be reached within 15 minutes
- ACCE30: the number of households that can be reached within 30 minutes
- ACCI15: the number of industrial jobs that can be reached within 15 minutes; the hypothesis is that industrial employment (the sum of construction, manufacturing, TCU, and wholesale) is more closely related to truck traffic than is total employment
- ACCI30: the number of industrial jobs that can be reached within 30 minutes
- ACCHH: the above measures are easy to understand, but they include a "cliff". For example, for ACCE30, the jobs in a zone that is 29.8 min away would be included but the jobs in the next zone over that is 30.3 min away would be excluded. This might not always be desirable. The ACCHH variable solves this problem by using a continuous function. It is computed for each zone as the sum of households for all zones divided by travel time (TT) squared. So this measure includes every zone in the region, but zones that are very distant from the subject zone don't

contribute much to its accessibility. The resulting statistic has no meaningful dimensions or reference values.

- ACCEMP: this is similar to ACCHH but is the sum of jobs/TT^2
- ACCIND: this is similar to ACCHH but is the sum of industrial jobs/TT^2
- ACCHH3: this is similar to ACCHH but is the sum of jobs/TT^3 (raising time to the third power in the denominator diminishes its impact; some prior studies have found that to be helpful)
- ACCEMP3: this is similar to ACCHH but is the sum of jobs/TT^3
- ACCIND3: this is similar to ACCHH but is the sum of industrial jobs/TT^3

- **Distance to the Cordon**

  The distance from each zone to the nearest cordon station (the edge of the modelled area) via the road network is calculated. This statistic has been shown elsewhere to be relevant to the external share of travel in a zone. Zones that are closer to the cordon tend to send and receive more trips to/from the external world.

- **Distance to the CBD**

  Although employment and economic activity is spread widely across the Atlanta region, downtown Atlanta remains the geographic center of activity. It seems possible that a zone's proximity to downtown might be an indicator of truck activity. For the purposes of this calculation, "downtown" for Atlanta is assumed to be the centroid of zone 16, which is near Piedmont Ave SE and Gilmer St SE and "downtown" for Birmingham is assumed to be the centroid of (old) zone 39, which is near 5th Ave N and 19th St N.

- **Zonal Density**

  Several of the statistics mentioned above are surrogates for the development density in a zone. In addition to those, three more "pure" density measures were calculated by zone: households per acre, employment per acre, and industrial employment per acre.

- **Employment Shares**

  As mentioned above, ARC maintains eight categories of employment. It seemed reasonable to think that the *percentage* of a zone's employment by type might provide some meaningful insight into the truck travel characteristics. Five different percentages were calculated for Atlanta: industrial (defined as noted above), retail, wholesale, manufacturing, and service, while two different percentages were calculated for Birmingham: industrial and retail.

iv. Estimation

As noted above, this is an aggregate model of the number of tour origins per zone. This means that the ATRI data needed to be adjusted in some way to reflect the universe of truck trips. The ATRI data represent a sample of truck trips, but there is no data available to calculate an expansion factor for these records. That is, the true *universe* of truck trips is unknown. The only available information on that universe for Atlanta is the 2010 truck trips estimated by the current ARC travel model. This information was used to adjust the ATRI *trip* data. Table 17 shows the ARC estimated medium + heavy truck trips and the ATRI trips by county (for each tour, the number of trips equals the number of stops plus one).

Table 17: Atlanta Trip Expansion

County	ARC Trips	ATRI Trips	Factor
Barrow	13,771	9,182	1.500
Bartow	15,882	72,635	0.219
Carroll	17,651	35,897	0.492
Cherokee	14,376	6,211	2.315
Clayton	30,244	52,380	0.577
Cobb	61,016	36,314	1.680
Coweta	14,169	26,261	0.540
DeKalb	60,477	74,363	0.813
Douglas	10,898	41,409	0.263
Fayette	8,154	1,874	4.351
Forsyth	13,556	3,289	4.122
Fulton	104,669	87,494	1.196
Gwinnett	60,514	51,102	1.184
Hall	16,345	50,071	0.326
Henry	11,882	28,830	0.412
Newton	10,879	6,515	1.670
Paulding	8,282	4,275	1.937
Rockdale	6,934	8,354	0.830
Spalding	12,233	22,869	0.535
Walton	6,655	12,442	0.535

This model reflects tour origins. Thus, X/I and X/X tours are excluded from this analysis. From Table 9, this results in 137,175 tour records. Application of the factors in Table 17 resulted in a total of 117,674 observed tour origins.

As for Birmingham, based on prior RPC data, the total of about 38,300 I/I + I/X tours was initially selected as the actual total of internally-generated truck tours (this would be later verified in the assignment validation phase).

Next, the tour records were summarized by the zone of the tour main origin. Then, a Cube script was written to calculate the ARC and derived variables described above. This produced a file with one record per zone with the observed data and several candidate explanatory variables. The study team's experience with aggregate generation models is that the traffic zone level is often unsuited to model estimation, because the observed data is too thin. The usual solution is to further aggregate the data to a district system. A good district system will have enough districts so that the differences in district-level tour origins is clearly related to the differences in the independent variables. For this study, a system of 198 districts for Atlanta provided reasonable aggregation – roughly 10 districts per zone, respecting county boundaries. As for Birmingham, a system of 179 districts provided reasonable aggregation, corresponding to the number of Census tracts in the modelled region. Several of the above candidate variables are zone-specific. These were converted to district-level variables by weighting them by an appropriate variable, usually total employment.

The calibration file was analyzed using linear regression in the SPSS statistical analysis package. Different approaches were tested, including forcing certain variables and allowing others to enter the equation in "stepwise" fashion, depending on their contribution to the model's accuracy. As for Atlanta, seven models were tested, as shown in Table 18, with the variable names defined in Table 19, while nine models were tested for Birmingham case (shown in Table 20, with the variable names defined in Table 21). The criteria used to evaluate the models included:

- logical signs on the coefficients
- Student's t scores above 1.96 (95% confidence that the coefficient is statistically different from zero)
- no duplication, overlap, or double-counting of variables
- high r^2 and F statistics

Table 18: Atlanta: Candidate Generation Models

Model	Equation	r2	F
1	445.1 + 0.01359**TOTEMP*	0.017	3.5
2	353.8 + 0.09679*TCU + 0.28980**CONST* – 0.35653*FIRE + 0.35796*WHOLE	0.261	17.0
3	160.6 + 649.18*TZONE + 3343.48*PCTIND – 2463.72*PCTMFG + 0.01536*POP – 0.01289*ACCH15 – 16.48*DISTCBD	0.453	26.4
4	727.01 + 742.24*TZONE + 0.33815*WHOLE – 0.25827*FIRE + 0.05271*TCU + 0.01316*POP – 0.01202*ACCH15 – 15.54*DISTCBD	0.416	19.3
5	768.79*TZONE + 0.01520*POP + 0.29702*WHOLE – 0.25986*FIRE + 0.06252*TCU – 0.01525*ACCH15 + 0.004395*ACCI30 - 0.001278*ACCE15	0.594	34.7
6	840.61 + 0.15301**WHOLE* + 0.01002*POP + 837.59*TZONE + 0.05582*TCU + 0.22789**CONST* – 0.01222*ACCH15 – 18.13*DISTCBD – 0.001507*ACCE15	0.399	15.7
7	528.86 + 861.07**PCTMFG* + 0.01652*POP + 863.48*TZONE + 4544.80*PCTWHL – 0.01376*ACCH15 – 18.45*DISTCBD	0.392	20.5

Note: all variables have t scores of 1.96 or higher, except those shown in italics.

Table 19: Atlanta: Candidate Generation Variables

Variable	Description
DISTRICT	District number (1-198)
ACRES	Total acres in district
COUNTY	Census (FIPS) county code
ATYPE	Computed 2010 area type (1-7)
TZONE	Truck zone flag (0/1)
TOURS	Tour origins (I/I + I/X) (this is the dependent variable)
POP	Population
HH	Households
TOTEMP	Total employment
CONST	Construction employment
MFG	Manufacturing employment
TCU	Transportation, communications, utilities employment
WHOLE	Wholesale employment
RETAIL	Retail employment
FIRE	Finance, insurance, real estate employment
SERVICE	Service employment
TOTPRIV	Total private employment (sum of above 7 categories)

Variable	Description
GOVT	Government employment
INDUST	Industrial employment (sum of CONST, MFG, TCU, WHOLE)
ACCH15	Households accessible within 15 min
ACCE15	Employment accessible within 15 min
ACCI15	Industrial employment accessible within 15 min
ACCH30	Households accessible within 30 min
ACCE30	Employment accessible within 30 min
ACCI30	Industrial employment accessible within 30 min
ACCHH	Household accessibility statistic (HH/$time^2$)
ACCEMP	Employment accessibility statistic (TOTEMP/$time^2$)
ACCIND	Industrial employment accessibility statistic (INDEMP/$time^2$)
ACCHH3	Household accessibility statistic (HH/$time^3$)
ACCEMP3	Employment accessibility statistic (TOTEMP/$time^3$)
ACCIND3	Industrial employment accessibility statistic (INDEMP/$time^3$)
POPDEN	Population/acre (this district)
EMPDEN	Employment/acre (this district)
HHDEN	Households/acre (this district)
TOTDEN	Combined density: (300*employment + 2000*HH)/acre

Variable	Description
DISTCOR	Distance to the nearest cordon station, miles
DISTCBD	Distance to the CBD (zone 16), miles
PCTIND	Fraction (0.0 – 1.0) of employment that is industrial
PCTRET	Fraction (0.0 – 1.0) of employment that is retail
PCTWHL	Fraction (0.0 – 1.0) of employment that is wholesale
PCTMFG	Fraction (0.0 – 1.0) of employment that is manufacturing
FLTIND	Industrial employees/acre in surrounding districts
FLTRET	Retail employees/acre in surrounding districts
DEVDENS	Combined density: 300*employment + 800*population)/acre

Model #4 for was selected for Atlanta as having the best fit to the criteria described above. This model says that the key variables are wholesale employment, truck zone flag, and population. FIRE employment, accessibility to households, and proximity to the CBD are negative factors, which seems logical.

Table 20: Birmingham: Candidate Generation Models

Model	Equation	r^2	F
1	129.2 + 0.03573*TOTEMP	0.078	14.9
2	101.2 + 0.35524*IND – 0.09276*OFF	0.393	57.0
3	**-458.2 + 3.72E-03*ACCI15 + 66.62202*ATYPE + 449.89929*PCTRET + 181.91428*TZONE**	**0.494**	**42.4**
4	118.0 + 0.12520**IND* – 0.03558**OFF* + 2.76E-03*ACCI15 – 0.02651*ACCHH	0.449	35.4
5	164.0 – 32.05466*POPDEN + 4.25E-03*ACCI15 + 0.11665*RET – 2.23E-04*ACCE30	0.490	41.8
6	157.1 + 19.46591*TZONE – 6.71E-05**EMP* – 35.05527*POPDEN + 3.15E-03*ACCI15	0.470	38.5
7	175.2 – 39.61360 + 3.61E-03*ACCI15	0.456	73.6
8	62.2 – 34.78976*POPDEN + 3.35E-03*ACCI15 + 390.91949*PCTRET + 193.23093*TZONE	0.487	41.3
9	248.45639*TZONE + 191.86710**PCTRET* + 3.05E-03*ACCI15 + 4.54692**ATYPE*	0.554	54.4

Note: all variables have absolute t scores of 1.96 or higher, except those shown in italics.

Table 21: Birmingham: Candidate Generation Variables

Variable	Description
DISTRICT	District number (1-179)
ACRES	Total acres in district
ATYPE	Computed 2010 area type (1-9)
TZONE	Truck zone flag (0/1)
TOURS	Tour origins (I/I + I/X) (this is the dependent variable)
POP	Population
HH	Households
TOTEMP	Total employment
IND	Industrial employment
OFF	Office employment
RET	Retail employment
ACCH15	Households accessible within 15 min
ACCE15	Employment accessible within 15 min
ACCI15	Industrial employment accessible within 15 min
ACCH30	Households accessible within 30 min
ACCE30	Employment accessible within 30 min

Variable	Description
ACCI30	Industrial employment accessible within 30 min
ACCHH	Household accessibility statistic (HH/time^2)
ACCEMP	Employment accessibility statistic (TOTEMP/time^2)
ACCIND	Industrial employment accessibility statistic (INDEMP/time^2)
ACCHH3	Household accessibility statistic (HH/time^3)
ACCEMP3	Employment accessibility statistic (TOTEMP/time^3)
ACCIND3	Industrial employment accessibility statistic (INDEMP/time^3)
POPDEN	Population/acre (this district)
EMPDEN	Employment/acre (this district)
HHDEN	Households/acre (this district)
TOTDEN	Combined density: (300*employment + 2000*HH)/acre
DISTCOR	Distance to the nearest cordon station, miles
DISTCBD	Distance to the CBD (zone 16), miles
PCTIND	Fraction (0.0 – 1.0) of employment that is industrial
PCTRET	Fraction (0.0 – 1.0) of employment that is retail
DEVDENS	Combined density: 300*employment + 800*population)/acre

Model #3 for Birmingham was selected as having the best fit to the criteria described above. This model says that the key variables are truck zone flag, area type, percent of employment that is retail, and accessibility to industrial employment within 15 min. The coefficients on these variables all have positive signs, which seems logical.

v. Validation

The model was validated by applying it to zone-level data and comparing the outputs to the observed tours. This required a number of adjustments:

- **Removal of constant term**

  SPSS can estimate a regression model with or without a constant term. The chosen method seems to be a matter of the analyst's preference; it is not clear that one method is always better than another. In this project, the model was estimated with a constant term, in order to get the proper coefficients on the other variables. However for model application at the zone level, the constant term was removed to prevent the estimation of truck tours in zones where none are indicated. This required adjusting the remaining coefficients to obtain the correct total tours.

  - **Districts vs. Zones**

    Some variables, such as population, are not geography-specific. The population of a district is the sum of the population in its zones. However, other variables, such as TZONE and ACCH15, have values that are related to the level of geographic aggregation. Switching from districts to zones requires adjustments in those coefficients to properly represent the effect of the variable.

- **Area Type Adjustment**

  In the subsequent assignment validation step (see below), the study team discovered that the Atlanta model was slightly overestimating volumes in the more developed areas. Thus, an area type adjustment was incorporated that multiplies the estimated tours by 0.9 in zones with area types 1-5. No adjustment is applied in the rural zones (area type 6, 7). Conversely, the Birmingham model was initially overestimating volumes in the less developed areas. Thus, an area type adjustment was incorporated that reduces the estimated tours in zones with area types 7-9. No adjustment is applied in other zones.

- **Negative** Check

  Since the equation includes negative coefficients, a check for negative values is included. These are re-set to zero for any zone.

- **External** Tours

  As originally developed, the tour generation model estimated total tour origins at internal zones, no matter where they were destined; that is, I/I plus I/X tours. However, during assignment validation, it was discovered that the modified equation could also be used to derive X/I tours. This is discussed further below.

The final zone-level regression equation for Atlanta is as follows:

Tours = [0.507*WHOLE – 0.158*FIRE + 0.079*TCU + 0.020*POP – 0.0002*ACCH15 – 0.953*DISTCBD] * area type factor + 990.897*TZONE (1A)

Similarly, the final zone-level regression equation for Birmingham is as follows:

Tours = [163.33523*TZONE + 1.01896*POPDEN + 40.13860*PCTRET + 0.0008547*ACCI15] * area type factor (1B)

In application, the aggregate estimates of tour starts in each zone are converted to a disaggregate file by writing out one record for each tour. The record contains a single value: the zone where the tour began. Three separate files are output: I/I, I/X, and X/I tours.

vi. External Tours

Equation (1A and 1B) estimates total tours. Initially, this was considered to be the sum of I/I and I/X tours. A method was needed to separate those. Previous work by the study team has indicated that this share is related to the zone's location with respect to the cordon. The closer the zone is to the cordon, the higher its I/X share. The ATRI tour data was tabulated and summarized as shown in Figure 27 (Atlanta) and Figure 28 (Birmingham). From these data, least squares model were estimated with the equation:

Atlanta: $$\text{I/X share} = 0.306 * \text{DISTCOR}^{-0.158} \qquad (2A)$$

Birmingham: $$\text{I/X share} = 0.39 - 0.00008 * \text{DISTCOR}^{2.59} \qquad (2B)$$

DISTCOR is the zone's over-the-road distance to the cordon in miles. This function is applied to each zone and a maximum cutoff value is applied of 90% (Atlanta) and constrained to be no less than 5% (Birmingham).

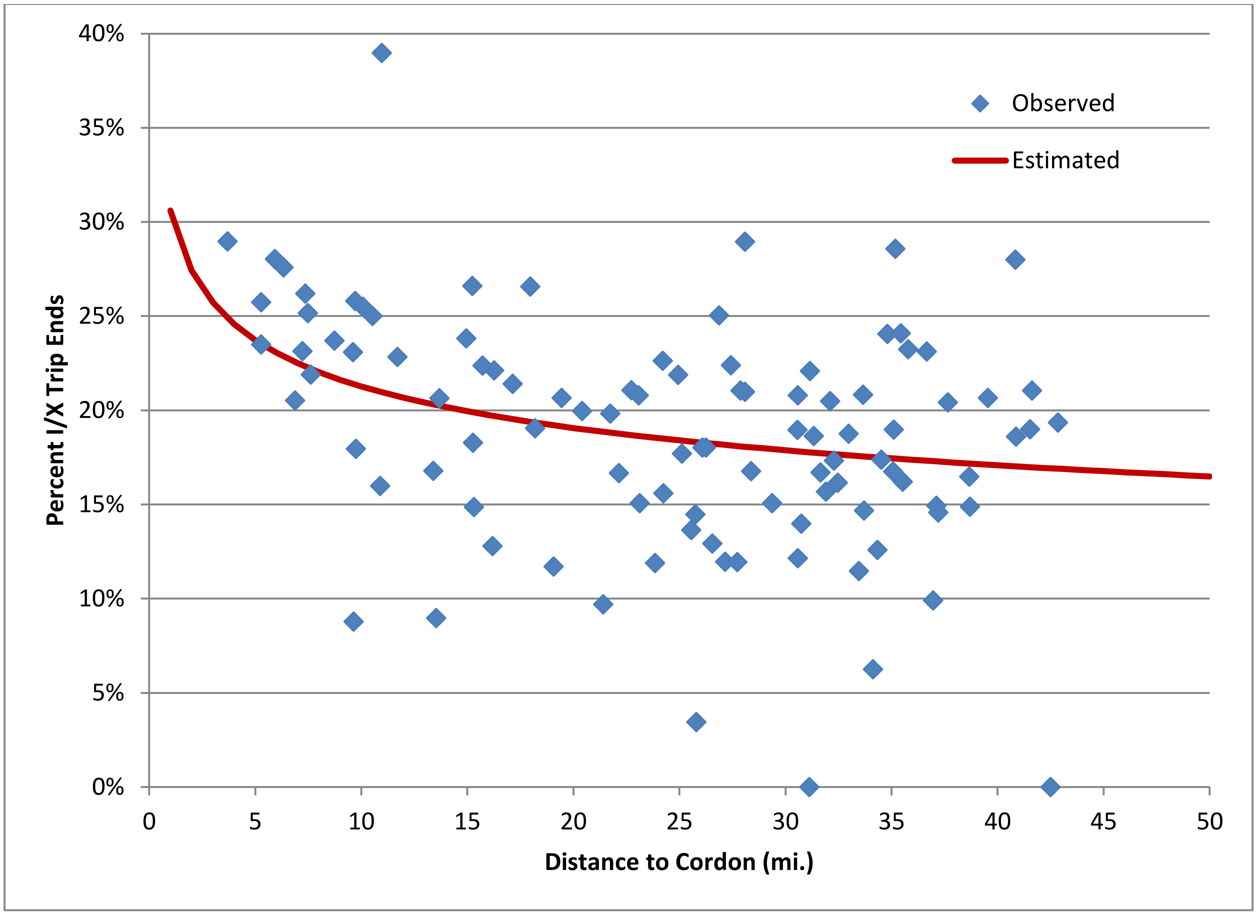


Figure 27: Atlanta I/X Share

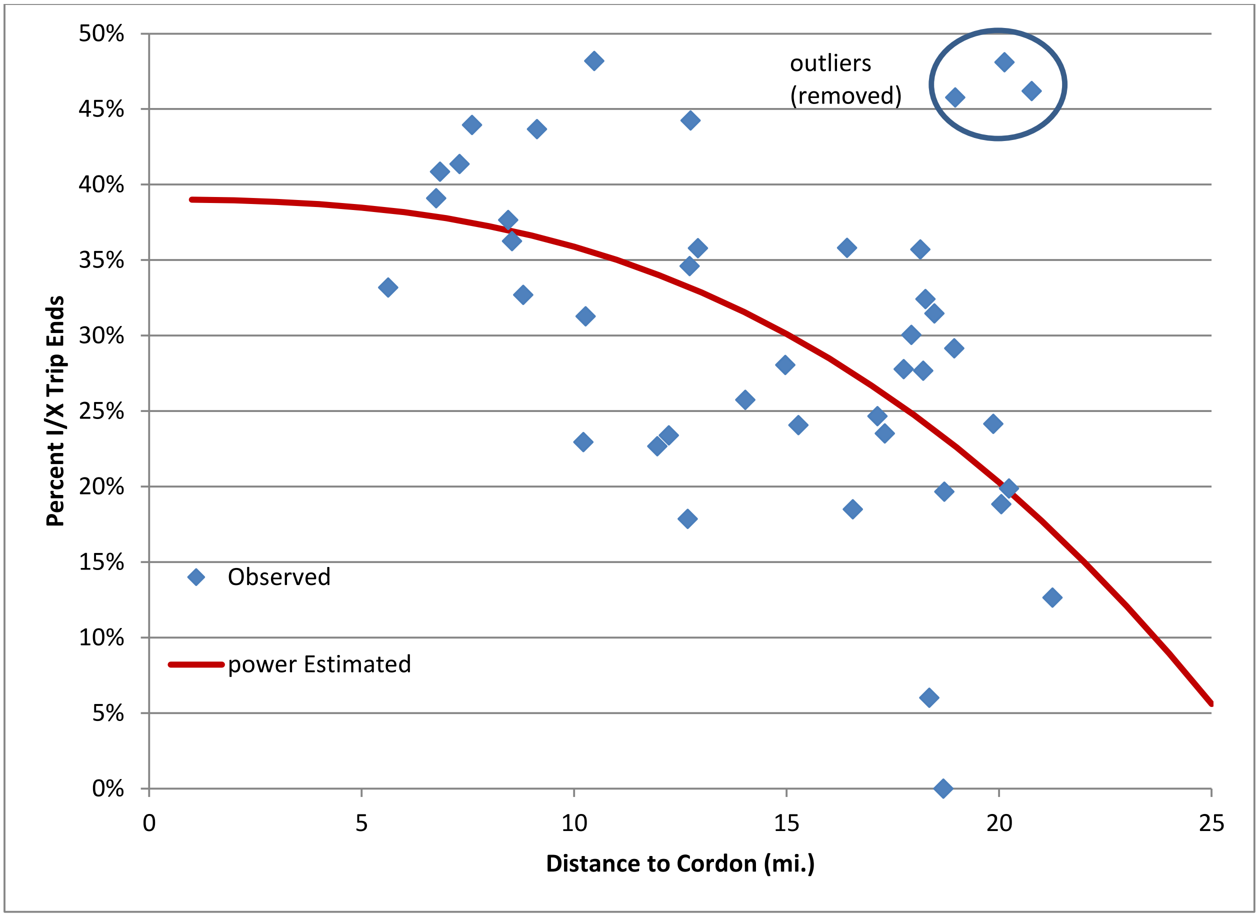


Figure 28: Birmingham I/X Share

During assignment validation, it was discovered that a similar function could be used to estimate X/I tours (tours that start outside the modelled region and end inside it). Equation (2A and 2B) was applied, with an adjustment that was determined so that the correct number of total tours was estimated at the cordon. That number of tours satisfies the following equation:

Atlanta: Cordon tours = I/X tours + X/I tours + 2*X/X tours (3)

The resulting X/I share equation is then:

Atlanta: $\text{X/I share} = 0.508 * \text{DISTCOR}^{-0.158}$ (4)

This share is also limited to a maximum of 90%. Equations 2-4 produce the cordon truck trips shown in Table 22. The Total figure is derived from applying the 2005 truck share (from GDOT classification counts) for each station to the 2010 total count (also GDOT data, as posted in the ARC network) (see Table 24). Similarly, the Total figure for Birmingham model is derived from applying the 2010 truck share (from ALDOT classification counts) for each station to the 2010 total count (also ALDOT data, as posted in the BMC network) (see Table 25).

Table 22: Atlanta External Tours

Tour Type	Sum
External	73,490
Through	60,796
Total	**134,286**

Table 23: Birmingham External Tours

Tour Type	Sum
External	20,375
Through	30,907
Total	**51,282**

vii. X/X Tours

Although the ATRI data provided good information on the number of X/X (through) tours, there were some geocoding discrepancies that prevented the direct derivation of an X/X table from this data. Instead, a synthetic X/X table was derived based both on the ATRI tour total and on the 2010 truck totals at each station shown in Table 24. Note that in this study, “X/X tour” refers to a tour that starts and ends outside of the modelled area, even if it makes one or more intermediate stops within the area. This is slightly different from the conventional definition (passing through with no intermediate stops).

The synthesis process started with past experience to estimate the external/through split at each cordon station. This is generally a function of roadway facility type and volume; major roads with higher volumes have a higher X/X share. Next, examination of the cordon station geography indicated X/X movements that were unlikely on the basis of geography. These station-station patterns were combined with the initial estimate of X/X trip ends to develop an initial X/X table by vehicle type. This initial table was then Fratared to match the estimated X/X trip ends. An adjustment was made to account for the major interstate movements through the modelled region (Atlanta: I-75 and I-20; Birmingham: I-65, I-59, and I-20). Finally, the daily X/X table was balanced, so that the volume is the same in each direction, which is a common assumption for X/X tables. The resulting tables were assigned to the network by themselves and the volumes were examined. This process produced a set of external trip tables that were judged to be reasonable. The resulting table includes 30,398 (Atlanta) and 15,453 (Birmingham) X/X trips (half the value shown in Table 22, because X/X trips cross the cordon twice).

The procedure to forecast through tours, used in almost all regional models, is to apply a growth rate to each external station and iteratively factor the table’s rows (origins) and columns (destinations) until the desired row and column totals are met. This is known as the “Fratar” process (Fratar, 1954). In this model, the tour generation step uses the calculated internal tours and input external tours to work backwards to calculate a through growth rate by station that maintains the correct cordon total at all stations.

Table 24: Atlanta Cordon Data

Station	Name	2010 Total	2010 X/X	2040 Total
2028	SR 113	640	0	998
2029	Chulio Rd/Euharlee Rd	143	0	211
2030	SR 20/US 411	2,726	1,361	3,261
2031	SR 293	215	0	298
2032	SR 140	961	0	1,397
2033	US 41	334	0	510
2034	I-75	20,520	12,306	27,533
2035	US 411	404	0	540
2036	SR 108	361	0	655
2037	I-575 (SR 5)	2,293	1,373	3,716
2038	SR 372	321	0	573
2039	SR 9	425	0	901
2040	Hopewell Rd	345	0	615
2041	SR 400/US 19	1,765	704	2,433
2042	Blue Ridge Overlook	306	0	513
2043	SR 53	375	0	526
2044	SR 136	302	0	574
2045	SR 60	865	345	1,640
2046	SR 115	191	0	390
2047	SR 52	212	0	406
2048	SR 284	167	0	297
2049	US 129	993	0	1,391
2050	SR 254	120	0	207
2051	Skitt Mtn Rd	139	0	238
2052	US 23/SR 365	2,260	1,240	3,880
2053	SR 51/Cornelia Hwy	189	0	328
2054	SR 51	255	0	427
2055	SR 52	172	0	245
2056	SR 82	156	0	274
2057	SR 11/US 129	954	0	1,624
2058	SR 60/SR 332	433	0	740
2059	SR 53	1,154	0	1,960
2060	I-85	15,826	9,492	25,752
2061	SR 124	681	0	1,037
2062	SR 53	546	0	878
2063	Jefferson Hwy	463	0	749
2064	Double Bridges Rd	144	0	206

Station	Name	2010 Total	2010 X/X	2040 Total
2065	SR 82	205	0	401
2066	SR 330 (Tallassee Rd)	285	0	474
2067	Atlanta Hwy	689	0	1,034
2068	SR 316/US 29	2,217	1,218	2,638
2069	Barber Creek Rd	65	0	139
2070	SR 53	380	0	615
2071	US 78	2,124	849	3,306
2072	Snows Mill Rd	69	0	106
2073	SR 186	168	0	245
2074	SR 83	303	0	441
2075	Monroe Hwy	68	0	102
2076	Pannell/Prospect Rd	92	0	153
2077	US 278	321	128	489
2078	I-20	8,037	4,826	11,639
2079	SR 142	506	0	611
2080	SR 11	282	0	427
2081	Henderson Mill Rd	240	0	390
2082	SR 212	568	0	833
2083	SR 36	356	0	648
2084	Keys Ferry Rd	190	0	275
2085	Old Jackson Rd	229	0	370
2086	SR 42/US 23	907	363	1,542
2087	I-75	18,856	11,322	29,476
2088	Jackson Rd	201	0	339
2089	SR 16	1,180	0	2,244
2090	SR 36	137	0	234
2091	Macon Rd	399	0	687
2092	US 41	1,073	592	1,619
2093	SR 155	1,072	429	1,617
2094	SR 362	653	0	810
2095	SR 18	68	0	127
2096	SR 85	188	0	291
2097	SR 54	78	0	124
2098	US 41	559	225	782
2099	I-85	9,162	5,504	15,147
2100	US 29	76	0	119
2101	Corinth Rd	143	0	273
2102	SR 34	530	0	864
2103	SR 1	839	337	1,145

Station	Name	2010 Total	2010 X/X	2040 Total
2104	Stoney Pt	122	0	414
2105	SR 100	321	0	142
2106	SR 100/SR 5	375	0	453
2107	SR 166	4,767	0	1,813
2108	SR 100	356	0	497
2109	SR 166	168	0	256
2110	I-20	11,447	6,868	20,929
2111	US 27	993	496	1,800
2112	SR 1 BUS	707	353	1,140
2113	SR 78	646	0	1,054
2114	SR 113	284	0	620
2115	SR 120	620	0	841
2116	Vinson Mtn Rd	234	0	398
2117	SR 101	530	0	681
2118	US 278	845	465	1,316
Totals		**134,286**	**60,796**	**203,053**

Table 25: Birmingham Cordon Data

Station	Name	2010 Trucks	2010 TRK X/X	2040 Trucks
964	US 31 N	100	0	190
965	2nd St	26	0	40
966	AL 79	90	10	170
967	AL 75	122	0	230
968	Deer Haven Rd	0	0	0
969	CR 30	0	0	0
970	I-59 N	6,070	3,764	14,310
971	US 11 N	112	0	200
972	CR 96/Whites Chapel Pkwy	59	0	100
973	I-20 E	13,764	8,534	32,450
974	US 411 E	166	0	310
975	US 78 E	64	0	120
976	CR 43/CR 55	0	0	0
977		40	0	90
978	AL 60	0	0	0
979	US 280	218	22	510
980	AL 145	22	0	40
981	I-65 S	8,010	4,966	18,880
982	US 31 S/AL 3	70	0	130
983	AL 155	46	0	90

Station	Name	2010 Trucks	2010 TRK X/X	2040 Trucks
984	CR 73	48	0	90
985	AL 25	42	0	80
986	CR 10/Marvel Rd	0	0	0
987	CR 12/Grey Hill Rd	38	0	60
988	Eastern Valley Rd	19	0	30
989	CR 20/Old Tuscaloosa Hwy	0	0	0
990	I-20 W/US 11 S	13,987	8,672	32,980
991	CR 36/Johns Rd	0	0	0
992	CR 21/Camp Oliver Rd	19	0	30
993	AL 269	22	0	40
994		0	0	0
995	CR 20/Horsecreek Blvd	0	0	0
996	Old US 78/AL 5	190	20	400
997	Bankston Rd	0	0	0
998	US 78 W	158	98	370
999	I-65 N	7,780	4,824	18,340
Total		**51,282**	**30,910**	**120,280**

Tour Main Destination Choice

i. Model Structure

The tour generation model established the starting point (zone) of the tour. The objective of the tour main destination choice model is to estimate the location of the tour's main destination zone. This is done using a logit destination choice model. This works as follows: a range of candidate destination zones is considered. For each candidate, the utility of going to that zone is calculated. For all candidates, the utilities are exponentiated and summed, and the probability of going to zone J is computed as the exponentiated utility for zone J divided by the sum of the exponentiated utilities of all candidate zones:

$$p_{ij} = \frac{e^{U_j}}{\sum_x e^{U_x}} \qquad (5)$$

where x is the range of candidate destination zones. U is a linear function of various attributes of the origin zone I and destination zone J. The model is applied in Monte Carlo fashion: once the probabilities are calculated using equation (5), they are sorted in ascending order and the cumulative probability of going to each zone established. A random number is generated and compared to these cumulative probabilities. The first destination zone whose cumulative probability exceeds the random number is selected as the tour main destination zone.

In application, this process is applied separately but identically to I/I and X/I tours, because those tours are both destined to internal zones, about which much is known. However, I/X tours are different because much less is known about the external stations as destinations. That model is described below.

ii. Estimation

The available ARC and RPCGB network and zonal data and newly generated statistics available for destination choice estimation are the same as described in sections 3.ii and 3.iii. As with the tour generation model, a Cube script was written to prepare the data for the estimation process.

For the main destination choice model, a process must be used to limit the choice of candidate destination zones. This is because in logit model estimation, the estimation program (ALOGIT) must have information on the possible choices. ALOGIT cannot accommodate all 2,027 (Atlanta) and 850 (Birmingham) possible internal zones. In addition, most of these zones are not reasonable alternatives to the chosen zone; they are too far from the origin and/or contain too few truck-attracting land uses. Since including these unlikely zones does affect the choice probabilities in a multinomial logit model, they are best excluded from the destination choice set. The typical solution is to select a sample of possible destination zones. Many analysts select 10-20 zones. This study uses the selected zone and 19 other candidates, for a total of 20.

In the early days of logit destination choice models, the practice was to make this selection randomly from the set of all internal zones. The idea was that random selection would produce a sample that would probably include zones that were fairly realistic candidates as well as those that were unlikely. However, recent research has indicated that a more robust process is to select the candidate zones with recognition of their likelihood of being true alternatives to the chosen zone. This is known as *importance sampling with replacement*, as described in (Bradley, Bowman, & Griesenbeck, 2010) and elsewhere. As they noted:

> *The available alternatives are sampled in a way that allows the probability of being drawn into the sample to be calculated for each drawn alternative. Statistical procedures are then used during model estimation and application to allow the sample to represent the entire set of available alternatives without biasing the results.*

A version of this process was implemented in this project. First, a new employment variable was computed for each zone: the sum of industrial employment plus 50% of non-industrial employment. It was assumed that weighting this variable towards industrial employment would relate more closely to truck travel. For each zone i, a zonal array was calculated as this employment variable divided by the square of the travel time from zone i to each other zone. Zones with no employment were excluded mathematically and zones that were more than 180 minutes from zone i were excluded logically. The resulting statistic was summed for zone i. Then for each destination zone j in the array, the statistic was divided by the sum, producing a value that could be interpreted as a probability:

$$p'_{ij} = \frac{\dfrac{emp*_j}{tt_{ij}^2}}{\sum \dfrac{emp*_j}{tt_{ij}^2}} \qquad (6)$$

where p'_{ij} is the probability of selecting destination j given origin i, emp* is the new employment variable, and tt^2 is the square of the off-peak zone-zone network travel time. These probabilities are sorted in ascending order and a cumulative probability is computed for each zone.

Next, a Monte Carlo process is used to select the alternative zones. A random number is generated and compared to the cumulative probabilities. This is done 19 times. If a duplicate destination zone is selected, another selection is made. The final choice set consists of the actual origin and destination zones and 19 alternative destination zones. For each destination zone, the variables shown in Table 26 are output to the estimation file.

Table 26: Atlanta: Candidate Destination Zone Variables

Variable	Description
ACRES	Total acres in district
TIME	Network travel time from tour origin zone
COUNTY	Census (FIPS) county code
TZONE	Truck zone flag (0/1)
TOTEMP	Total employment
POP	Population
ATYPE	Computed 2010 area type (1-7)
INDUST	Industrial employment (sum of CONST, MFG, TCU, WHOLE)
ACCE30	Employment accessible within 30 min
ACCI30	Industrial employment accessible within 30 min
ACCHH	Household accessibility statistic (HH/time^2)
ACCEMP	Employment accessibility statistic (TOTEMP/time^2)
ACCIND	Industrial employment accessibility statistic (INDEMP/time^2)
DISTCOR	Distance to the nearest cordon station, miles
DISTCBD	Distance to the CBD (zone 16), miles
CONST	Construction employment
MFG	Manufacturing employment
TCU	Transportation, communications, utilities employment
WHOLE	Wholesale employment

Table 27: Birmingham: Candidate Destination Zone Variables

Variable	Description
ACRES	Total acres in district
TIME	Network travel time from tour origin zone
TZONE	Truck zone flag (0/1)
TOTEMP	Total employment
POP	Population
ATYPE	Computed 2010 area type (1-9)
INDUST	Industrial employment
ACCE30	Employment accessible within 30 min
ACCI30	Industrial employment accessible within 30 min
ACCHH	Household accessibility statistic (HH/time^2)
ACCEMP	Employment accessibility statistic (TOTEMP/time^2)
ACCIND	Industrial employment accessibility statistic (INDEMP/time^2)
DISTCOR	Distance to the nearest cordon station, miles
DISTCBD	Distance to the CBD, miles

ALOGIT applies the maximum likelihood estimation technique for estimating coefficients, but it does not automatically identify the best variables to use. Therefore, logit model estimation is a trial-and-error process to identify that set of variables and coefficients that provides the best fit to the data. The criteria for model selection were as follows:

Highest value of the ρ^2 statistic. This is an ALOGIT statistic that is analogous to the r^2 statistic from linear regression analysis. It ranges from 0.0 to 1.0. Higher values are better.

Coefficients should have student's t scores of 1.96 or higher (in absolute value; this provides 95% confidence that the coefficient is statistically different from zero).

The variables should be reasonably related to the choice of destination and have logically correct signs.

- Cross-correlation (double-counting) among variables should be minimized.

The I/I tour model was estimated first. A variety of models was considered, as shown in Table 28. Typically, destination choice models have three types of variables:

Travel time: network time from tour origin to tour destination. In this study, off-peak time is used, on the assumption that truck destination choice is less sensitive to congestion than to other factors. The following logic is applied. Most truck trips are made for the purpose of delivering goods. This reflects a contract between the shipper and receiver. The truck driver is merely fulfilling that prior contract -- he has no control whatsoever over the locations where he is to make his deliveries. He MUST go where the goods are to be delivered, regardless of how congested that location is. Therefore, the truck's destination cannot be conditioned on the level of congestion and it would be inappropriate to use congested travel times in the determination of truck trip patterns. This is fundamentally different from personal travel. People can select their destinations based on congestion level. Sometimes that reflects a longer-term choice, such as for work or school. Sometimes it's a choice that can be made in real time, such as shopping trips. Where congestion enters the picture is in the timing of deliveries. In fact, a major ongoing trend in larger cities is to require truck deliveries in congested areas to be made in off-peak hours, like midnight - 6 am.

Variables describing the *size* of the destination zone. These include various breakdowns of employment. By common convention, the natural logarithm of these variables is used in the utility function (Daly, 1982).

Variables describing the *characteristics* of the destination zone, separate from the size variables. For example, prior research (Kim, 2011; Kim, Park 7 Kim, 2011) has suggested that employment accessibility can have both positive and negative impacts on truck destination choice. The positive effect ("agglomeration") is that truck drivers are more likely to prefer destinations if they are highly accessible. The negative effect ("competition") is that a potential destination that is surrounded by other potential destinations effectively competes with those other adjacent opportunities.

Table 28: Atlanta: I/I Tour Main Destination Choice Models

Run	Variables	Results	rhosq(0)	time coeff
a	first run: time, ln(tot emp)	not great	-0.3510	-0.0297
b	time, ln(non-ind), ln(const), ln(manuf), ln(TCU), ln(whole), ln(other)	much better but TCU sign wrong	0.2818	-0.0184
c	time, ln(non-ind), ln(const), ln(manuf+TCU), ln(whole), ln(other), tzone	Manuf+TCU sign wrong	0.2511	-0.0133
d	time, ln(non-ind), ln(indust), tzone	TZONE has wrong sign	0.2151	-0.0131
e	time, ln(non-ind), ln(indust), urban dummy (atype=1,2)	urb dum helped a bit; sign and t OK (< 0)	0.2540	-0.0107
f	time, ln(non-ind), ln(indust), rural dummy (atype=5,6,7)	rur dum helped a lot; sign and t OK (> 0)	0.3316	-0.0088
g	time, ln(non-ind), ln(indust), urban dummy (AT=1,2), rural dummy (AT=5-7)	combined dummy helped a little; signs OK	0.3386	-0.0087
h	model g + dist to cordon	helped; sign OK (< 0)	0.3761	-0.0210
i	add dist to cbd	helped a tiny bit; sign OK? (< 0); not as good as dist cordon	0.3762	-0.0205
j	model h + acc emp 30	big improvement in rhosq but sign is < 0; competition effect?	0.4641	-0.0162
k	model h + acc ind 30	minor improvement	0.3775	-0.0207
l	model h + emp acc (continuous)	big improvement in rhosq but sign is < 0; competition effect?	0.4799	-0.0154
m	model h + hh acc (continuous)	small improvement; sign > 0	0.3767	-0.0213
n	model l + tzone	small improvement; sign > 0	0.4855	-0.0143
o	model n + pop	medium improvement; sign > 0	0.5089	-0.0151
p	**model o + dev density**	**medium improvement; sign < 0; Urban and Rural signs flipped**	**0.5280**	**-0.0152**
q	model p + bias constants	estimation failed		

Note: model shown in bold was selected.

Table 29: Birmingham: I/I Tour Main Destination Choice Models

Run	Variables	Results	rhosq(0)	time coeff
a	first run: time, Size: ind, non-ind emp	t's, signs OK	-0.0618	-0.0177
b	revise calib file to randomize alt. no. of chosen alt; re-do run a	t's, signs OK	-0.0622	-0.0176
c	model b + bias constants	t's, signs OK	-0.0433	-0.0177
d	model b + truck zone	t's, signs OK	-0.0622	-0.0176
e	model b + urban dummy (atype=1-3)	t OK, sign < 0	-0.0160	-0.0166
f	model e + rural dummy (atype=8,9)	t OK, sign > 0	0.0467	-0.0079
g	model f + add pop to Size	t OK, sign > 0	0.1339	-0.0085
h	model g + distance to cordon	t OK, sign < 0	0.1357	-0.0087
i	model g + distance to CBD	t OK, sign < 0, not as good as distCor	0.1339	-0.0084
j	model h + accemp30	t OK, sign < 0 (competition effect?)	0.1703	-0.0077
k	model h + empacc	t OK, sign < 0 (competition effect?); rho-sq not as good as model j	0.1533	-0.0100
l	**model j + development density**	**t OK, sign < 0, big improvement in rho-sq**	**0.1996**	**-0.0094**

Note: model shown in bold was selected.

The final Atlanta I/I tour main destination choice model estimation report is shown in Table 30. In this model, the most significant variables (based on the "T" Ratios) are travel time, truck zone flag, employment accessibility, and development density. Travel time has a negative coefficient, as it should. The coefficients on employment accessibility and development density are negative, which indicates a competitive effect. On the other hand, the urban dummy is positive and the rural dummy is negative, which works slightly in the opposite direction. Distance to the cordon has a negative coefficient, meaning that zones close to the cordon are less likely to be truck destinations (which is consistent with the rural coefficient).

Table 30: Atlanta: I/I Tour Main Destination Choice Selected Model

```
Hague Consulting Group                                                  Page 18
ALOGIT Version 3F/2 (602)                                  17:09:49 on 11 Nov 13

       Ga Tech Truck Tour Based Model: ARC: Tour Destination Choice I/I

Convergence achieved after 12 iterations
Analysis is based on 55606 observations
Likelihood with Zero Coefficients =-166580.6888
Likelihood with Constants only    =        .0000
Initial Likelihood                =-115885.9477
Final value of Likelihood         = -78620.4582
   "Rho-Squared" w.r.t. Zero      =  .5280
   "Rho-Squared" w.r.t. Constants =  .0000

ESTIMATES OBTAINED AT ITERATION 12

Likelihood = -78620.4582

             time      tzone      urban      rural     distcor     accemp

 Estimate  -.1517E-01  .6466      .1547     -.3832E-01 -.3733E-02 -.2671E-03
Std. Error   .360E-03   .162E-01   .631E-01   .176E-01   .874E-03   .309E-05
"T" Ratio  -42.1       40.0        2.5       -2.2       -4.3      -86.6

           devdens    nonIndEmp  indEmp      pop

 Estimate  -.3853E-03  1.000      3.879      2.362
Std. Error   .558E-05   .000       .157       .158
"T" Ratio  -69.0         .0       24.8       15.0
```

Note: "Estimate" refers to the coefficient value.

Estimation of the destination choice model for X/I tours was done in exactly the same manner. This model was estimated following the I/I model. Table 31 shows the candidate models and Table 32 shows the final estimation report. The results are consistent with those of the I/I model except that travel time now has a positive coefficient. This makes sense given that the origins are all external stations; it means that the destinations are more likely to be in the interior of the modelled region (downtown) than in outlying areas. This is consistent with the negative coefficient on DISTCBD.

Table 31: Atlanta: X/I Tour Main Destination Choice Models

Run	Variables	Results	rhosq(0)	time coeff
a	time, ln(non-ind), ln(indust), urban (AT=1,2), rural (AT=5-7); dist to cordon; emp acc; tzone	sign on time > 0; dist to cordon duplicates time	0.0726	0.0164
b	time, ln(non-ind), ln(indust), urban (AT=1,2), rural (AT=5-7); dist to cbd; emp acc; tzone	sign on time > 0	0.0778	0.0160
c	time, ln(non-ind), ln(indust), urban (AT=1,2), rural (AT=5-7); emp acc; tzone	sign on time > 0	0.0711	0.0167
d	time, ln(non-ind), ln(indust), urban (AT=1,2), rural (AT=5-7); emp acc; tzone, time^2	sign on time > 0	0.0729	0.0343
e	ln(non-ind), ln(const), ln(manuf), ln(TCU), ln(whole), urban (AT=1,2), rural (AT=5-7); emp acc; tzone	disaggregating empl didn't help	0.0551	
f	ln(non-ind), ln(indust), urban (AT=1,2), rural (AT=5-7); emp acc; tzone; suburb (AT=3,4)	failed run	0.0392	
g	ln(non-ind), ln(indust), urban (AT=1,2), rural (AT=5-7); emp acc; tzone; hh acc	didn't help much	0.0395	
h	model c + pop on size	pop helped a lot, sign OK (> 0)	0.1222	0.0154
i	model c + pop on size, dist to cbd	dist to cbd helped a little; sign < 0	0.1234	0.0152
j	**model c + pop on size, dist to cbd, dev density**	**devdens helped a lot; sign < 0; signs on Urban and Rural are flipped**	**0.1722**	**0.0139**

Table 32: Atlanta: X/I Tour Main Destination Choice Selected Model

```
Hague Consulting Group                                                       Page 18
ALOGIT Version 3F/2 (602)                                       16:55:49 on 11 Nov 13

       Ga Tech Truck Tour Based Model: ARC: Tour Destination Choice X/I

Convergence achieved after   8 iterations

Analysis is based on 25410 observations

Likelihood with Zero Coefficients = -76121.5571

Likelihood with Constants only    =       .0000

Initial Likelihood                = -90904.4278

Final value of Likelihood         = -63012.7172

   "Rho-Squared" w.r.t. Zero      =  .1722

   "Rho-Squared" w.r.t. Constants =  .0000

ESTIMATES OBTAINED AT ITERATION   8

Likelihood = -63012.7172

             time       tzone      urban      rural      distcbd     accemp

 Estimate   .1390E-01  .9380      .5914     -.1604      -.2834E-01 -.2819E-03
Std. Error   .264E-03   .194E-01   .679E-01   .219E-01   .618E-03    .384E-05
"T" Ratio   52.6       48.5        8.7       -7.3       -45.9      -73.3

           devdens    nonIndEmp  indEmp      pop

 Estimate  -.5027E-03  1.000      3.551      2.217
Std. Error   .686E-05   .000       .158       .159
"T" Ratio  -73.3          .0      22.4       14.0
```

The final Birmingham I/I tour main destination choice model estimation report is shown in Table 33. In this model, the most significant variables (based on the “T” Ratios) are travel time, truck zone flag, area type dummies, distance to the cordon, employment accessibility, and development density. Travel time has a negative coefficient, as it should. The coefficients on employment accessibility and development density are negative, which indicates a competitive effect. The Urban dummy is negative and the rural dummy is positive, which works in the same direction. Distance to the cordon has a positive coefficient, meaning that zones close to the cordon are more likely to be truck destinations (which is consistent with the rural coefficient).

Table 33: Birmingham: I/I Tour Main Destination Choice Selected Model

```
Hague Consulting Group                                                   Page 16
ALOGIT Version 3F/2 (602)                                     17:20:34 on 17 Mar 14

    Ga Tech/UAB Truck Tour Based Model: Birmingham Tour Destination Choice I/I


Convergence achieved after   8 iterations

Analysis is based on 25766 observations


Likelihood with Zero Coefficients = -77188.0378

Likelihood with Constants only    = -75807.5521

Initial Likelihood                = -79057.0161

Final value of Likelihood         = -61784.8794


   "Rho-Squared" w.r.t. Zero      =  .1996

   "Rho-Squared" w.r.t. Constants =  .1850

ESTIMATES OBTAINED AT ITERATION  8

Likelihood = -61784.8794

             time       tzone      urban      rural     distcor    accemp30

 Estimate  -.9364E-02  .5070     -.8760      .9929      .1962E-01 -.8908E-06
Std. Error   .483E-03   .196E-01   .420E-01   .246E-01   .194E-02   .145E-07
"T" Ratio  -19.4       25.9      -20.9       40.4       10.1      -61.3


           devdens    nonIndEmp   indEmp      pop

 Estimate  -.2729E-03  1.000      4.092      1.656
Std. Error   .508E-05   .000       .196       .188
"T" Ratio  -53.8         .0       20.9        8.8
```

Note: “Estimate” refers to the coefficient value.

Estimation of the destination choice model for X/I tours was done in exactly the same manner. This model was estimated following the I/I model. Table 34 shows the candidate models and Table 35 shows the final estimation report. The results are consistent with those of the I/I model except that travel time was dropped from the equation because it consistently had a positive coefficient. This would mean that inbound external trucks prefer to go to the furthest internal destination possible, which seems illogical. Distance to the cordon now has a positive coefficient. This makes sense given that the origins are all external stations; it means that the destinations are more likely to be in the interior of the modelled region (downtown) than in outlying areas. This is also consistent with the negative coefficient on DISTCBD. The density and accessibility effects are similar to the I/I model.

Table 34: Birmingham: X/I Tour Main Destination Choice Models

Run	Variables	Results	rhosq(0)	time coeff
a	start with I/I model j	sign on time > 0	0.2514	0.0432
b	model a w/o distcor	run failed		
c	model a w/o time	t's and signs OK but rho-sq not as good	0.1714	
d	model b + distcbd	t's and signs OK but rho-sq better; sign on time > 0	0.2949	0.0363
e	**tzone, urban, rural, distcbd, distcor, accemp30, dev dens**	**t's and signs OK**	**0.2594**	**0**

Table 35: Birmingham: X/I Tour Main Destination Choice Selected Model

```
Hague Consulting Group                                                   Page 16
ALOGIT Version 3F/2 (602)                                   9:55:29 on 28 Apr 14

    Ga Tech/UAB Truck Tour Based Model: Birmingham Tour Destination Choice X/I


Convergence achieved after   9 iterations

Analysis is based on 22139 observations


Likelihood with Zero Coefficients = -66322.5168

Likelihood with Constants only    = -66215.9570

Initial Likelihood                = -70123.6960


Final value of Likelihood         = -49120.4160

   "Rho-Squared" w.r.t. Zero      =  .2594

   "Rho-Squared" w.r.t. Constants =  .2582


ESTIMATES OBTAINED AT ITERATION  9

Likelihood = -49120.4160

            tzone      urban      rural     distcor    distcbd    accemp30

 Estimate   1.079     -1.248      1.894     -.7333E-01 -.1595     -.1171E-05
Std. Error   .215E-01   .485E-01   .266E-01   .223E-02   .166E-02   .162E-07
"T" Ratio   50.1      -25.7       71.2      -32.8      -95.8      -72.1


           devdens    nonIndEmp   indEmp      pop

 Estimate  -.2972E-03  1.000      2.825     -.6592
Std. Error   .616E-05   .000       .985E-01   .997E-01
"T" Ratio  -48.2         .0       28.7        -6.6
```

iii. I/X Model

As noted above, the tour destination choice model for I/X tours is different. Initially, the research team attempted to estimate this model in ALOGIT in the same manner as for the I/I and X/I tours. However, none of the candidate models was suitable. Generally, the coefficients did not have logical signs, especially on the key external station size variable: volume. This is probably due to inaccurate geocoding of the external GPS records to ARC's external stations.

Instead, an I/X logit model was synthesized using a very simple utility equation:

Atlanta: $U = -0.003 * time + 0.79 * \ln(cordon\ volume)$ (7A)

Birmingham: $U = -0.003 * time + 1.0 * \ln(cordon\ volume)$ (7B)

This says that the likelihood of a tour from zone I being destined to external station J is based on the travel time from I to J and the natural log of the daily truck count at station J, which seems logical. An initial coefficient on time was borrowed from the I/I model and adjusted during assignment validation. Also, the coefficient on ln (cordon volume) was adjusted during assignment validation so as to produce a more accurate total truck volume at the external stations.

iv. Validation

The model was applied to the estimated set of tour origins. Initial examination of the average tour time (network time directly from tour origin to tour main destination, excluding intermediate stops) for I/I tours indicated that the average estimated tour time was too long and there were far too few intrazonal tours. The solution was to reduce the algebraic values of the `time` coefficient (make it more negative for I/I and external tours). The I/I time coefficient was changed to -0.0675 and the external time coefficient was changed to -0.003 for Atlanta model. As for the Birmingham model, the I/I time coefficient was changed to -0.044. Also, an intrazonal dummy variable was added to estimate a higher share of intrazonal (round-trip) tours, with a coefficient of 5.25. For X/I tours, the estimated tour time was too short. This was solved by adding a *small* positive coefficient on travel time, which is what most of the X/I calibration runs had suggested. These changes produced a reasonably close comparison of observed and estimated average tour travel time, as shown in Table 36.

Table 36: Atlanta: Tour O/D Average Time

Tour Type	Observed	Estimated
I/I	34.89	35.12
External (I/X + X/I)	73.97	74.30

Table 37: Birmingham: Tour O/D Average Time

Tour Type	Observed	Estimated
I/I	17.02	15.91
External (I/X + X/I)	58.95	51.92

Table 38 shows a comparison of observed (GPS) and estimated I/I tour patterns. The correlation between these two datasets is 0.84 (Atlanta) and 0.78 (Birmingham).

As noted above, the coefficient on ln (cordon volume) was calculated so that the sum of the estimated I/X +X/I tours (plus twice the X/X trips) would equal the total cordon trips at each external station, this is a basic input to the model. The correlation between estimated and observed cordon volumes is 0.997 (Atlanta).

Table 38: Atlanta: I/I Tour Patterns

Observed

Destination District

		1	2	3	4	5	6	Total
O	1 Atlanta	21651	3484	2940	3525	3143	0	34743
r	2 North	4970	9610	2593	2193	1806	0	21172
i	3 East	3680	2025	11197	1669	1518	0	20089
g	4 South	4489	2309	1743	10378	1545	0	20464
i	5 West	3348	1581	1258	1447	7322	0	14956
n	6 External	0	0	0	0	0	0	0
	Total	38138	19009	19731	19212	15334	0	111424

Estimated

Destination District

		1	2	3	4	5	6	Total
O	1 Atlanta	16443	8128	8962	5666	3579	0	42778
r	2 North	3977	8579	2103	701	1725	0	17085
i	3 East	4035	2100	11302	974	397	0	18808
g	4 South	3522	981	1374	5400	1090	0	12367
i	5 West	1054	1000	244	550	2040	0	4888
n	6 External	0	0	0	0	0	0	0
	Total	29031	20788	23985	13291	8831	0	95926

Table 39: Birmingham: I/I Tour Patterns

Observed

		1	2	3	4	5	6	7	Total
O	1 Central	4265	444	70	55	1365	299	0	6498
r	2 North	428	1274	29	43	602	128	0	2504
i	3 East	105	70	206	28	279	41	0	729
g	4 South	91	85	42	609	435	133	0	1395
i	5 West	1560	756	150	148	8970	594	0	12178
n	6 Shelby	340	176	30	61	761	1934	0	3302
	7 External	0	0	0	0	0	0	0	0
	Total	6789	2805	527	944	12412	3129	0	26606

Estimated

		1	2	3	4	5	6	7	Total
O	1 Central	3385	1022	410	511	2051	744	0	8123
r	2 North	85	707	32	22	145	54	0	1045
i	3 East	45	41	212	18	38	22	0	376
g	4 South	82	56	43	349	166	170	0	866
i	5 West	282	216	81	125	2444	192	0	3340
n	6 Shelby	35	37	14	54	75	994	0	1209
	7 External	0	0	0	0	0	0	0	0
	Total	3914	2079	792	1079	4919	2176	0	14959

Intermediate Stop Models

i. Model Structure

The intermediate stop model is patterned after the Brunswick model (Allen, 2011). Two decisions are modelled: 1) how many stops to make, and 2) the locations (zones) of those stops. For model #1, the first step is to analyze the observed number of stops. Figure 29 shows the distribution of tours by type and number of stops. Internal tours have about twice as many stops (mean = 3.00 (Atlanta); 2.26 (Birmingham)) than external tours (mean = 1.43 (Atlanta); 0.96 (Birmingham)). For all tours (excluding X/X), 34.4% (Atlanta) and 46.7% (Birmingham) made no stops. This confirms the value of using the tour-based approach for trucks. Examination of the data in Figure 29 and Figure 30 indicate that 91.3% of Atlanta tours and 95.1% of Birmingham tours made 0 – 6 stops. Therefore, six stops was chosen as the highest number of stops to model.

Model #2 is developed independently of model #1. That is, once the number of stops is estimated, a separate process is used to identify where those stops are. This stop location model is similar to the main destination choice model and is a simplified version of other such models. Some other models attempt to estimate the sequence of stops or impose some kind of elapsed time constraint or other techniques to represent the locus of the tour. The model proposed here takes a much simpler approach (similar to Brunswick) and models each stop independently. For example, on a tour with three intermediate stops, the location of stop 2 is not conditioned on the location of stop 1 and the location of stop 3 is not conditioned on the location of stop 2. All three stops are estimated based on the tour origin and main destination zones and are otherwise assumed to be independent of each other. This assumption *greatly* simplifies the process of identifying stop locations. In all other respects, the stop location model uses the same procedures as the main destination choice model.

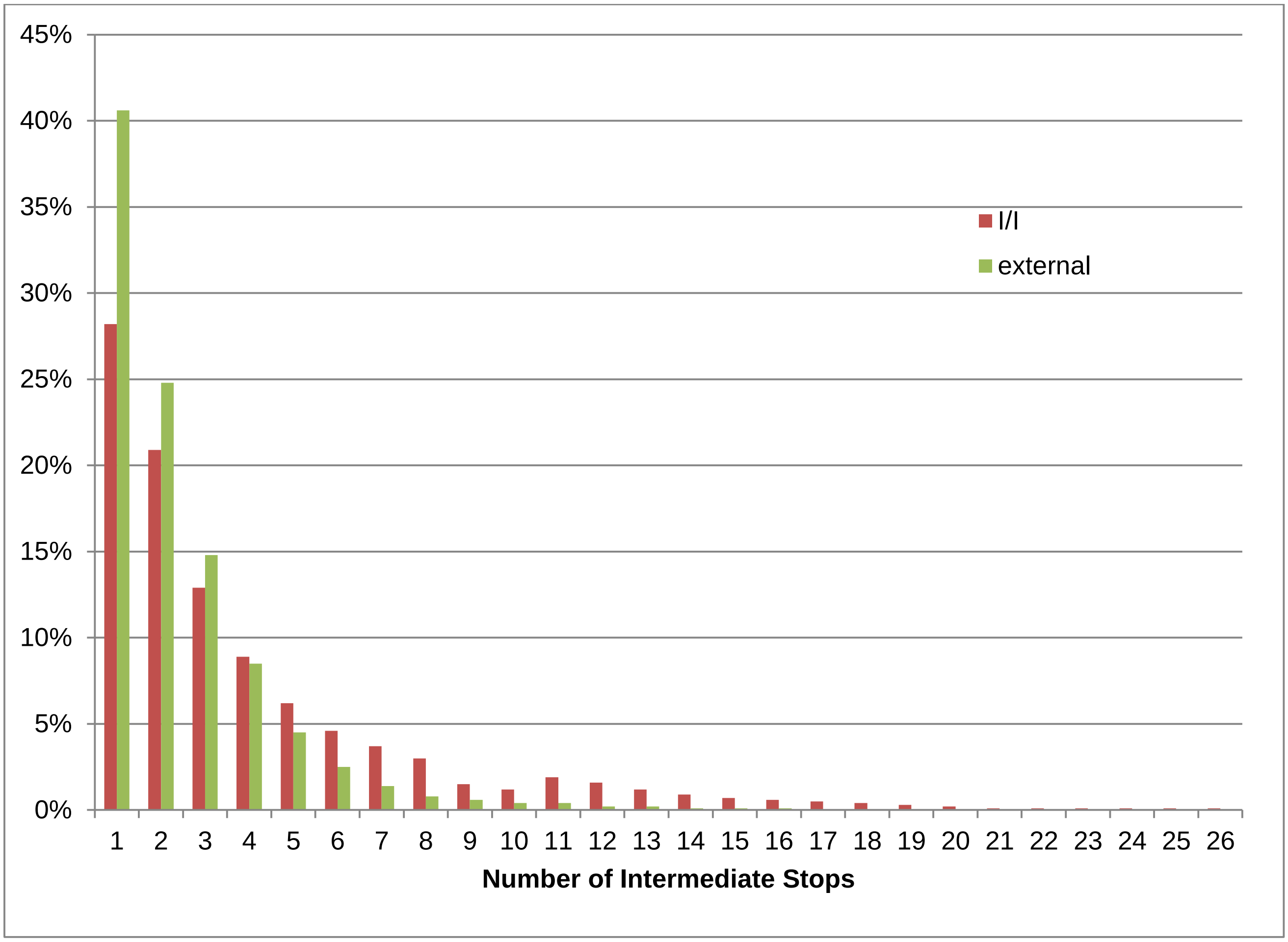


Figure 29: Atlanta Distribution of Intermediate Stops

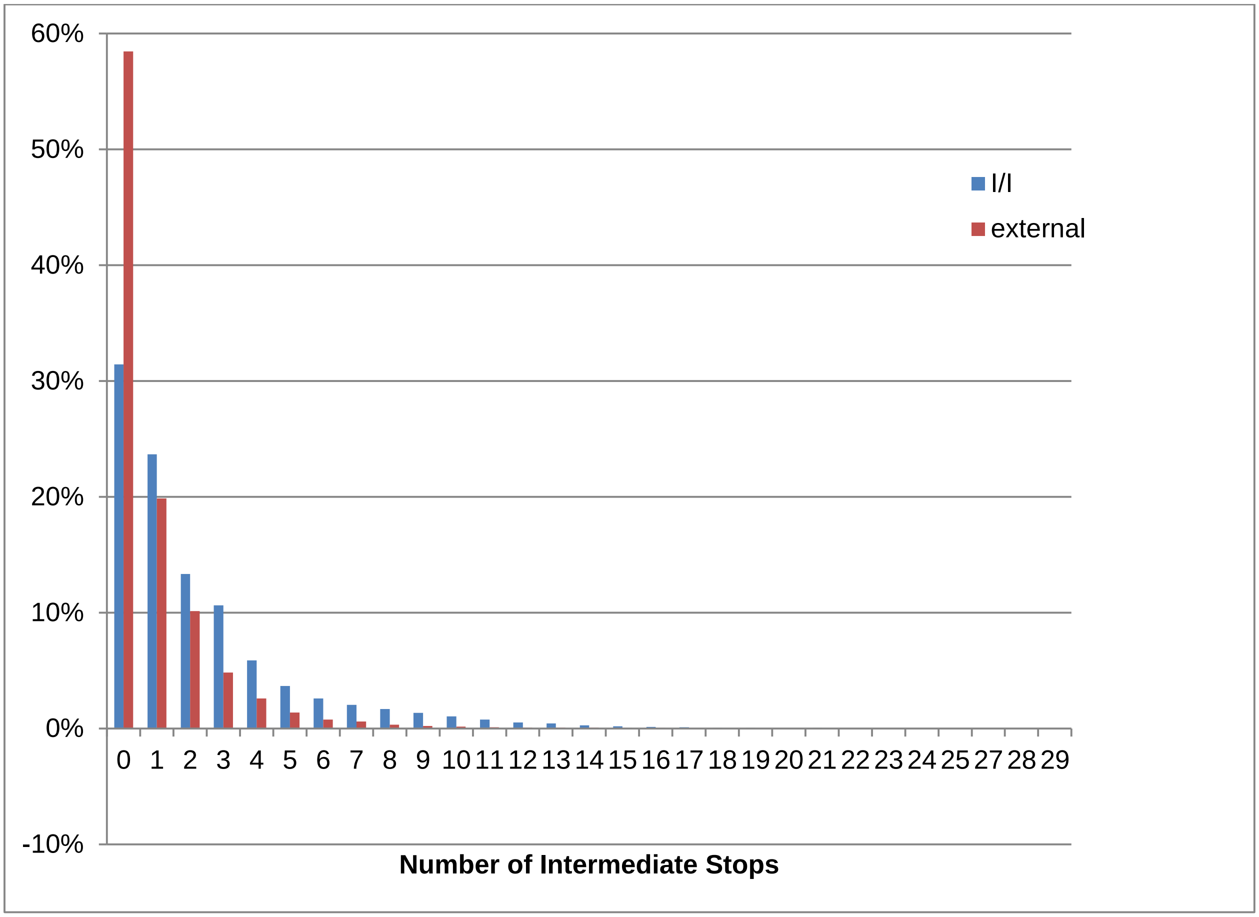


Figure 30: Birmingham Distribution of Intermediate Stops

ii. Estimation: Number of Stops

The available ARC and RPCGB network and zonal data and newly generated statistics available for destination choice estimation are the same as described in the Tour Generation section (ii Available Model Data and iii Generated Data). As with the other models, a Cube script was written to prepare the data for the estimation process.

For the intermediate stop model, only I/I tour records were used, because only those records have complete information on the tour origin and main destination zones. In addition to the independent variables listed in Table 19 and Table 21, the models included extra candidate variables, similar to those used in Brunswick. These included the following:

- Industrial employment and total employment within a circle of 0.5, 1.0, 2.0, and 3.0 miles of the origin and destination zones (16 separate variables). The idea is that if there is much employment near the tour origin or destination zones, there might be fewer intermediate stops.
- Industrial employment, industrial employment density, and total employment within a circle whose diameter is the straight-line distance between the tour origin and destination zone centroids, centered on a point midway between those two centroids.
- Industrial employment and total employment within a rectangle whose length is the straight-line distance between the tour origin and destination zone centroids and whose width is 30% of that distance.

In these calculations, the inclusion of a zone's employment in each variable's calculation is based on the location of the zone's centroid; it does not use a GIS-based calculation of the zone boundaries. The calibration file consisted of the tour origin and main destination zones, the number of stops, several items from Table 19 and Table 21, and the items described above, for the origin and destination zones.

For this model, a different approach was used in Birmingham than in Atlanta. In Atlanta, one model was estimated for all tour types (I/I, external). Further review in Birmingham suggested that a different approach would be more productive. In Birmingham, the number of stops model was expanded into four separate models:

1. I/I tours where the tour began and ended in the same zone (i.e., a complete round-trip tour)
2. I/I tours where the tour began in one zone and ended in another
3. I/X tours
4. X/I tours

Each of these models was estimated in the same manner. As with the main destination choice model, ALOGIT was used to estimate a multinomial model with seven choices of the number of intermediate stops: 0, 1, 2, 3, 4, 5, 6+. The same criteria described above were used to evaluate the different models, which are listed in Table 40 (Atlanta) and Table 41 (Birmingham). The final model estimation reports are shown in Table 42(Atlanta) and Table 43 (Birmingham). The model includes bias coefficients on all alternatives except zero tours, for which the disutility is defined as zero.

Table 40: Atlanta: Number of Intermediate Stops Models

Run	Variables	Results	rhosq(0)	rhosq(C)
a	first run: bias coeffs only		0.1482	0.0000
b	add time	helped a little	0.1502	0.0023
c	add origin AT	helped a little	0.1508	0.0031
d	add dest AT	helped a little	0.1512	0.0035
e	try ind emp within 0.5 mi of origin	didn't help; sign OK (< 0)	0.1512	0.0035
f	try ind emp within 1.0 mi of origin	no help; poor t; sign > 0	0.1512	0.0035
g	try ind emp within 2.0 mi of origin	no help; t OK; sign > 0	0.1512	0.0035
h	try ind emp within 3.0 mi of origin	some help; good t; sign > 0	0.1514	0.0038
i	try tot emp within 0.5 mi of origin	no help; t OK; sign < 0	0.1512	0.0035
j	try tot emp within 1.0 mi of origin	no help; poor t; sign > 0	0.1512	0.0035
k	try tot emp within 2.0 mi of origin	no help; t OK; sign > 0	0.1512	0.0035
l	try tot emp within 3.0 mi of origin	some help; good t; sign > 0; not quite as good as run h	0.1513	0.0037
m	try ind emp within 0.5 mi of destination	some help; good t; sign < 0	0.1515	0.0039
n	try ind emp within 1.0 mi of destination	some help; good t; sign < 0	0.1514	0.0037
o	try ind emp within 2.0 mi of destination	no help; barely good t; sign < 0	0.1512	0.0035
p	try ind emp within 3.0 mi of destination	no help; bad t; sign > 0	0.1512	0.0035
q	try tot emp within 0.5 mi of destination	some help; good t; sign < 0	0.1515	0.0038
r	try tot emp within 1.0 mi of destination	some help; good t; sign < 0	0.1513	0.0036
s	try tot emp within 2.0 mi of destination	no help; barely good t; sign < 0	0.1512	0.0035
t	try tot emp within 3.0 mi of destination	no help; bad t	0.1512	0.0035
u	try ind empl in O-D circle	some help; good t; sign < 0	0.1515	0.0039
v	try tot empl in O-D circle	same as model u	0.1515	0.0039
w	try ind empl in O-D rectangle	similar to model u; not quite as good	0.1515	0.0038
x	try tot empl in O-D rectangle	similar to model u; not quite as good	0.1514	0.0038
y	try ind emp density in O-D circle	no help	0.1512	0.0035
z	try tot emp in orig zone	no help	0.1512	0.0035
aa	try tot emp in dest zone	some help; good t; sign < 0	0.1515	0.0038
ab	try ind emp in orig zone	no help; barely good t; sign < 0	0.1512	0.0035
ac	try ind emp in dest zone	similar to model u	0.1515	0.0039
ad	try pop in orig zone	no help; bad t	0.1512	0.0035
ae	try pop in dest zone	no help; t OK	0.1512	0.0035
af	combine models d, h, ac	helped a little	0.1518	0.0042
ag	model af + short trip dummy (15 min)	helped a little; sign < 0 (good)	0.1526	0.0052
ah	**model ag +long trip dummy (45 min)**	**helped a little; sign > 0 (good)**	**0.1527**	**0.0053**

Note: model shown in bold was selected.

Table 41: Birmingham: Number of Intermediate Stops Models

Run	Variables	Results	rhosq(0)	rhosq(C)
Model 1: I/I tours where tour starts and ends in same zone				
a	bias	t's OK, signs < 0	0.0701	0
b	bias, atype	t OK, sign < 0	0.0702	0.0001
c	bias, atype, emp	t low	0.0702	0.0001
d	bias, atype, ln(emp)	t low	0.0702	0.0001
e	bias, atype, pop	t OK, sign > 0	0.0728	0.0029
f	bias, atype, ln(pop)	t OK, sign > 0, not as good as pop	0.0708	0.0016
g	bias, atype, pop, ind	t low	0.0720	0.0029
h	bias, atype, pop, ind emp 3 mi from zone	t marginal	0.0721	0.0029
i	bias, atype, pop, tot emp 3 mi from zone	t OK, sign > 0, zonal AT drops out	0.0728	0.0037
j	bias, pop, tot emp 3 mi from zone	t's, signs OK	0.0728	0.0037
k	bias, pop, tot emp 2 mi from zone	t's, signs OK, a little better	0.0736	0.0046
l	bias, pop, tot emp 1 mi from zone	t's, signs OK, a little worse	0.0728	0.0029
m	bias, pop, ind emp 2 mi from zone	t's, signs OK, similar to model k	0.0740	0.0042
n	bias, pop, tot emp 2 mi from zone, fix problem with ln(0) pop zones	t's, signs OK	0.0741	0.0043
o	**bias, pop, tot emp 3 mi from zone**	**t's, signs OK (not as good as model n, but other models use 3 mi variable, so easier to apply)**	**0.0735**	**0.0037**
Model 2: I/I interzonal tours				
a	bias coeffs only	t's OK	0.2422	0.0000
b	bias, time	t OK, sign > 0	0.2427	0.0007
c	bias, time, origin AT	t OK, sign < 0	0.2437	0.0021
d	bias, time, orig AT, dest AT	t OK, sign < 0	0.2441	0.0026
e	bias, time, orig AT, dest AT, ind emp within 3 mi of origin	t OK, sign > 0	0.2444	0.0030
f	bias, time, orig AT, dest AT, tot emp within 3 mi of origin	t OK, sign > 0, a little better than run e	0.2446	0.0032
g	bias, time, orig AT, dest AT, tot emp within 2 mi of origin	t low	0.2441	0.0026
h	bias, time, orig AT, dest AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest	t OK, sign > 0	0.2447	0.0033
i	bias, time, orig AT, dest AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest; ind emp in OD circle	t OK, sign < 0 (illogical)	0.2449	0.0036
j	bias, time, orig AT, dest AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest; tot emp in OD circle	t OK, sign < 0 (illogical)	0.2449	0.0036
k	bias, time, orig AT, dest AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, orig pop	t low	0.2447	0.0033
l	bias, time, orig AT, dest AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, dest pop	t low	0.2447	0.0033
m	bias, time, orig AT, dest AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, short trip (<15)	t OK, sign < 0, dest AT drops out	0.2452	0.0040
n	bias, time, orig AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, short trip (<15), long trip (>45)	t low	0.2452	0.0040
o	bias, time, orig AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, short trip (<15), dest Rural	t marginal, sign < 0	0.2452	0.0041
p	bias, time, orig AT, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, short trip (<15), dest Urban	t OK, sign < 0	0.2453	0.0042
q	**bias, time, orig Urban, tot emp w/in 3 mi of orig, tot emp w/in 3 mi of dest, short trip (<15), dest Urban**	**t OK, sign < 0**	**0.2453**	**0.0043**
Model 3: I/X tours				
a	bias, time	t OK, sign < 0 (illogical)	0.3460	0.0028
b	bias, origUrban	t marginal, sign > 0	0.3443	0.0001
c	bias, origRural	t OK, sign < 0	0.3450	0.0012
d	bias, origRural, tot emp w/in 3 mi of origin	t good, sign > 0, origRural drops out	0.3477	0.0053
e	bias, tot emp w/in 2 mi of origin, drop origRural	t good, sign > 0, a little better than model d	0.3464	0.0033
f	bias, tot emp w/in 1 mi of origin	t good, sign > 0, not as good as model e	0.3461	0.0028
g	bias, ind emp w/in 3 mi of origin	t good, sign > 0, better than model e	0.3489	0.0072
h	bias, ind emp w/in 2 mi of origin	t good, sign > 0, not as good as model g	0.3484	0.0063
i	bias, ind emp w/in 3 mi of origin, orig zone pop	t OK, sign < 0	0.3490	0.0073
j	bias, ind emp w/in 3 mi of origin, orig zone pop, short trip dummy (<15)	t marginal, sign > 0	0.3491	0.0074
k	bias, ind emp w/in 3 mi of origin, orig zone pop, long trip dummy (>45)	t good, sign < 0 (illogical); orig pop drops out	0.3499	0.0086
l	bias, ind emp w/in 3 mi of origin, origin zone pop, time	t good, sign < 0 (now OK); orig pop drops out	0.3505	0.0095
m	**bias, ind emp w/in 3 mi of origin, time**	**t's OK**	**0.3505**	**0.0095**
Model 4: X/I tours				
a	bias, time	t OK, sign > 0 (different from I/X, but acceptable)	0.3536	0.0008
b	bias, time, tot emp w/in 3 mi from dest	t good, sign > 0	0.3564	0.0052
c	bias, time, tot emp w/in 1 mi from dest	t good, sign > 0, not as good as model b	0.3553	0.0035
d	bias, time, ind emp w/in 3 mi from dest	t good, sign > 0, slightly better than model b	0.3564	0.0052
e	bias, time, ind emp w/in 3 mi from dest, dest pop	t OK, sign < 0	0.3566	0.0055
f	**bias, time, ind emp w/in 3 mi from dest, dest pop, dest Urban**	**t OK, sign < 0**	**0.3567**	**0.0056**

Note: models shown in bold were selected.

As for the results of the Atlanta model, the number of stops increases as the tour O-D time increases and even more if that time exceeds 45 min (the `longtrip` dummy variable), which is very logical. The number of stops also increases with increasing industrial employment within 3 miles of the origin zone, but the logic of this is less clear. The number of stops decreases with reduced density at either end of the tour (i.e., increasing values of `origAT` and `destAT`). The number of stops decreases if the tour O-D distance is very short (under 15 min) and with increasing industrial employment in the tour destination zone.

Table 42: Atlanta: Number of Intermediate Stops Selected Model

```
Hague Consulting Group                                                Page  6
ALOGIT Version 3F/2 (602)                                  11:58:34 on 21 Nov 13

       Ga Tech Truck Tour Based Model: ARC: Number of Intermediate Stops

Convergence achieved after   5 iterations

Analysis is based on 78795 observations

Likelihood with Zero Coefficients =-153327.9902

Likelihood with Constants only    =-130605.7713

Initial Likelihood                =-153327.9902

Final value of Likelihood         =-129918.5142

   "Rho-Squared" w.r.t. Zero      =  .1527

   "Rho-Squared" w.r.t. Constants =  .0053

ESTIMATES OBTAINED AT ITERATION  5

Likelihood =-129918.5142

            bias1      bias2      bias3      bias4      bias5      bias6

 Estimate  -.1186     -.5151     -1.065     -1.499     -1.924     -.7177
Std. Error   .588E-01   .591E-01   .596E-01   .604E-01   .615E-01   .592E-01
"T" Ratio   -2.0       -8.7       -17.9      -24.8      -31.3      -12.1

             time       origAT     destAT     orind30    dsindemp   shorttrp

 Estimate   .4170E-02 -.6048E-01 -.8520E-01  .8661E-05 -.5848E-04 -.4471
Std. Error   .574E-03   .743E-02   .724E-02   .923E-06   .492E-05   .269E-01
"T" Ratio    7.3       -8.1       -11.8        9.4      -11.9      -16.6

            longtrip
  Estimate   .1239
Std. Error   .274E-01
"T" Ratio    4.5
```

The results of the four models of Birmingham case were mixed. Travel time was significant in models #2 - #4, but had a negative coefficient in #3, meaning that a shorter tour had more stops. It's not clear if that is illogical. Model #1 is inherently difficult to estimate, because the tour began and ended in the same zone. No effort was made to analyze other stop locations, so the amount of data available to the logit estimation was limited. For models #2 - #4, if the tour origin or destination zone had more activity (total employment, industrial employment, or population), there were more stops. If the tour destination was in an Urban zone, there were fewer stops. For all models, the bias coefficients were relatively important and the $\rho^2(c)$ values were low, indicating that the independent variables did not explain a lot of the variation in number of stops.

Table 43: Birmingham: Number of Intermediate Stops Selected Models

Model #1 (I/I, intrazonal)

```
Hague Consulting Group                                                  Page  4
ALOGIT Version 3F/2 (602)                                  9:46:10 on 18 Apr 14

     Ga Tech/UAB Truck Tour Based Model: BMH: Number of Intermediate Stops #1


Convergence achieved after   4 iterations

Analysis is based on  9831 observations


Likelihood with Zero Coefficients = -17614.7873

Likelihood with Constants only    = -16380.0565

Initial Likelihood                = -17614.7873


Final value of Likelihood         = -16320.1921


   "Rho-Squared" w.r.t. Zero      =  .0735

   "Rho-Squared" w.r.t. Constants =  .0037

ESTIMATES OBTAINED AT ITERATION   4

Likelihood = -16320.1921

            bias2      bias3      bias4      bias5      bias6     ortot30

 Estimate  -1.166     -.9718     -1.607     -2.081     -.8485      .3705E-05
```

```
Std. Error   .481E-01   .468E-01   .519E-01   .578E-01   .460E-01   .626E-06
"T" Ratio  -24.3      -20.8      -31.0      -36.0      -18.4        5.9

           origPop

 Estimate   .2481E-03
Std. Error   .272E-04
"T" Ratio    9.1
```

Model #2 (I/I, interzonal)

```
Hague Consulting Group                                                Page  6
ALOGIT Version 3F/2 (602)                                 16:50:04 on 26 Mar 14

     Ga Tech/UAB Truck Tour Based Model: BMH: Number of Intermediate Stops #2


Convergence achieved after   5 iterations

Analysis is based on 15974 observations


Likelihood with Zero Coefficients = -31083.9687

Likelihood with Constants only    = -23556.8824

Initial Likelihood                = -31083.9687


Final value of Likelihood         = -23455.9780


   "Rho-Squared" w.r.t. Zero      =  .2454

   "Rho-Squared" w.r.t. Constants =  .0043

ESTIMATES OBTAINED AT ITERATION  5

Likelihood = -23455.9780

            bias1      bias2      bias3      bias4      bias5      bias6

 Estimate  -1.292     -1.683     -2.371     -2.900     -3.355     -2.372
Std. Error   .558E-01   .573E-01   .615E-01   .669E-01   .738E-01   .615E-01
"T" Ratio  -23.1      -29.4      -38.6      -43.4      -45.5      -38.6


             time     destUrb    origUrb    ortot30    dstot30    shortDum

 Estimate   .4381E-02 -.2886     -.2893      .6039E-05  .3606E-05 -.2837
Std. Error   .118E-02   .996E-01   .949E-01   .602E-06   .589E-06   .463E-01
"T" Ratio    3.7       -2.9       -3.0       10.0        6.1       -6.1
```

Model #3 (I/X)

```
Hague Consulting Group                                                Page  4
ALOGIT Version 3F/2 (602)                                 15:49:15 on  4 Apr 14

     Ga Tech/UAB Truck Tour Based Model: BMH: Number of Intermediate Stops #3


Convergence achieved after   6 iterations

Analysis is based on 11513 observations


Likelihood with Zero Coefficients = -22403.2635

Likelihood with Constants only    = -14691.3693

Initial Likelihood                = -22403.2635
```

```
Final value of Likelihood         = -14551.3690


   "Rho-Squared" w.r.t. Zero      =  .3505

   "Rho-Squared" w.r.t. Constants =  .0095

ESTIMATES OBTAINED AT ITERATION  6

Likelihood = -14551.3690

            bias1      bias2      bias3      bias4      bias5      bias6

 Estimate  -.9057     -1.565     -2.419     -2.885     -3.439     -2.771
Std. Error   .560E-01   .595E-01   .684E-01   .766E-01   .907E-01   .743E-01
"T" Ratio  -16.2      -26.3      -35.3      -37.7      -37.9      -37.3


             time     orind30

 Estimate  -.6564E-02  .3676E-04
Std. Error   .796E-03   .262E-05
"T" Ratio   -8.2       14.0
```

```
Model #4 (X/I)
Hague Consulting Group                                                   Page  4
ALOGIT Version 3F/2 (602)                                      16:20:23 on  4 Apr 14

     Ga Tech/UAB Truck Tour Based Model: BMH: Number of Intermediate Stops #4


Convergence achieved after   6 iterations

Analysis is based on 22148 observations


Likelihood with Zero Coefficients = -43098.0180

Likelihood with Constants only    = -27881.3097

Initial Likelihood                = -43098.0180


Final value of Likelihood         = -27725.8154


   "Rho-Squared" w.r.t. Zero      =  .3567

   "Rho-Squared" w.r.t. Constants =  .0056

ESTIMATES OBTAINED AT ITERATION  6

Likelihood = -27725.8154

            bias1      bias2      bias3      bias4      bias5      bias6

 Estimate  -1.476     -2.157     -2.845     -3.534     -4.238     -3.513
Std. Error   .459E-01   .482E-01   .526E-01   .605E-01   .740E-01   .602E-01
"T" Ratio  -32.2      -44.7      -54.1      -58.4      -57.3      -58.4

              time     destUrb    dsind30    destPop
 Estimate   .4021E-02 -.2359      .2801E-04 -.5930E-04
Std. Error   .600E-03   .907E-01   .194E-05   .148E-04
"T" Ratio    6.7       -2.6       14.4       -4.0
```

iii. Estimation: Stop Locations

The available ARC and RPCGB network and zonal data and newly generated statistics available for destination choice estimation are the same as described in the Tour Generation section. As with the tour generation model, a Cube script was written to prepare the data for the estimation process.

The estimation data for this model used only the I/I records, since there was insufficient confidence in the accuracy of the external station geocoding of the external tour records. For each I/I tour record with at least one stop, a record was created with the origin zone, main tour destination zone, and one stop zone. So if a tour had three stops, three separate records were created. There are 111,424 I/I tour records, of which 79,869 had at least one stop. This produced 333,899 stop location records. If the tour origin zone or a selected stop zone had no employment, the record was omitted. This resulted in 301,249 usable records. As for Birmingham, there are 26,606 I/I tour records, of which 18,242 had at least one stop. This produced 45,906 stop location records.

As with the main destination choice model, a process must be used to limit the choice of candidate destination zones. The same procedure described above for the main destination choice model to implement importance sampling with replacement was used. It is assumed that in the context of selecting intermediate stop locations, fewer alternative zones would be considered (compared to the selection of the tour main destination zone). Thus, only 10 alternatives were used for estimating this model: the chosen stop zone and nine other selected stop zones.

In addition to the independent data listed in Table 19, three new variables were created to describe the *detour time*. In intermediate stop modelling, detour time is the difference between the network time between tour origin and main destination zones, and the network time for the origin – stop – destination tour. In addition, the origin – stop and stop – destination travel times were output to the estimation file.

The candidate models for Atlanta are listed in Table 44. The final model, shown in Table 45, has reasonable variables, logical coefficient signs, and good t scores. The coefficients seem reasonable:

- The `detour` variable is very strong and the negative coefficient means that truck drivers try to minimize their detour time, which seems reasonable. In addition, the positive `shortDum` variable (1 if the detour time is under 5 min) gives an additional boost to zones with a very short detour time.
- The positive `tzone` coefficient means that truck zones are more likely to be stops.
- The positive `atype` coefficient means that less developed zones (higher numerical area type) are more likely to be stops. This may seem counterintuitive, but it could mean that highly developed areas are too congested to be considered as intermediate stops, or it could be the "competitive" effect mentioned above (a zone in a developed area is itself less likely to be selected because it is competing with other nearby developed zones). This effect is supported by the negative coefficient on the number of jobs accessible within 30 min (`accemp30`).
- The size variables are non-industrial employment, industrial employment (more important), and population (not too important).

Table 44: Atlanta: Intermediate Stop Location Models

Run	Variables	Results	rhosq(0)
a	first run: size: non-ind emp, ind emp, pop; detour tm	all signs, t's OK	0.8750
b	add stop AT	AT has a high t; sign > 0	0.8943
c	add truck zone	small improvement; good t; sign > 0	0.8952
d	add acc emp 30	some improvement; good t; sign < 0	0.9063
e	model c + acc ind 30	almost no change; t low but OK; sign > 0	0.8953
f	model c + tot emp acc (continuous function)	estimation failed	
g	model c + ind emp acc (continuous function)	tiny improvement; t OK; sign < 0, which seems illogical	0.8958
h	model c + hh acc (continuous function)	some improvement; good t; sign < 0	0.9011
i	**model d + short detour dummy (< 5 min)**	**some improvement; good t; sign > 0**	**0.9065**
j	model i + dist to CBD	tiny improvement; t OK; sign > 0; t on pop becomes insignificant	0.9070
k	model j + orig-stop time (drop Pop from Size)	estimation failed	
l	model j + stop-dest time	estimation failed	
m	model j + Size = 4 individual elements of industrial employment	not as good; t's and signs OK	0.9017
n	model j + drop Pop from Size	estimation failed	
o	model j + Size = 3 groups of ind emp	estimation failed	
p	model j + Size = 3 different groups of ind emp	OK	0.9016
q	model I + dist to cordon	similar to run j; t on pop is small (1.5)	0.9069
r	model q + drop Pop	estimation failed	

Table 45: Atlanta: Intermediate Stop Location Selected Model

```
     Ga Tech Truck Tour Based Model: ARC: Intermediate Stop Location Model

Convergence achieved after  11 iterations

Analysis is based on301249 observations

Likelihood with Zero Coefficients =-693651.4567

Likelihood with Constants only    =        .0000

Initial Likelihood                = -94544.4092

Final value of Likelihood         = -64886.9670

   "Rho-Squared" w.r.t. Zero      =  .9065

   "Rho-Squared" w.r.t. Constants =  .0000

ESTIMATES OBTAINED AT ITERATION 11

Likelihood = -64886.9670

            detour     tzone      atype     accemp30   shortDum   nonIndEmp

 Estimate  -.7887E-02  .5358      .3254     -.1080E-05  1.742      1.000
Std. Error   .224E-03   .167E-01   .760E-02   .111E-07   .124       .000
"T" Ratio  -35.3       32.0       42.8      -97.5       14.0         .0

            indEmp      pop

 Estimate   1.623     -.2785
Std. Error   .476E-01   .494E-01
"T" Ratio   34.1       -5.6
```

For Birmingham, as with the number of stops models, the estimation of the stop location model was split into two parts: model #1, where the tour begins and ends in the same zone, and model #2, where it doesn't.

The candidate models for Birmingham are listed in Table 46. The final models, shown in Table 47, have reasonable variables, logical coefficient signs, and good t scores. The coefficients seem reasonable:

- The `detour` variable was not useful. This is an odd result that runs counter to theory and the experience in Atlanta. In the round-trip model, the stop-destination time was relevant and in the interzonal model the origin-stop and stop-destination times were relevant, although the origin-stop time had a positive coefficient, which seems odd.
- The positive `tzone` coefficient means that truck zones are more likely to be stops, which makes sense.
- The positive `atype` coefficient means that less developed zones (higher numerical area type) are more likely to be stops. This may seem counterintuitive, but it could mean that highly developed areas are too congested to be considered as intermediate stops, or it could be the "competitive" effect mentioned above (a zone in a developed area is itself less likely to be selected because it is competing with other nearby developed zones). This effect is supported by the negative coefficient on the number of jobs accessible within 30 min (`accemp30`).
- The size variables are non-industrial employment, industrial employment (more important), and population (not too important).
- Distance to the CBD was significant with a positive coefficient, meaning that zones farther from the CBD were more likely to be stops.
- A short trip dummy (origin – stop time < 5 min) was significant with a positive coefficient, meaning that zones very close to the origin are more likely to be stops.

Table 46: Birmingham: Intermediate Stop Location Models

Run	Variables	Results	rhosq(0)
Model 1: I/I tours where tour starts and ends in same zone			
a	first run: size: non-ind emp, ind emp, pop; timeIK	t OK, sign > 0 (illogcal? But maybe OK)	0.2884
b	Size: non-ind emp, ind emp, pop; timeKJ	t OK, sign > 0 (illogcal? But maybe OK)	0.2879
c	Size: non-ind emp, ind emp, pop; timeIK, truck zone	t OK, sign > 0	0.3065
d	Size: non-ind emp, ind emp, pop; timeIK, truck zone, stop AT	t OK, sign > 0	0.3604
e	Size: non-ind emp, ind emp, pop; timeIK, truck zone, stop AT, acc emp 30	t OK, sign < 0	0.4236
f	Size: non-ind emp, ind emp, pop; timeIK, truck zone, stop AT, acc ind 30	t OK, sign < 0, not as good as model e	0.4024
g	Size: non-ind emp, ind emp, pop; timeIK, truck zone, stop AT, acc emp 30, short trip dummy (< 5)	t OK, sign > 0	0.4262
h	model g + dist to CBD	t OK, sign > 0	0.4305
i	model h but replace stop AT with urban (1-3) and rural (8,9) dummies	t's OK, urban sign < 0, rural sign > 0, but not as good as model h	0.4239
j	**Size: non-ind emp, ind emp, pop; timeIK, tzone, stop AT, accemp30, short dum (< 5), long dum (>30)**	**t's OK**	**0.4312**

Run	Variables	Results	rhosq(0)
Model 2: I/I interzonal tours			
a	first run: size: non-ind emp, ind emp; detour time	t OK but sign > 0 (illogical)	0.2420
b	Size: tot emp; detour time	t OK but sign > 0 (illogical)	-0.2227
c	Size: tot emp; timeIK	t OK but sign > 0 (illogical)	-0.1905
d	Size: tot emp; timeKJ	t OK, sign < 0	-0.1992
e	Size: ind emp; timeKJ	t OK, sign < 0	-0.1261
f	Size: ind, non-ind emp; timeKJ	t OK, sign < 0	0.2322
g	Size: ind, non-ind emp; timeKJ, timeIK	t OK, sign IK > 0, may be OK since sign KJ < 0	0.3170
h	Size: ind, non-ind emp; timeKJ, timeIK, truck zone	t OK, sign > 0	0.3172
i	Size: ind, non-ind emp; timeKJ, timeIK, truck zone, stop AT	t OK, sign > 0	0.4175
j	Size: ind, non-ind emp; timeKJ, timeIK, truck zone, stop AT, short detour dummy (< 5 min)	t OK, sign > 0	0.4240
k	model j + add pop to Size	t OK, sign > 0	0.4826
l	model j + add pop to Size; acc emp 30	t OK, sign < 0	0.5308
m	model j + add pop to Size; acc ind 30	t OK, sign < 0, not as good as model l	0.5134
n	model j + add pop to Size; tot emp acc (emp/t^2)	t OK, sign < 0, not as good as model l	0.4931
o	model j + add pop to Size; HH acc	t OK, sign < 0, not as good as model l	0.4998
p	**model j + add pop to Size; acc emp 30, dist to cbd**	**t OK, sign > 0, small improvement**	**0.5309**
q	model j + add pop to Size; acc emp 30, dist to cordon	t low	0.5308

Table 47: Birmingham: Intermediate Stop Location Selected Models

```
Model #1 Round-Trip Tours
Hague Consulting Group                                       Page   9
ALOGIT Version 3F/2 (602)                          10:36:35 on 18 Apr 14

  Ga Tech/UAB Truck Tour Based Model: BMH: Intermediate Stop Location: Intrazonal

Convergence achieved after   8 iterations
Analysis is based on 25796 observations

Likelihood with Zero Coefficients = -59397.4851
Likelihood with Constants only    =       .0000
Initial Likelihood                = -47627.5828
Final value of Likelihood         = -33785.5379

   "Rho-Squared" w.r.t. Zero       =  .4312

   "Rho-Squared" w.r.t. Constants =  .0000

ESTIMATES OBTAINED AT ITERATION  8

Likelihood = -33785.5379

            timeIK     tzone      atype     distcbd    accEmp30   shortDum

 Estimate  -.4873E-02  .6641      .3545      .5297E-01 -.1439E-05  .2272
Std. Error   .137E-02   .246E-01   .836E-02   .237E-02   .169E-07   .247E-01
"T" Ratio   -3.6       26.9       42.4       22.3      -85.0        9.2


           longDum    nonIndEmp  indEmp      pop
```

```
 Estimate   .3807      1.000      3.510      .6068
Std. Error   .423E-01   .000       .128       .122
"T" Ratio    9.0         .0       27.3        5.0
```

```
Model #2 Interzonal Tours
Hague Consulting Group                                                       Page  8
ALOGIT Version 3F/2 (602)                                       16:59:27 on  9 Apr 14

  Ga Tech/UAB Truck Tour Based Model: BMH: Intermediate Stop Location: Interzonal


Convergence achieved after   6 iterations
Analysis is based on 20110 observations

Likelihood with Zero Coefficients = -46304.9862
Likelihood with Constants only    =       .0000
Initial Likelihood                = -32012.5519

Final value of Likelihood         = -21720.8936


   "Rho-Squared" w.r.t. Zero      =  .5309

   "Rho-Squared" w.r.t. Constants =  .0000

ESTIMATES OBTAINED AT ITERATION  6

Likelihood = -21720.8936

            timeIK     timeKJ     tzone      atype     distcbd    accEmp30

 Estimate   .5842E-01 -.6678E-01  .8545      .4696      .1135E-01 -.1379E-05
Std. Error   .139E-02   .133E-02   .326E-01   .111E-01   .352E-02   .211E-07
"T" Ratio   41.9      -50.4       26.2       42.4        3.2      -65.2


           shortDum   nonIndEmp  indEmp      pop

 Estimate   .5966      1.000      1.423     -1.103
Std. Error   .265E-01   .000       .845E-01   .765E-01
"T" Ratio   22.5         .0       16.8      -14.4
```

iv. Validation

Both these models were applied, in sequence, to the estimated tour records. Initial examination indicated that the model was estimating too few stops for I/I tours and too many stops for external tours for Atlanta, and the I/X model (#3) was estimating too many stops for Birmingham. Thus, during validation, an additional set of bias coefficients were added, stratified by I/I vs. external, as shown in Table 48.

Table 48: Atlanta: Number of Stops Added Bias

Number of Stops	I/I	External
1	0.32	0.02
2	0.24	-0.07
3	0.39	-0.17
4	0.47	-0.35
5	0.55	-0.49
6+	0.78	-1.24

Table 49: Birmingham: Number of Stops Added Bias (I/X model)

Number of Stops	Change in Bias
1	-0.3
2	-0.2
3	-0.2
4	-0.2
5	-0.2
6+	-0.2

The resulting distribution of tours by number of average stops was closer to the observed, as shown in Table 50 (this includes internal and external but not through tours).

Table 50: Atlanta: Tours by Stops

Number of Stops	Observed	Estimated
0	34.4%	35.4%
1	22.8	22.6
2	13.9	14.0
3	8.7	8.2
4	5.3	5.2
5	3.6	3.4
6+	11.3	11.2

Table 51: Birmingham: Tours by Stops

Model Type:	1: Round-Trip		2: Interzonal		3: I/X		4: X/I	
Number of Stops	Obs	Est	Obs	Est	Obs	Est	Obs	Est
0			50.4%	50.7%	58.2%	54.6%	58.6%	61.0%
1	32.3%	31.2%	18.5	18.7	19.8	20.8	19.9	18.4
2	14.6	14.5	12.6	11.9	10.3	11.5	10.1	9.9
3	17.8	18.2	6.3	6.4	4.4	4.7	5.1	4.5
4	9.5	9.3	3.7	3.7	2.7	3.0	2.5	2.4
5	5.9	6.0	2.3	2.3	1.6	1.9	1.3	1.3
6+	19.9	20.8	6.2	6.3	3.0	3.6	2.5	2.5

The stop location model can be evaluated by comparing the observed and estimated trip length frequency distributions and the mean values. This uses the trip times, which are the times from the tour origin to the first stop, between stops, and from the last stop to the tour destination. This is shown in Figure 31. The observed mean is 34.07 min and the estimated mean is 34.34 min.

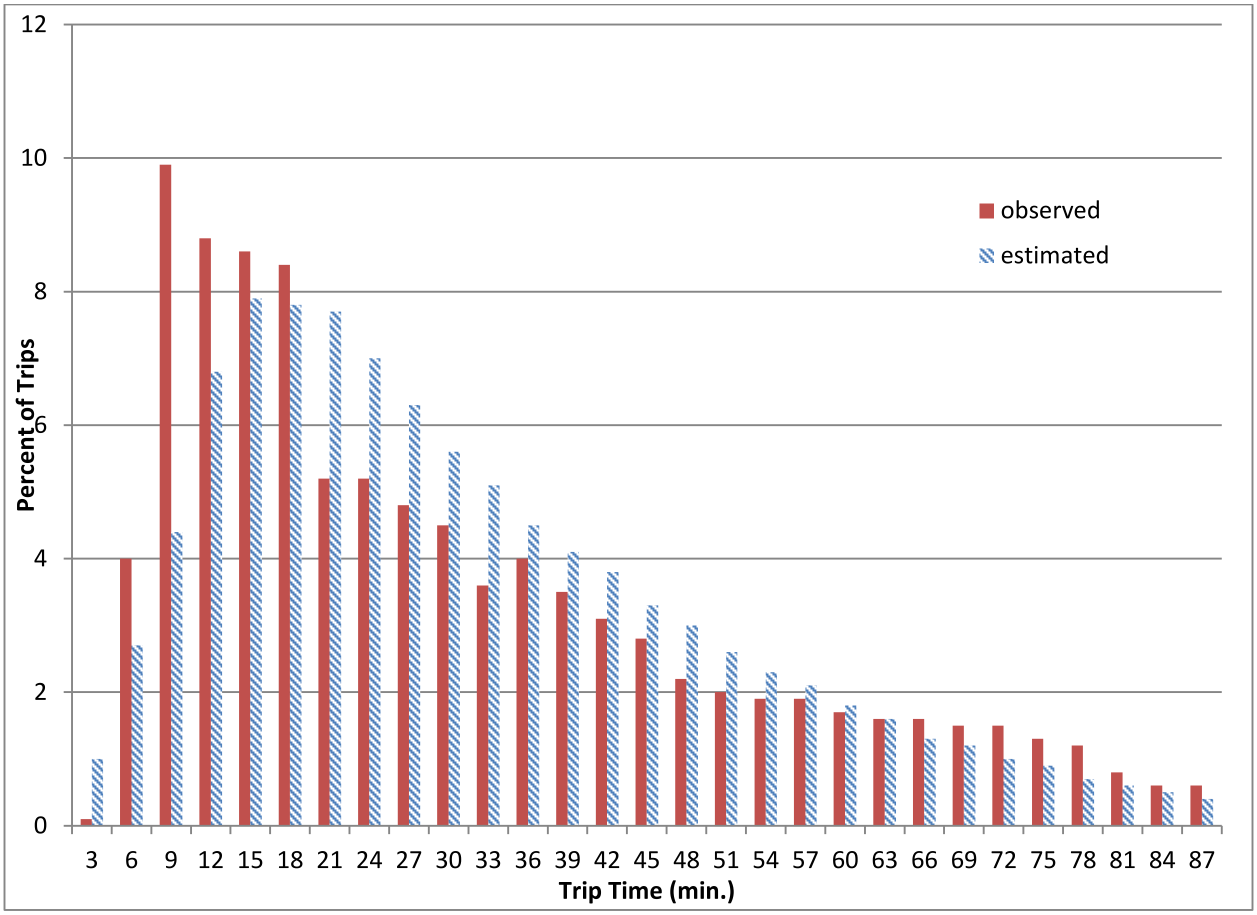


Figure 31: Atlanta: Trip Length Frequency Distributions

Time Period of Tour Starts

i. Model Structure

The time of day process models the time period of the start of the tour. This uses the four time periods currently used: AM peak = 6 – 10 am, Midday = 10a – 3 p, PM peak = 3 – 7 pm, Night = 7p – 6am (for Atlanta model); AM peak = 6 – 9 am, Midday = 9a – 3 p, PM peak = 3 – 6 pm, Night = 6p – 6a (for Birmingham model). The entire tour is assigned to a period, based on the start time. A logit model is used with four alternatives.

At the start of this effort, it was not clear which of the available independent variables would (or should) influence the choice of the tour start time period. The worst case would be a model that consisted only of bias coefficients, i.e., a fixed time split, uninfluenced by any other variables. However, it seemed reasonable to hypothesize that geographic location (the “rolling peak”), trip length, and other location-related variables might play a role.

ii. Estimation

The available ARC and RPCGB network and zonal data and newly generated statistics available for destination choice estimation are the same as described in sections 3.ii and 3.iii. As with the other models, a Cube script was written to prepare the data for the estimation process. Only the I/I tour records were used for model estimation, because most of the independent variables of interest are available only for internal zones. This resulted in 111,424 (Atlanta) and 26,606 (Birmingham) observations. As is standard practice in logit modelling, one alternative (AM peak) is required to have a utility of zero.

As with the number of intermediate stops model, ALOGIT was used to estimate a multinomial model with four choices of time period: AM, MD, PM, NT. The same criteria described above were used to evaluate the different models, which are listed in Table 52. The final model estimation report is shown in Table 53. The model includes bias coefficients on all alternatives except AM peak, for which the utility is defined as zero.

Table 52: Atlanta: Time Period Models

Run	Variables	Results	rhosq(0)
a	bias only	OK	0.0576
b	add origin AT	helped a little; t ok; sign < 0	0.0577
c	try originUrban, originRural dummies	a little better; t's ok; urb>0, rur<0	0.0578
d	add destUrban, destRural dummies	no help; t's low	0.0578
e	try destUrban, destRural dummies alone (without origin dummies)	no help; t's low	0.0576
f	model c + origin, dest accessibility	a little better; t's ok; both signs > 0	0.0583
g	model f + orig dist to cbd	some help; t's ok; sign < 0	0.0589
h	model f + dest dist to cbd	better; t ok; sign < 0; but destAcc t drops too low	0.0592
i	model f + orig dist to cordon	some help; t's ok; sign > 0	0.0586
j	model f + dest dist to cordon	better; t ok; sign > 0; but destAcc t drops too low	0.0588
k	model g but replace accessibility with tot emp density	nope; both t's too low	0.0586
l	model g but replace accessibility with ind emp density	nope; orig t too low	0.0587
m	model g but replace accessibility with pop density	nope; orig t too low	0.0588
n	model g but add dest pop density	better; all t's ok	0.0590
o	model n but put system variables on 'util1'	doesn't work; all system coeffs are zero	0.0576
p	model n but use different coeffs on system variables by period	better but some t's are too low	0.0605
q	model p + consolidate some coeffs	better but some t's are too low	0.0594
r	model p + consolidate more coeffs	better but some t's are too low	0.0593
s	model r + time	better; time is significant	0.0674
t	model s + consolidate more coeffs	better but origUrb t is too low	0.0683
u	**model t but drop origUrb**	**all t's OK**	**0.0683**

Note: model shown in bold was selected.

Table 53: Atlanta: Time Period Selected Model

```
Hague Consulting Group                                                    Page  5
ALOGIT Version 3F/2 (602)                                    13:36:44 on 30 Dec 13

               Ga Tech Truck Tour Based Model: ARC: Time Period

Convergence achieved after   4 iterations

Analysis is based on 111424 observations


Likelihood with Zero Coefficients =-154466.4629

Likelihood with Constants only    =-145572.2528

Initial Likelihood                =-154466.4629

Final value of Likelihood         =-143914.3225

   "Rho-Squared" w.r.t. Zero      =  .0683

   "Rho-Squared" w.r.t. Constants =  .0114

ESTIMATES OBTAINED AT ITERATION  4

Likelihood =-143914.3225

            bias2      bias3      bias4       time     origRur2   origAcc2

 Estimate   .4881     -.6986      .5358      .1514E-01 -.7226E-01 -.3543E-07
Std. Error   .359E-01   .390E-01   .354E-01   .314E-03   .222E-01   .126E-07
"T" Ratio   13.6       -17.9       15.2       48.3       -3.2       -2.8

           destAcc2   destAcc3   destAcc4   origCBD2   origCBD3   origCBD4

 Estimate   .1246E-06  .9450E-07  .1194E-06 -.1947E-01 -.8030E-02 -.1432E-01
Std. Error   .127E-07   .154E-07   .125E-07   .693E-03   .803E-03   .673E-03
"T" Ratio    9.8        6.1        9.6      -28.1      -10.0      -21.3

          destPden2  destPden3

 Estimate   .4504E-01  .3828E-01
Std. Error   .494E-02   .467E-02
"T" Ratio    9.1        8.2
```

Unlike the other logit models, in which the same coefficients were used on all alternatives, this model used different coefficients by alternative for some variables. The findings include:

- Somewhat surprisingly, tour O-D direct travel time turned out to be an especially significant variable. Longer travel time tends to push tours out of the AM peak.

- If the tour origin is rural (area type = 5-7) or is farther from the CBD, the tour is more likely to start in the AM peak. This makes sense in the context of such tours being longer and thus having to start earlier.

- If the origin is more accessible to employment, the tour is more likely to start in the AM peak. If the tour main destination is more accessible to employment or has a higher population density, the tour is less likely to start in the AM peak. These effects are less clear.

Table 54: Birmingham: Time Period Models

Run	Variables	Results	rhosq(0)	rhosq(c)
a	bias only	OK	0.1179	
b	bias, origUrb (pk,op), origRur (pk,op)	t's OK exc origUrb op	0.1187	0.0009
c	bias, destUrb (pk,op), destRur (pk,op)	t's OK only on destRur op	0.1183	0.0004
d	bias, origUrb pk, destRur op	t's OK	0.1183	0.0005
e	bias, origUrb pk, destRur op, time	t's OK	0.1247	0.0077
f	bias, origUrb pk, destRur op, time, orig emp den	t's OK	0.1252	0.0082
g	bias, origUrb pk, destRur op, time, dest emp den	t's OK, not as good as model f	0.1250	0.0080
h	bias, origUrb pk, destRur op, time, orig ind den	t's OK, better than model f	0.1258	0.0090
i	bias, origUrb pk, destRur op, time, dest ind den	t's OK, better than model f	0.1261	0.0092
j	bias, origUrb pk, destRur op, time, dest ind den, orig pop den	t low on orig pop den pk	0.1264	0.0096
k	bias, origUrb pk, destRur op, time, dest ind den, dest pop den	t low on dest pop den pk, destRur op	0.1264	0.0096
l	bias, origUrb pk, time, dest ind den, dest pop den op	all t's OK	0.1264	0.0096
m	bias, origUrb pk, time, dest ind den, dest pop den op, dest dist to CBD	t's OK	0.1281	0.0116
n	bias, origUrb pk, time, dest ind den, dest pop den op, dest dist to CBD, orig acc	new t's OK, dest ind den pk drops out	0.1285	0.0120
o	bias, origUrb pk, time, dest ind den, dest pop den op, dest dist to CBD, dest acc	new t's OK, dest ind den op drops out	0.1287	0.0122
p	bias, origUrb pk, time, dest pop den op, dest dist to CBD, dest acc	all t's OK	0.1283	0.0118
q	**bias, origUrb pk, time, dest pop den op, dest dist to CBD, dest acc, intra flag**	**all t's OK**	**0.1552**	**0.0423**

Note: model shown in bold was selected.

Table 55: Birmingham: Time Period Selected Model

```
Hague Consulting Group                                                     Page   4
ALOGIT Version 3F/2 (602)                                       9:26:11 on 18 Apr 14

               Ga Tech/UAB Truck Tour Based Model: BMH: Time Period

Convergence achieved after   5 iterations

Analysis is based on 26606 observations


Likelihood with Zero Coefficients = -36883.7478

Likelihood with Constants only    = -32534.5400

Initial Likelihood                = -36883.7478


Final value of Likelihood         = -31159.5792


   "Rho-Squared" w.r.t. Zero      =  .1552

   "Rho-Squared" w.r.t. Constants =  .0423

ESTIMATES OBTAINED AT ITERATION  5

Likelihood = -31159.5792

            bias2      bias3      bias4     origUrbP   destAccP   destAccO

 Estimate   1.307      .4870      1.611      .2544      .2365E-06  .2290E-06
Std. Error   .679E-01   .729E-01   .675E-01   .985E-01   .402E-07   .329E-07
"T" Ratio   19.2         6.7       23.9         2.6        5.9        7.0


           intraMD    intraPN    destCBDp   destCBDo  destPdenO    timePM

 Estimate  -.1951     -1.393     -.2143E-01 -.1224E-01  .3970E-01  .1234E-01
Std. Error   .573E-01   .580E-01   .353E-02   .274E-02   .989E-02   .190E-02
"T" Ratio   -3.4      -24.0       -6.1       -4.5        4.0        6.5


            timeOP

 Estimate   .6545E-02
Std. Error   .170E-02
"T" Ratio    3.8
```

The findings for Birmingham model include:

- If the tour origin is urban (area type = 1-3), the tour is more likely to start in the peak periods. This may have to do with the business hours of establishments in urban areas.
- The longer the tour travel time, the less likely the tour is to start in the AM peak. This is logical as a response to avoiding congestion.

- If the tour main destination is more accessible to employment or has a higher population density, the tour is less likely to start in the AM peak. These effects are less clear, but are similar to what was found in Atlanta.
- If the tour is round-trip, it is slightly less likely to start in Midday and a lot less likely to start in the PM peak or Night. This may have something to do with the nature of local delivery schedules.

iii. Validation

The model was applied to the estimated set of tours. Initial examination of the split of tours by period (internal + external) indicated a slight difference from the observed data. The solution was to modify the bias coefficients for the midday, PM, and night periods slightly until the observed shares were matched, which resulted in the comparison shown in Table 56.

Table 56: Atlanta: Tours by Period

Period	Observed	Estimated
AM	16.65%	16.89%
MD	29.78	29.70
PM	15.25	15.15
NT	38.32	38.26

Table 57: Birmingham: Tour Starts by Period

Period	Observed	Estimated
AM	8.4%	8.3%
MD	35.6	35.3
PM	14.0	14.2
NT	42.0	42.2

Trip Accumulator

The time of day step is the final logit model in the process. Its output is a set of tour records (I/I, I/X, X/I) with the tour origin, main destination, number of stops (0-6), list of up to 6 stop locations, and the time period (1-4). The next step in the process is a *trip accumulator*. This step breaks up the tour records into individual trip records (origin – stop, stop – stop, stop – destination), in preparation for assignment. Separate trip tables by period are then built. These are aggregated to daily trips for the purpose of computing an estimated daily trip length frequency distribution.

The trip accumulator step includes a step to forecast X/X tours. The tour generation step described above also outputs a set of X/X growth factors, which are computed so that the sum of the estimated external and through trip ends at each external station matches the input station total. The cordon total truck volume by station and a matrix of 2010 X/X tours are basic inputs. The forecasted change in external tours (I/X + X/I) is based mainly on the change in employment in the modelled area. The X/X growth factors are computed in order to make the forecasted X/X tours consistent with the forecasted external tours and the input cordon totals.

In this step, these computed X/X growth factors are used to Fratar the base (2010) X/X tour matrix and split those tours by time period.

Traffic Assignment

i. Atlanta Model

The research team integrated the tour-based truck model with the existing ARC trip-based assignment methodology. The first step in the ARC process is to separate truck trips by whether they begin or end within the I-285 loop ("The Perimeter"). Then, the passenger car trips are extracted from a run of the ARC model and both sets of trips are assigned simultaneously by time period.

The ARC assignment begins with a separate step to load the X/X trips (passenger car and truck) using a one-pass all-or-nothing assignment. This assumes that X/X trips use the fastest time paths, independent of any congestion effects. The second step starts with the output of the X/X assignment, treating the X/X volumes as a "pre-load" and then assigns the auto and truck trips in a multi-class assignment with the equilibrium volume averaging technique, using the bi-conjugate Frank-Wolfe algorithm as implemented in Cube. Separate paths are built and loaded for SOV, HOV-2, HOV-3, HOV-4+, and Trucks. The "non-I-285" trucks are loaded on paths that do not go inside the Perimeter and the other trucks are loaded on paths that do. For the purposes of computing a volume/capacity ratio for the capacity restraint process, the truck volume is multiplied by 2.0 to reflect the greater effect of heavy trucks on congestion (greater vehicle length, slower acceleration/deceleration).

ii. Birmingham Model

The team also integrated the tour-based truck model with the RPC trip-based assignment methodology. This was complicated by the fact that, as noted above, the RPC model is in the midst of a change. The new process assigns trips by time period and makes a number of other changes from the previous assignment protocol. For this study, the team created a “hybrid” assignment script that is based in part on the old and new procedures.

In addition, the team created a 2010 auto-only trip table by time of day. This was done via the following steps:

- Interpolate between RPC 2008 and 2012 trip tables to get 2010.
- Removed the RPC truck (and taxi) I/I trip tables.
- For external (I/X + X/I) and through (X/X) trips, remove an average of 10.7% of the vehicle trips, which is the estimated truck share of traffic at the cordon, based on ALDOT counts. This percentage varies by external station.
- Apply the new time of day splits, based on data provided by UAB.

The hybrid assignment protocol uses separate assignment steps by time period. The period capacity was computed as 9% of the daily capacity, multiplied by the following factors: AM=2.22, MD=5.16, PM=2.92, NT=3.28. Those are based on hourly count data, are intended to reflect peaking that occurs within each time period, and were provided by UAB. O/D paths are based on an impedance cost that includes time and toll, and accounts for the value of time. In early versions, link distance and the vehicle operating cost were also considered, but these were later omitted to produce more accurate assignments. RPC’s link usage restrictions and occupancy classes were used (SOV, HOV-2, HOV-3, TRK) and UAB’s newer volume/delay functions were used. The Cube standard equilibrium volume averaging method was used with MAXITERS=30, and Relative Gap=0.005. Calibration runs included the use of Cube Cluster for multiprocessing, with 4 processors. The RPC auto-only trips (SOV, HOV-2, HOV-3) are assigned along with trucks, in order to produce a more realistic capacity constraint condition.

Model Application

The entire truck model (including assignment) is applied using a single Cube script (Cube's Application Manager is not used). Table 58 lists the steps that are used. The main part of the model is applied in a series of MATRIX steps that read and write tour-related records. Due to the use of Monte Carlo simulation, a key feature of the script is the use of Cube's (pseudo-) random number generator. As part of each logit step, the Cube RANDSEED function is applied once, using a statement like

```
if (reci.recno == 1) q = randseed(100)
```

Setting the random number seed to the arbitrary value of 100 at the start ensures that the results are reproducible. True stochastic modelling could be achieved by applying the model 10 or 100 times, varying the random number seed differently each time. This would produce a variety of answers, which could be used to analyze the mean and variance of the model's responses. However, in the typical real-world application of such models, such stochastic modelling is rarely done.

The model was developed using Cube Voyager version 6.1.0 and should run with Voyager version 6 or later.

Before running the model, the input data must be set up in directories as follows:

```
\scenario1
   \inputs
      input files
\scenario2
   \inputs
      input files
\model.ATL (in the case of Birmingham: \model.BMH)
   model files
```

Table 58: Atlanta: Model Application Steps

Step	Program	Function
1	MATRIX	Calculate zonal accessibility values
2	MATRIX	Calculate zonal distance to CBD
3	MATRIX	Calculate zonal distance to nearest external station
4	MATRIX	Output base (2010) X/X trip ends
5	MATRIX	Tour generation model
6	MATRIX	Tour main destination choice model (separately for I/I and X/I)
7	MATRIX	Tour main destination choice model (I/X)
8	MATRIX	Tour length frequency distributions
9	SQZ	Compress tours to districts for reporting
10	MATRIX	Intermediate stop model
11	MATRIX	Time of day model
12	MATRIX	Trip accumulator
13	MATRIX	Sort trip records
14	MATRIX	Trip length frequency distributions
15	FRATAR	Growth factor X/X trips
16	MATRIX	Separate truck and E/E (X/X) trips
17	HIGHWAY	E/E pre-load by period (4 steps)
18	NETWORK	Round/rename X/X volumes by period (4 steps)
19	HIGHWAY	Highway assignment by period (4 steps)
20	NETWORK	Round/rename volumes by period (4 steps)

Table 59: Birmingham: Model Application Steps

Step	Program	Function
1	MATRIX	Calculate zonal accessibility values
2	MATRIX	Calculate zonal distance to CBD
3	MATRIX	Calculate zonal distance to nearest external station
4	MATRIX	Output base (2010) X/X trip ends
5	MATRIX	Tour generation model
6	MATRIX	Tour main destination choice models (separately for I/I and X/I)
7	MATRIX	Tour main destination choice model (I/X)
8	MATRIX	Intermediate stop models (separately by 4 tour types)
9	MATRIX	Time of day model
10	MATRIX	Trip accumulator
11	MATRIX	Sort trip records
12	MATRIX	Trip length frequency distributions
13	FRATAR	Growth factor X/X trips
14	MATRIX	Tour length frequency distributions
15	SQZ	Compress tours to districts and report
16	MATRIX	Separate truck and E/E (X/X) trips
17	HIGHWAY	Highway assignment by period (4 steps)
18	NETWORK	Round/rename volumes by period (4 steps)

The “\scenario” directories can be named anything the user likes, but the “\model.ATL” (“\model.BMH”) directory and “\inputs” subdirectories must have those particular names. For this project, two scenarios were run, “2010” and “2040” (future scenario for Birmingham is “\2035”). In “\model.ATL” (and “\model.BMH”) are stored those files that do not change by scenario.

The necessary files and their derivation for Atlanta are shown in Table 60. Note that many of the ARC model files are specifically identified with a two-digit year code embedded in the file name (e.g., FF10HWY.SKM, representing 2010). In order to make this model's code more generic (non-year-specific), these files have been re-named. So in order to run the current model script as is, the user must first run the ARC model according to the instructions for that model, find the files shown in Table 60, as specified in the Source column, re-name them as specified in the New File Name column, and copy them as shown in the New Location column.

The necessary files and their derivation for Birmingham are shown in Table 60. Note that in the RPC's older zonal socioeconomic file (SEDATA2.DBF), some of the fields are specifically identified with a two-digit year code embedded in the field name (e.g., POP12 for 2012, POP35 for 2035). The truck model script includes a “key” named YR that must be set to the last two digits of the forecast year. If the data structures for the new RPC model are different, the main model script may need to be modified accordingly.

Once the input files are in place, running the model is very simple. The entire model is in one Cube script. To run the model, open this script in a Cube window, press the F9 key, enter the name of the directory where the inputs are located (the “\scenario” directory) in the “Work Directory” dialog box, and press the Start button.

Table 60: Atlanta: Truck Model Files

New File Name	New Location	Description	Source (1)
ffhwy.skm	\inputs	auto skim file (5)	\20YY\ffYYhwy.skm (3)
nwtaz.prn	\inputs	zonal land use file	\20YY\inputs\nwtazYY.prn (2)
trkxx10.trp	\model.ATL	2010 X/X trip table (5)	(4)
external.prn	\inputs	external station truck volumes	(4)
znedat.dat	\inputs	zonal area type data	\20YY\znedatYY.dat (3)
truck zones.dbf	\inputs	list of truck zones	\20YY\parameters\ truck zones.dbf (2)
dist6.eqv	\model.ATL	zone-district equivalency	(4)
sqz.exe	\model.ATL	SQZ program	
hwyff.net	\inputs	highway network	\20YY\inputs\hwyYYff.net (2)
todam.vtt	\inputs	AM auto trip table file (5)	\20YY\TOD\todamYY.vtt (3)
todmd.vtt	\inputs	MD auto trip table file (5)	\20YY\TOD\todmdYY.vtt (3)
todpm.vtt	\inputs	PM auto trip table file (5)	\20YY\TOD\todpmYY.vtt (3)
todnt.vtt	\inputs	NT auto trip table file (5)	\20YY\TOD\todntYY.vtt (3)
com.trp	\inputs	commercial vehicle trip table (5)	\20YY\com.trp (3)
truck.s	\model.ATL	truck model script	(4)

Notes:
(1) YY represents the last 2 digits of the year: ‘10’ = 2010, ‘40’ = 2040.
(2) These files are input to the ARC model.
(3) These files are output from the ARC model.
(4) These files were created for the tour-based truck model.
(5) These are binary matrices in Cube format.

Table 61: Birmingham: Truck Model Files

New File Name	New Location	Description	Source
tkfree.skm	\inputs	truck skim file (4)	\Base\H20yy\tkfree.skm (2)
sovfree.skm	\inputs	auto skim file (4)	\Base\H20yy\sovfree.skm (2)
speedcap.net	\inputs	highway network	\Base \H20yy\speedcap.net(1)
sedata2.dbf	\inputs	zonal land use file	\Base\H20yy\sedata2.dbf (1)
newEmpl.dat	\model.BMH	Census LEHD employment file	(3)
acres850.dbf	\model.BMH	zonal area file	obtained from RPC
trkxx10.trp	\model.BMH	2010 X/X trip table (4)	(3,4)
trkpct.prn	\inputs	external station truck volumes	(3)
areatype.prn	\inputs	zonal area type data	\Base\H20yy\areatype.prn (2)
truck zones.dat	\inputs	list of truck zones	(3)
dist7.eqv	\model.BMH	zone-district equivalency	(3)
sqz.exe	\model.BMH	SQZ program	
am.vtt	\inputs	AM auto trip table file	(5)
md.vtt	\inputs	MD auto trip table file	(5)
pm.vtt	\inputs	PM auto trip table file	(5)
nt.vtt	\inputs	NT auto trip table file	(5)
truck.s	\model.BMH	truck model script	(3)

Notes:
(1) These files are input to the RPC model.
(2) These files are output from the RPC model.
(3) These files were created for the tour-based truck model.
(4) These are binary matrices in Cube format.
(5) These files are created by the research team’s TOD.S script, included in the Appendix.

The full Cube Voyager model script is attached as an Appendix. As currently written, the script is set up to use Cube Cluster, which is the Cube software module that permits the use of multiple processors on a single computer. This greatly reduces the running time for the highway assignment step. If the model is being run on a computer that does not have Cluster or does not have multiple processors, the user must first modify the script by removing the four lines in `truck.s` that read as follows:

For Atlanta,

- `*cluster TECH 1-3 Start Exit (before the assignment loop)`
- `DISTRIBUTEINTRASTEP PROCESSID='TECH', PROCESSLIST=1-3 (in the E/E assignment)`
- `DISTRIBUTEINTRASTEP PROCESSID='TECH', PROCESSLIST=1-3 (in the main assignment)`
- `*cluster TECH 1-3 Close Exit (after the assignment loop)`

For Birmingham,

- `*cluster BHAM 1-3 Start Exit (before the assignment loop)`
- `DISTRIBUTEINTRASTEP PROCESSID='BHAM', PROCESSLIST=1-3 (in the assignment)`
- `*cluster BHAM 1-3 Close Exit (after the assignment loop)`

Note that the model was developed and initially applied using Cluster with four processors. Without Cluster (or with Cluster and using a different number of processors), the results may be slightly different than those reported here.

Assignment Validation for Atlanta

Observed 2010 data on truck volumes was provided indirectly by Georgia DOT. GDOT's Office of Transportation Data provided a document listing the percentage of weekday trucks and annual average daily traffic (AADT) on various links, keyed to the county and a four-digit traffic count code (TC). This was related to the CNTSTATION field in the ARC highway network. The daily truck count was computed as the weekday percent truck multiplied by the AADT multiplied by 1.10 (to account for the fact that the model estimates weekday traffic which is slightly higher than the average daily traffic volume throughout the entire year). This produced truck counts on 118 directional links (59 two-way roadway segments). Although the GDOT document does not mention how they defined “truck”, the research team believes that it is consistent with the definition being used in this study.

The initial application of the model indicated that the model was slightly overestimating truck volumes, particularly in the more urbanized areas. The solution was to reduce the number of estimated tours slightly, using the area type based adjustment shown in Table 62. Other adjustments were tested:

- Calculate truck paths using a perceived time that is 20% higher for non-freeways (in the end, this was not adopted)
- Various area type factors (other than the final ones shown in Table 62).
- Adjust the I/X tour main destination choice model so as to more accurately match the cordon volumes (adopted).
- Balance the external tours on a daily basis (i.e., adjusting the values to ensure that on a daily basis, the I/X trips would equal the X/I trips) (this was not adopted).
- Incorporating counts at the external stations (this was not adopted, because those volumes were computed differently from the other counts and also because those volumes are actually an input to the model and thus it would not be proper to use them to compare the outputs).

Table 62: Atlanta: Area Type Adjustment

Area Type	Factor
1 (CBD)	0.9
2	0.9
3	0.9
4	0.9
5	0.9
6	1.0
7 (rural)	1.0

With the adjustments described above, the model replicates the 2010 counts very well, as shown in Table 63. "Volume/count" represents the aggregate volume to count ratio for all counted links. Closer to 1.0 is better. "% RMSE" is the percent root-mean-square error, which is a better indicator of accuracy because it treats over- and under-estimation as equally bad. It is computed as the square root of the sum of the squared error for all counted links, divided by the average count. Lower values are better. The overall value of 27.8% is an excellent value for a truck model. Most truck models have %RMSE values around 60-80%. For comparison, the old ARC truck model (prior to the 2005 recalibration) had volume/count = 0.73 with 117% RMSE. The current ARC truck model (as recalibrated in 2005) has volume/count = 1.14 with 49% RMSE. In addition, the link-level r^2 is 0.946; closer to 1.0 is better and values result over 0.9 are considered acceptable. This result confirms that the tour-based structure is appropriate for truck models.

Table 63: Atlanta: Observed/Estimated Link Comparison

Area Type	Volume/Count	% RMSE	No. of Links
1 (CBD)	1.23	31.6%	8
2	1.41	54.2	8
3	0.93	21.6	15
4	0.85	28.2	12
5	0.98	27.3	61
6	0.94	15.3	6
7 (rural)	1.07	31.0	8
Facility Type			
Freeway	0.97	20.6%	64
Arterial	1.33	106.4	50
Collector	3.10	215.0	4
Total	**0.99**	**27.8%**	**118**

Figure 32 shows the link-level observed vs. estimated volume plot, which indicates that the counted links generally straddle the 45° line that indicates a perfect fit.

The truck trip and VMT results can also be compared to those of the current ARC trip-based model for 2010 (sum of that model's medium + heavy truck trips). The tour-based model estimates 453,500 trips and 12,178,000 VMT, while the ARC model estimates 523,700 trips and 13,753,000 VMT. So the tour-based model has 13% fewer trips and 11% less VMT, but those differences may be caused by the different calibration timeframes. The ARC truck model was last recalibrated in 2010, to 2005 counts which were taken before the recent economic recession. The tour-based model was calibrated to 2010 counts which reflect lower traffic volumes: a nationwide phenomenon due to the recession, which was just starting to end in 2010-11.

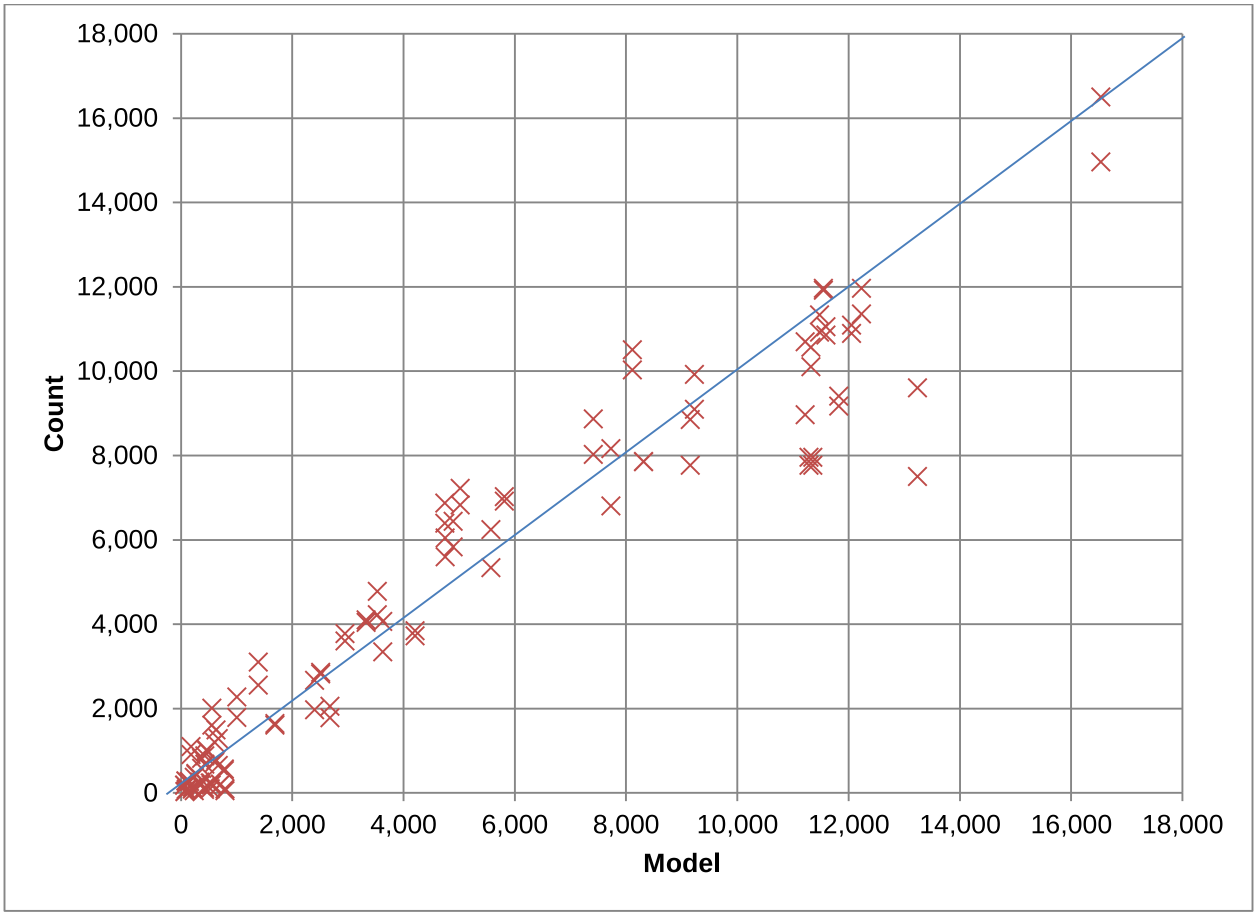


Figure 32: Atlanta: Observed/Estimated Link Plot

Assignment Validation for Birmingham

i. Validation

Truck counts were provided by Alabama DOT. The counts were transmitted in a file named BHAM10LINK_RPC2_ALDOT1_AAWT_Truck_final.dbf, fields TRUCKCOMBO and TRUCKSINGU. UAB tried to obtain further documentation on this data, but none was forthcoming. It is assumed that the TRUCKCOMBO value represents heavy trucks (FHWA class 8-13) and that the counts represent weekday counts in the 2010 time frame. This file contains truck counts on 600 directional links (300 two-way roadway segments), with counts dropped where considered to be duplicative or inconsistent with adjacent counts. Truck counts by hour or time period were not available.

The initial application of the model indicated that the model was overestimating truck volumes, particularly in the rural areas. In a few other areas, the model's results were different from the ATRI GPS data. The following adjustments were made:

- Calculate paths using time and tolls only, but no distance-related factors.
- Various area type factors (including the final ones are shown in Table 64).
- Adjust the tour destination choice model to estimate more intrazonal tours.
- Adjust the tour destination choice model to estimate longer external tours.
- Adjust the number of intermediate stops model to better match the GPS data.
- Adjust the stop location model to estimate fewer stops in rural areas.
- Adjust the time of day model to better match the GPS data.

Table 64: Birmingham: Area Type Adjustment

Area Type	Factor
1 (CBD)	1.0
2	1.0
3	1.0
4	1.0
5	1.0
6	1.0
7	0.2
8	0.2
9 (rural)	0.2

ii. Adaptable Assignment

The tour destination choice model, and all other destination choice models in current use, presumes that the choice of destination is a relatively simple phenomenon. As an overall theory, this makes sense: the choice of a destination *in general terms* is clearly influenced by the number of attractions available to satisfy their needs and how distant those attractions are from their home. In the case of truck trips, zonal "attractiveness" is largely correlated with employment, especially industrial employment. However, there are a great many other factors that influence that choice on a daily basis, most of which can never be practically measured or known. Moreover, the list of factors and their relative influence probably changes daily. In truth, travel behavior is composed of a somewhat predictable element and a completely random component and a truly accurate model would probably have as many variables as there are job classes in the study area.

This reality notwithstanding, travel models are expected to replicate the actual traffic volumes that were counted for some base year on a number of roadways, to some specified degree of accuracy. Without that replication, the model does not garner the credibility needed for reviewers to have any confidence in the forecasted volumes. The research team's experience over many years of developing and using travel models suggests that models based on theoretical constructs, no matter how well-crafted and sound, rarely achieve a level of base year assignment accuracy that public agencies and other reviewers deem satisfactory.

Some kind of adjustment to the model or post-processing of its results is almost always required. The challenge is to adjust the model in ways which do not alter the basic travel relationships on which it is built. Doing so would render the model useless for forecasting. Many models suffer this fate, because of undue emphasis placed on calibration accuracy, to the exclusion of other considerations.

In order to address this dilemma, a procedure was developed to modify the basic O/D travel patterns prior to assignment. This change consists of relatively minor modifications to the truck trip table on an O/D cell-by-cell basis, such that the resulting assignment more closely matches the base year counted volumes. A procedure has been developed to accomplish this, called *adaptable assignment (or AA)*. This is basically a method (one of many) of determining a trip table from counts, generically known as “origin/destination matrix estimation (ODME)”. The result is a “delta” trip table, so called because it is added to the model’s calculated trip table before assignment. Most of the individual cell entries in the delta table are small values, but their cumulative effect is to change the theoretically estimated travel patterns to more closely match the traffic counts in the base year.

AA is an iterative process. It works by “skimming” the count and the assigned volume on the path connecting each O/D pair. Those values are used to factor the trips by O/D. Figure 33 shows the improvement in estimated vs. count error in each iteration of this process.

Since the delta trip table can be thought of as a calibration adjustment, it is used to develop the model’s forecasts as well. The delta trip table is added to the future modelled trip table, in the same fashion as for calibration. This same procedure has been used in a number of other projects with positive results. The research team believes that this process produces results which meet the twin goals of accurate base year calibration and a credible procedure for producing forecasts. The principal disadvantage of using the delta table is that if the zone system is modified, the delta table must be adjusted accordingly. As Table 65 shows, the net regional effect of this adjustment is small.

iii. Results

With the adjustments described above, the model replicates the 2010 counts quite well, as shown in Table 66. “Volume/count” represents the aggregate volume to count ratio for all counted links. Closer to 1.0 is better. “% RMSE” is the percent root-mean-square error, which is a better indicator of accuracy because it treats over- and under-estimation as equally bad. It is computed as the square root of the sum of the squared error for all counted links, divided by the average count. Lower values are better. The overall value of 29.7% is an excellent value for a truck model. Most truck models have RMSE values around 60-80%. The comparable value for Atlanta is 27.8%. No prior truck RMSE value for Birmingham was provided by RPC, but the research team computed a value of 204% based on RPC’s 2012 estimate of link truck (+ taxi) volumes and ALDOT’s 2010 counts.

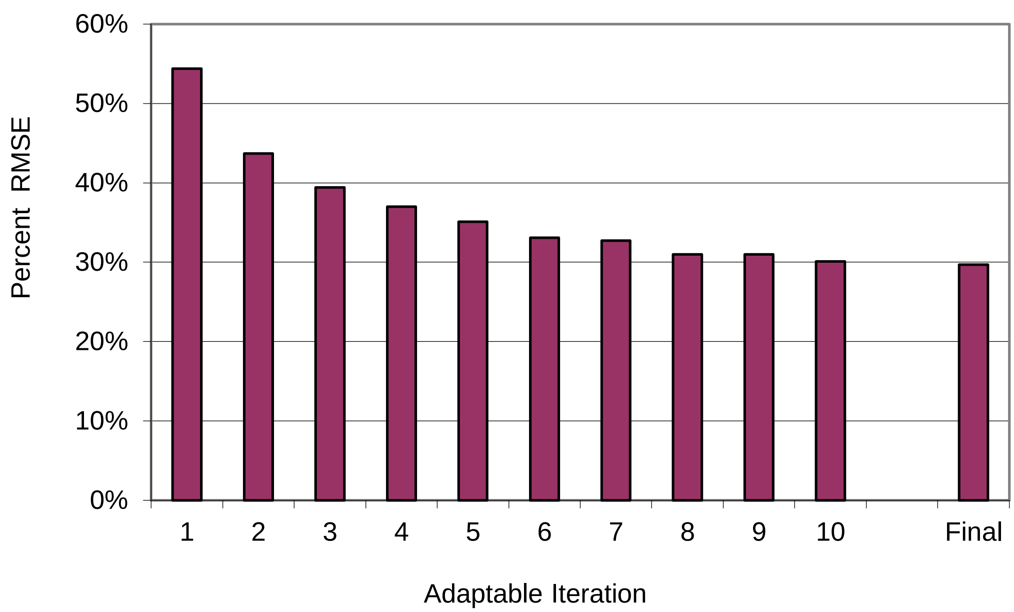


Figure 33: Adaptable Assignment Accuracy

Table 65: Calibration Adjustment

Tour-Based Truck Model: Birmingham
Model Estimated Trips

Destination District

		1	2	3	4	5	6	7	Total
O	1 Central	11753	1753	656	985	3202	1682	2022	22053
r	2 North	544	4122	402	207	897	355	1182	7709
i	3 East	222	395	1006	132	174	186	514	2629
g	4 South	328	251	174	1677	551	591	580	4152
i	5 West	1036	1005	217	440	12403	1052	2182	18335
n	6 Shelby	180	298	185	554	776	8275	1761	12029
	7 External	590	1218	323	309	2748	3069	17286	25543
	Total	14653	9042	2963	4304	20751	15210	25527	92450

Tour-Based Truck Model: Birmingham
AA Revised Trips

Destination District

		1	2	3	4	5	6	7	Total
O	1 Central	11217	1565	621	790	2161	1702	3602	21658
r	2 North	440	4136	285	192	938	218	1444	7653
i	3 East	283	243	1299	61	105	26	585	2602
g	4 South	556	105	68	2060	381	331	563	4064
i	5 West	952	987	319	487	11494	887	2999	18125
n	6 Shelby	299	176	72	446	976	9005	1264	12238
	7 External	991	1826	259	259	4772	2990	14891	25988
	Total	14738	9038	2923	4295	20827	15159	25348	92328

Tour-Based Truck Model: Birmingham
AA Trip Difference

Destination District

		1	2	3	4	5	6	7	Total
O	1 Central	-536	-188	-35	-195	-1041	20	1580	-395
r	2 North	-104	14	-117	-15	41	-137	262	-56
i	3 East	61	-152	293	-71	-69	-160	71	-27
g	4 South	228	-146	-106	383	-170	-260	-17	-88
i	5 West	-84	-18	102	47	-909	-165	817	-210
n	6 Shelby	119	-122	-113	-108	200	730	-497	209
	7 External	401	608	-64	-50	2024	-79	-2395	445
	Total	85	-4	-40	-9	76	-51	-179	-122

Table 66: Birmingham: Observed/Estimated Link Comparison

Area Type	Volume/Count	% RMSE	No. of Links
1 (CBD)	1.17	28.4%	27
2	0.97	16.6	9
3	1.01	16.4	4
4	1.04	30.4	36
5	1.11	27.6	86
6	1.06	31.6	218
7	1.09	22.5	66
8	1.06	17.9	78
9 (rural)	2.45	306.5	76
Facility Type			
Freeway	1.00	12.6	156
Arterial	2.14	228.6	425
Collector	2.02	227.2	19
Total	**1.08**	**29.7%**	**600**

Figure 34 shows the link-level observed vs. estimated volume plot, which indicates that the counted links with significant volumes (mostly freeways) generally straddle the 45° line that indicates a perfect fit. However, it appears that the model overestimates truck volumes on the lower volume roads.

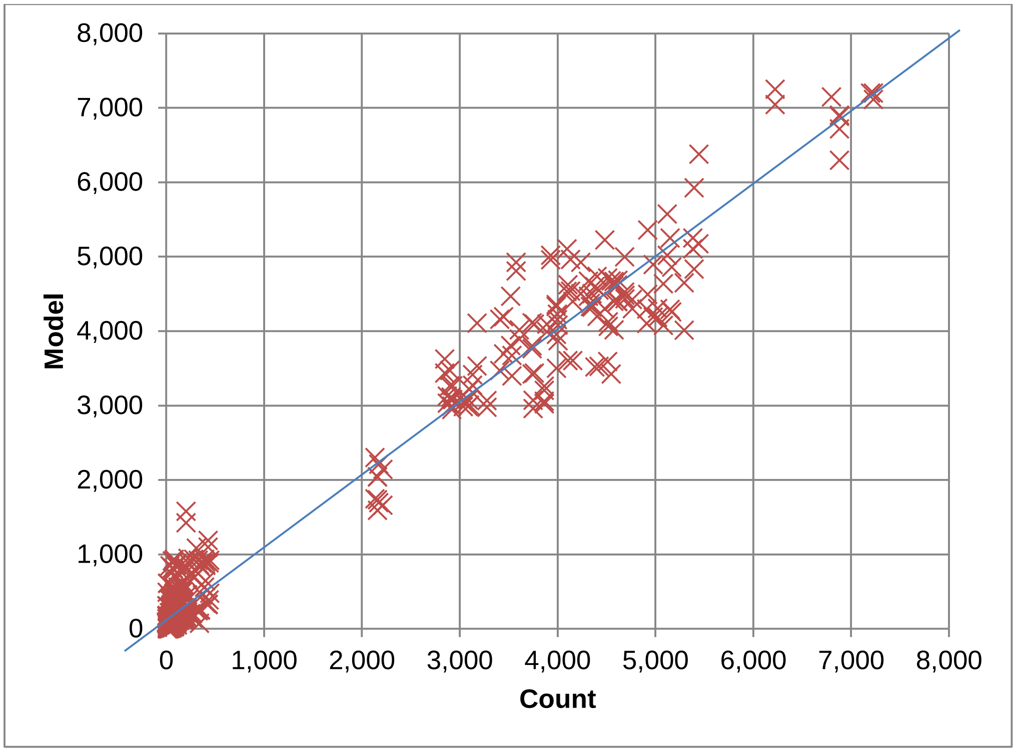


Figure 34: Birmingham: Observed/Estimated Link Plot

Forecast

Atlanta Truck Forecast

Data for the 2040 estimate was taken from the ARC model. Table 67 shows the change in the basic demographic variables by county. This forecast shows a 61% increase in households and a 68% increase in employment. According to the data in Table 67, the future external volumes (taken from the ARC file 2040\cmhext.prn) will increase by 51% from 2010 to 2040.

The traffic assignment step takes considerably longer to run for 2040 because the increase in travel requires many more iterations of equilibrium volume averaging (e.g., 84 iterations in 2040 vs. 38 in 2010 for the AM peak). Table 68 shows the change in truck travel and compares the newly estimated change to the ARC estimated change (based on the ARC model script

`ATLMain_Plan2040_1022013.s`). The tour-based model estimates a smaller growth in truck travel from 2010 to 2040 than does the ARC model. It is not clear how much of the difference in growth is due to the different approach of the models and how much is due to the different calibration time frames.

Table 67: Atlanta: Forecast Demographics

	2010			2040		
County	**HH**	**Population**	**Employment**	**HH**	**Population**	**Employment**
Barrow	23,879	65,670	14,568	49,615	130,793	34,006
Bartow	34,556	93,551	29,900	64,165	166,902	62,174
Carroll	41,391	108,234	35,886	72,938	183,113	66,999
Cherokee	75,687	206,136	43,620	152,285	398,146	116,148
Clayton	99,583	277,971	113,850	117,501	313,407	158,045
Cobb	255,229	662,919	304,696	333,190	830,509	458,382
Coweta	43,363	119,236	30,983	93,353	246,575	67,010
DeKalb	280,510	720,960	289,110	360,758	887,121	424,201
Douglas	47,301	127,089	37,620	95,924	253,002	75,422
Fayette	37,392	105,178	35,854	61,513	166,132	72,989
Forsyth	62,433	176,104	57,678	141,711	376,542	128,979
Fulton	391,664	937,391	672,574	548,811	1,257,223	1,033,638
Gwinnett	265,100	751,938	288,930	425,050	1,153,982	508,847
Hall	61,857	176,612	66,340	125,247	340,980	124,857
Henry	68,915	192,470	45,153	159,542	429,736	108,971
Newton	35,532	96,251	19,636	76,145	197,980	38,973

Paulding	45,957	129,003	20,425	104,901	281,896	51,077
Rockdale	29,890	83,834	28,660	58,530	157,381	47,028
Spalding	24,748	64,631	20,815	44,258	110,909	36,615
Walton	28,198	78,018	17,275	57,515	152,717	36,992
Totals	**1,953,185**	**5,173,196**	**2,173,573**	**3,142,952**	**8,035,046**	**3,651,353**

Table 68: Atlanta: Truck Forecasts

	Tour-Based Model			ARC Model		
	2010	**2040**	**Change**	**2010**	**2040**	**Change**
Trips	453,500	550,000	21%	523,700	772,700	48%
VMT	12,178,000	15,992,000	31%	13,753,000	19,507,000	42%

Birmingham Truck Forecast

Data for the 2035 estimate was taken from the older RPC model. Table 69 shows the change in the basic demographic variables by county. This forecast shows a 9% increase in households and a 24% increase in employment. According to the data in Table 25, the future external truck volumes (derived from the RPC file ExtCounts35.dbf) will increase by 120% from 2010 to 2035 -- an annual growth rate of 3.2%. Cordon truck trips are assumed to increase at the same rate as total cordon travel.

Table 70 shows the tour model's estimated change in truck travel and compares it to the RPC estimated change . The tour-based model estimates a larger growth in truck travel from 2010 to

2035 than does the RPC model. However, the RPC figures include taxi trips, which makes direct comparison with the truck tour results difficult. In the truck tour model, almost all of the growth in truck trips and VMT is due to external and through travel.

Table 69: Birmingham: Forecast Demographics

	2012			2035		
County	**HH**	**Population**	**Employment**	**HH**	**Population**	**Employment**
Jefferson	268,953	657,268	349,377	272,688	666,053	418,157
Shelby	54,005	140,869	58,026	79,799	207,876	85,460
Totals	322,958	798,137	407,403	352,487	873,929	503,617

Table 70: Birmingham: Truck Forecasts

	Tour-Based Model			RPC Model		
	2010	**2035**	**Change**	**2012**	**2035**	**Change**
Trips	92,500	125,800	+36%	382,600*	453,000*	+18%
VMT	1,773,000	3,314,000	+87%	3,197,000	3,842,000	+20%

* I/I only; includes taxi.

New Zone System and Model Updates

Near the end of the development of the tour-based truck model, UAB advised the research team that RPC had recently changed its traffic analysis zone (TAZ) system, going from 999 zones and external stations to 1,986. Many of the old zones were subdivided, several zone boundaries were modified, and the modelled area was expanded. The truck tour model was developed using the old 999 zone system because that is what the ATRI GPS records were geocoded to.

For the most part, the truck tour model is zone-independent. However, it appears that in addition to changing its zone system, RPC made a number of other changes to its model. Some of the zonal socioeconomic and network variables may have changed. The user will need to carefully examine the truck tour model script to be sure that it works properly with the new RPC model.

As of this writing, the research team is aware of some files that must be changed for the new zone system:

- The main model script, TRUCK.S, defines a number of "keys" at the beginning of the script. When the model runs, Cube replaces the keys with their equivalent numerical value. The keys that define the old zone system are as follows:

```
maxzone = 999
extsta  = '964-999'
intzone = '1-850'
fext    = 964
liz     = 850
```

- These must be modified as follows:

```
maxzone = 1986
extsta  = '1935-1986'
intzone = '1-1934'
fext    = 1935
liz     = 1934
```

- TRUCK.S requires the user to select one TAZ to identify the CBD. In the old zone system, this is zone 39. The same zone in the new system is 27. This is located near line 78 of TRUCK.S.
- The truck tour model uses a matrix file called DELTA.TRP, which contains the calibration adjustments needed to produce better assignments. This is a Cube binary matrix file with four tables that represent the adjustments for AM, MD, PM, and NT periods. In order to work with a new zone system, this file must be renumbered accordingly. The research team recommends that the user create an equivalency file between the old and new zone systems. This can be used in a standard Cube MATRIX run to convert this file to the new zone system. The user must be careful to include Cube's bucket rounding function (ROWFIX) because the existing DELTA.TRP values are all integers.

SECTION IV. PLANNING APPLICATION: Atlanta

Truck Link-Volume Comparison: Existing ARC Model vs. Tour-based Truck Model

ARC's current trip-based truck model is a traditional four-step model that is calibrated to match with the 2005 traffic count data. The model subcategorizes trucks into three groups: the medium truck, which includes F3 to F7 of the FHWA 13-bin Vehicle Classification; the heavy truck, which include F8 to F13 of the FHWA 13-bin Vehicle Classification; and the Commercial Vehicle, which include light trucks, vans, and SUVs used for business purpose and not for personal transportation. This section summarizes the major steps of the model, which are trip generation, trip distribution, and trip assignment, according to ARC's 2010 documentation of the model.

In contrast, the proposed tour-based truck model attempts to model truck movements as individual tours, which may or may not return to the starting point and which may or may not have intermediate stops. The tour's main destination zones and the number of intermediate stops, the stop locations, and the tour's start time, are identified by using a series of logit models and Monte Carlo simulation process. Using ATRI's truck GPS data, the model was developed for two different sized metropolitan areas: Atlanta and Birmingham, and the model was designed to be somewhat generic to be transferable to other cities. The major steps of this model include: tour generation, tour main destination choice, identification of the number and locations of intermediate stops, identification of time period of tour start, trip accumulator, and traffic assignment.

Figure 35 shows "Link-Volume Comparison" (54,560 network links) between newly developed Tour-based model and ARC's trip-based model by time of day for 2010. ARC model volumes are forecasts (The truck component is stratified by medium and heavy truck and calibrated to 2000 counts and updated to 2005 counts.) and Tour-based model volume is for base year and validated with 2010 observed data. The ARC model overestimates for AM, PM and MD and underestimates for NT.

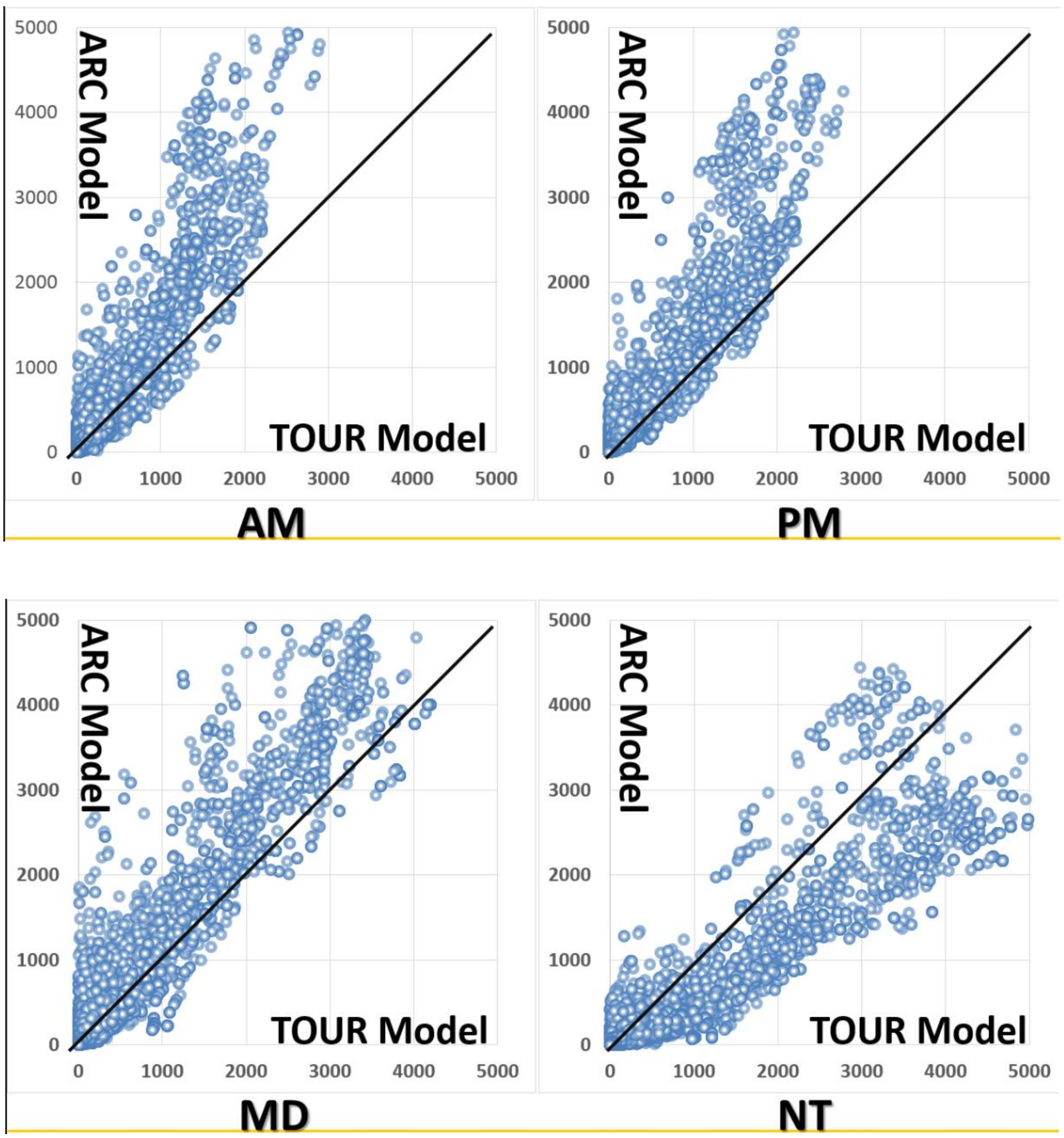


Figure 35: Trip-based vs. Tour-based Model Link Volume Comparison (54,560 Network Links)

Performance Measures

Truck Traffic Estimates

The estimated average daily truck traffic volumes on the roadway network are shown in Figure 36. Corridors with high truck traffics include the following Corridors: I-75 from the beltway, I-285 passing through Cobb and Bartow counties, beltway I-285, I-85 from the beltway I-295 to North of Gwinnett County, I-75 along Fulton, Clayton, and Henry counties.

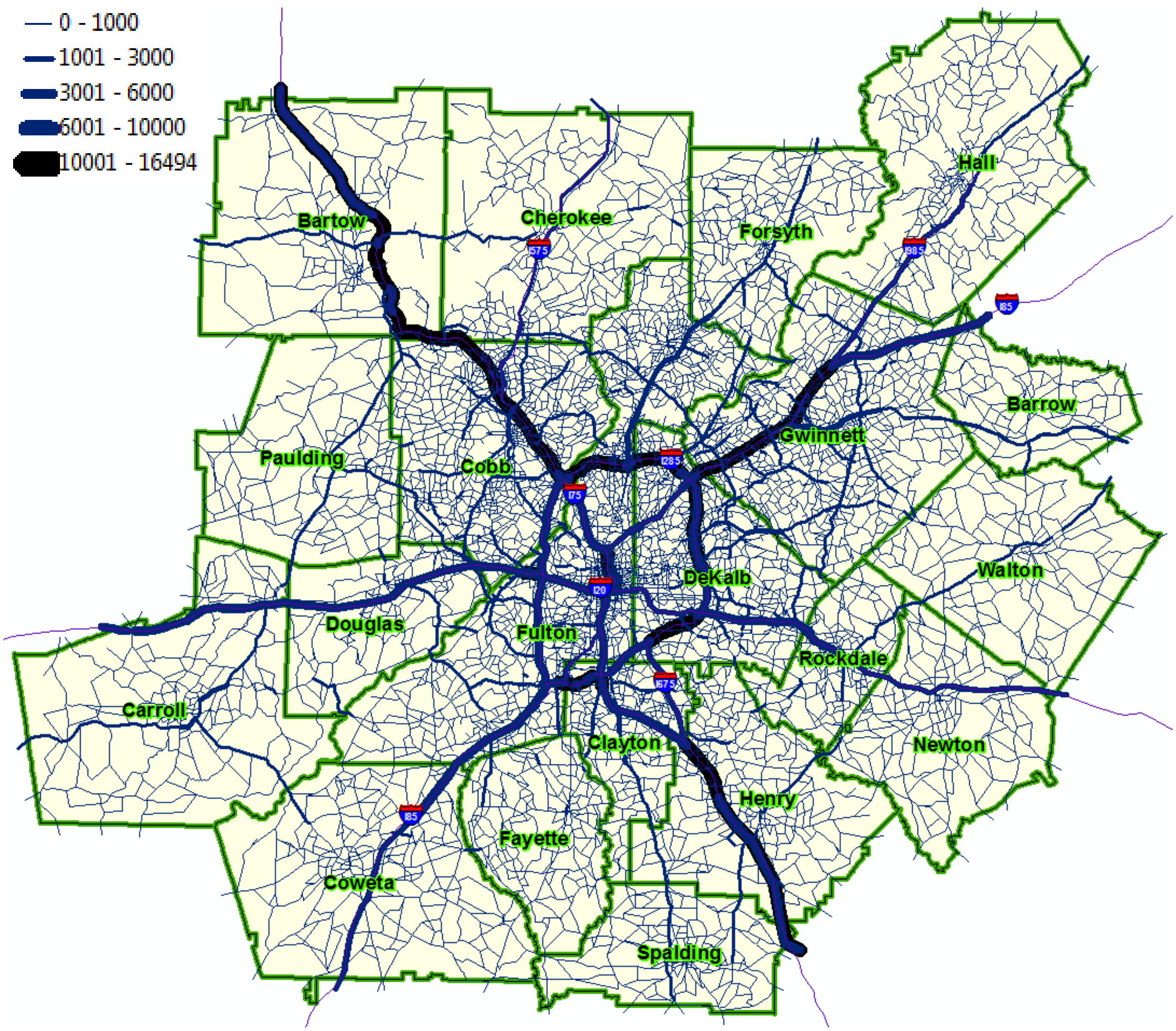


Figure 36: 2010 Truck Traffic Estimates on ARC Modelled Area Network with Tour-based Model

Figure 37 shows the Interstate highway/Freeway (FACTYPE=1) segments with congested speeds as a percentage of free flow speed. In the network file, speed limit information is less complete than free flow speed information. Therefore free flow speed is used to calculate the percent congested speed versus free flow speed in order to capture how much congestion and associated delay occur during each time of day by facility type (FACTYPE). Figure 37 shows the percent congested speed with an average daily traffic, while Figure 38 shows the same measure at different time of day (AM, MD, PM, and NT). Speeds around metro area slow down heavily during the peak hours (AM and PM), and especially during the PM peak (3:00 PM – 7:00 PM) most of the major interstate highways including I-285 beltway and major corridors such as I-85, I-75, I-20, and GA 400 show the congested speed under 60% of free flow speed. Mid-day period (10:00 AM – 3:00 PM) shows relatively milder speed slowdowns and during night time (7:00 PM – 6:00 AM) the speed stays close to the free flow speed level.

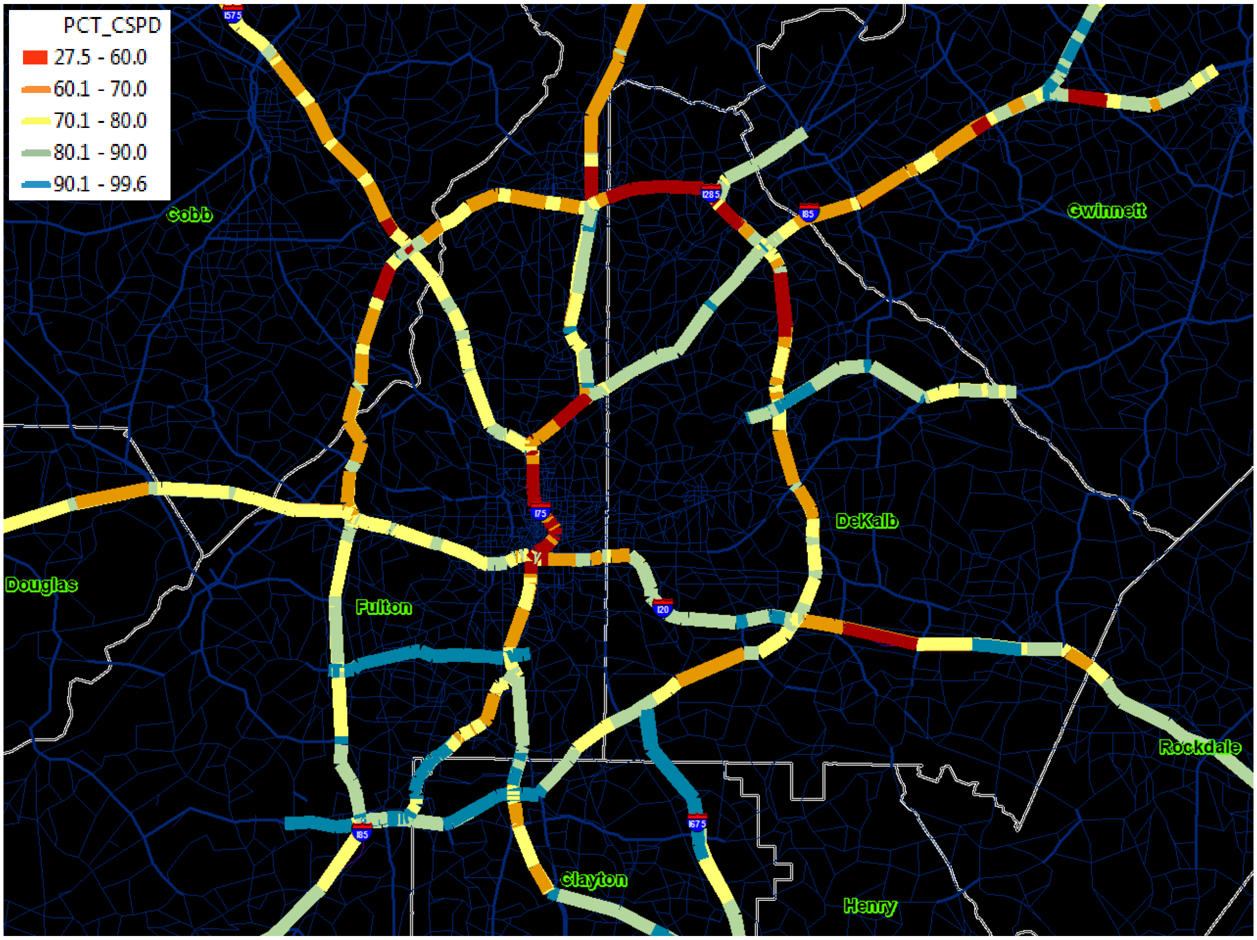


Figure 37: 2010 Congested Speeds as a Percent of Free-Flow Speed for Interstate (FACTYPE=1) with Tour Model (Day Level)

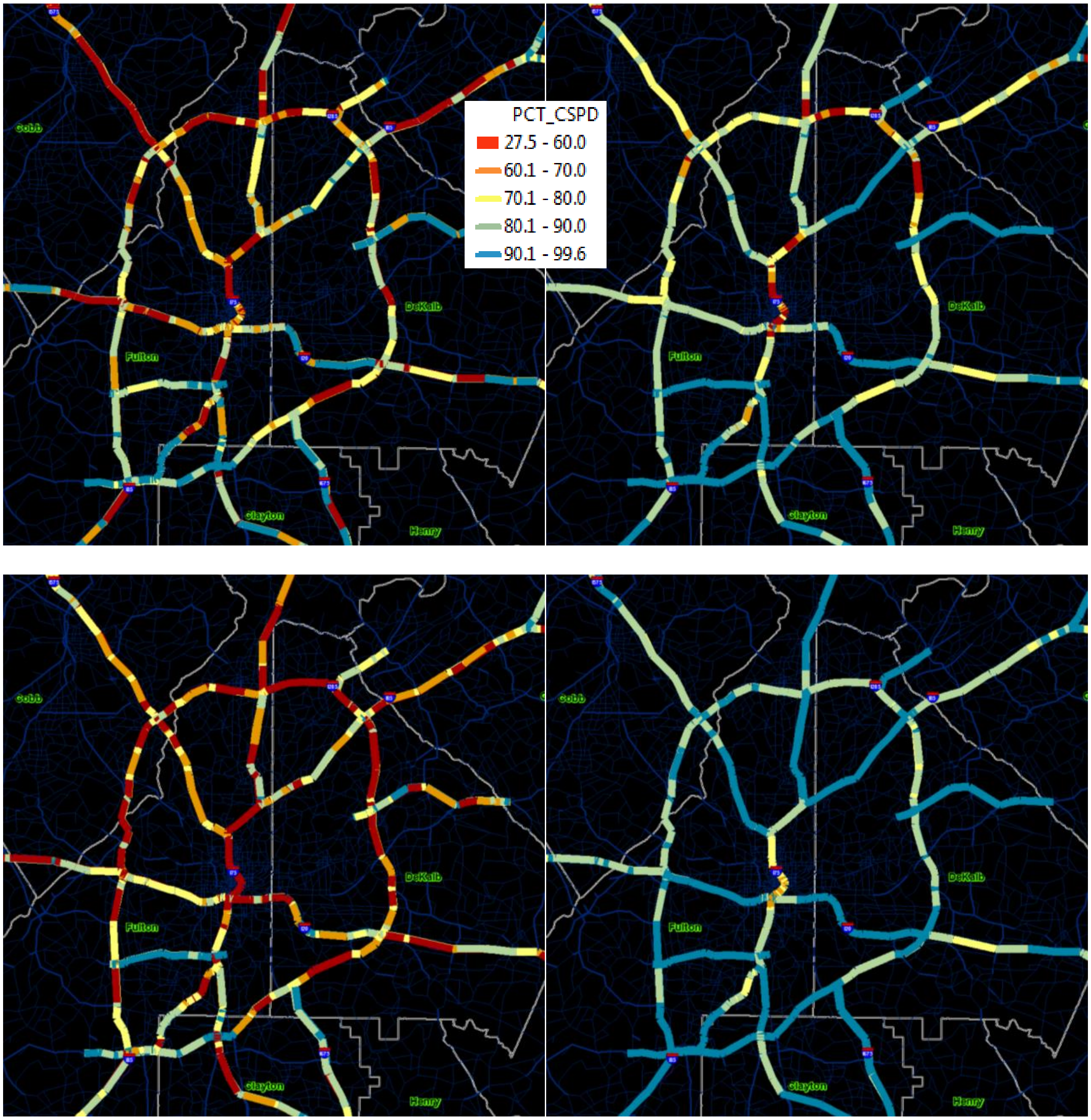


Figure 38: 2010 Congested Speeds as a Percent of Free-Flow Speed for Interstate (FACTYPE=1) with Tour Model: AM (Upper Left); MD (Upper Right); PM (Under Left); NT (Under Right)

In order to analyze how much truck traffic contributes to the congested roadway segments during each time of day, percent of truck volumes and the percent of congested speed were calculated. Table 71 and Table 72 show the 20 roadway segments with the highest speed drop.

Table 71: Top 20 Roadway Segments with High Congestion Speed Drop during AM Peak

A	B	DIST	NAME	V_TRKAM	V_TOTAM	SPEED	CGSTDSPD	PCT_TRKAM	PCT_CSPD
2785	2844	0.20	I-75/85 North	1800	36735	55	14	4.90	24.58
2839	2785	0.20	I-75/85 North	1800	36735	55	14	4.90	24.58
8877	2839	0.10	I-75/85 North	1774	36857	55	16	4.81	29.53
2780	2783	0.10	I-75/85 North	1353	25519	55	16	5.30	29.54
2783	8877	0.20	I-75/85 North	1353	25519	55	16	5.30	29.54
5235	4755	0.90	I-285 North	2096	35901	55	17	5.84	31.42
2799	2800	0.20	I-75/85 North	1826	30864	55	18	5.92	32.63
2786	2849	0.20	I-75/85 North	1775	34854	55	20	5.09	35.51
2843	2786	0.05	I-75/85 North	1775	34854	55	20	5.09	35.51
2844	2843	0.11	I-75/85 North	1775	34854	55	20	5.09	35.51
3253	3254	0.07	I-75	1232	27384	63	22	4.50	35.70
3254	3255	0.12	I-75	1232	27384	63	22	4.50	35.70
3273	3253	0.10	I-75	1232	27384	63	22	4.50	35.70
4002	4003	0.10	I-20 West	936	20450	61	22	4.58	36.09
4003	17877	0.17	I-20 West	936	20450	61	22	4.58	36.09
2724	2725	0.05	I-20 West	1009	24327	55	20	4.15	36.13
2725	8858	0.09	I-20 West	1009	24327	55	20	4.15	36.13
2788	2796	0.05	I-75/85 North	1830	34403	55	20	5.32	36.69
2796	2797	0.10	I-75/85 North	1830	34403	55	20	5.32	36.69
2797	2798	0.10	I-75/85 North	1830	34403	55	20	5.32	36.69

Table 72: Top 20 Roadway Segments with High Congestion Speed Drop During PM Peak

A	B	DIST	NAME	SPEED	V_TRKPM	V_TOTPM	CGSTDSPD	PCT_TRKPM	PCT_CSPD
4943	4945	0.14	GA 400 North	58	504	23128	9	2.18	15.74
2841	3147	0.20	I-75/85 South	55	1660	39931	12	4.16	21.48
3147	2840	0.10	I-75/85 South	55	1660	39931	12	4.16	21.48
5253	5565	0.09	I-285 South	58	1851	38092	13	4.86	22.02
4759	5261	0.90	I-285 South	55	2021	41110	12	4.92	22.24
2781	2937	0.10	I-75/85 South	55	1238	28149	13	4.40	24.17
6973	6975	0.22	I-85 East	61	1345	15070	15	8.93	24.81
2840	2781	0.30	I-75/85 South	55	1660	39850	14	4.17	25.76
2855	3154	0.07	I-75/85 South	55	1706	34291	14	4.98	26.01
3154	2853	0.07	I-75/85 South	55	1706	34291	14	4.98	26.01
15655	3167	0.17	I-85 East	58	1148	20997	15	5.47	26.52
59236	7015	1.19	SR 316 - East	61	537	15548	16	3.45	26.64
2792	2793	0.05	I-75/85 South	55	1606	33941	15	4.73	27.13
5258	5255	0.38	I-285 South	61	2001	41833	17	4.78	27.89
4080	4056	0.18	I-285 South	61	1808	29901	17	6.05	27.92
3127	2938	0.20	I-20 East	55	1076	32232	16	3.34	28.52
2853	3155	0.20	I-75/85 South	55	1744	38541	16	4.53	28.63
3155	2852	0.15	I-75/85 South	55	1744	38541	16	4.53	28.63
4796	4797	0.09	I-75 North	58	1163	25703	17	4.52	28.95
4797	4801	0.15	I-75 North	58	1163	25703	17	4.52	28.95

Truck Vehicle Miles of Travel

Daily vehicle miles traveled (VMT) is the number of vehicles on the roadway network per day times the length of roadway they travel. It is an indicator of the travel levels on the roadway system by motor vehicles. It is often used to estimate congestion level, on-road vehicle fuel consumption, air quality status, and potential gasoline-tax revenues.

State departments of transportation are required to include Annualized Average Daily Traffic (AADT) counts (based on a statistical sample) and mileage for all roadway for each urban area as part of their annual Highway Performance Management System (HPMS) submittal. The

HPMS based VMT can be summarized by roadway functional classification as well as by area type and can be compared to the volumes produced from an agency's models.

Georgia Department of Transportation (GDOT) produces the 400 Series Reports (known as Roadway Mileage & Characteristics Reports) every year. The reports depict mileage and Daily Vehicle Miles Traveled (DVMT) in several categories for each county in Georgia and for the whole state. Report 445 shows county-specific mileage by route type and functional classification. See

http://www.dot.ga.gov/informationcenter/statistics/RoadData/Pages/default.aspx

Table 73 and Figure 39 show comparisons of DVMT that were produced from (1) ARC's current trip based model and (2) the proposed tour-based model, compared to those values from report 445. Overall, both models produce very close values of daily VMT by county.

Table 73: Daily Vehicle Miles Traveled 2010

	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE
TRIP model results	7,905,976	18,353,781	3,943,215	20,607,297	4,254,686	33,087,824	20,401,579	5,859,974	2,653,614
TOUR model results	7,759,706	18,091,109	3,895,886	20,380,836	4,250,464	32,447,049	20,133,653	5,903,179	2,668,110
GDOT report 445	7,715,000	19,109,000	3,969,000	21,057,000	4,404,000	33,309,000	20,964,000	6,563,000	3,066,000

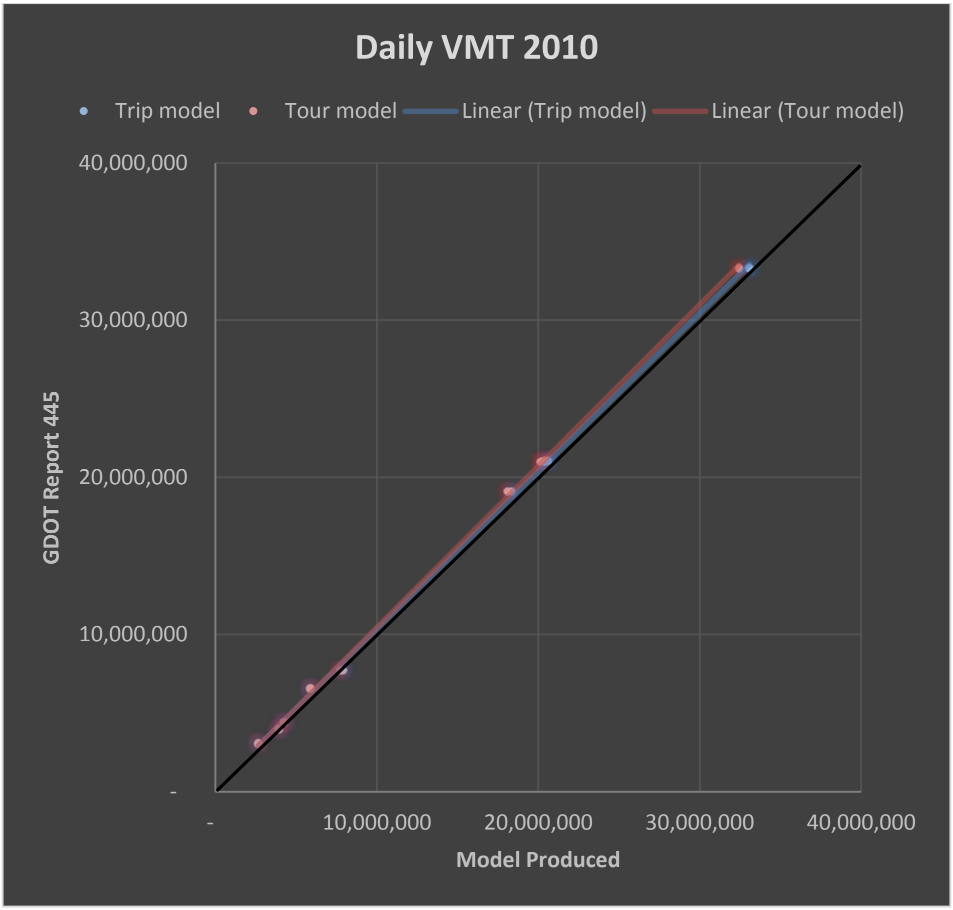


Figure 39: Daily Vehicle Miles Traveled 2010

Truck VMT was also derived from both ARC's current trip based model and the proposed tour-based model. The truck VMT for each model link was estimated by multiplying the truck volume by the link length. For each volume group j, truck VMT is calculated by summing the truck VMT of all sections of roads in that group, as formulated in the following equation, where lij is the roadway length for section i in volume group j, and Vij is the corresponding truck volume on that section.

$$truck\ VMT_j = \sum_{i=1}^{n_j} (l_{ij})(truck\ V_{ij})$$

Table 74 and Figure **40** show the estimated truck VMT. Unlike the daily VMT, there were no reference values available to compare the model estimates with. Therefore, Figure **40** shows the comparison between the results of the two models. The trip model shows higher truck VMT estimate overall and the gaps are especially higher within urban counties (Fulton, Gwinnett, DeKalb, and Cobb), while rural counties show similar estimates for both models.

Table 74: Truck Daily Vehicle Miles Traveled 2010

	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE
TRIP model results	816,447	1,637,806	471,926	1,690,523	516,370	2,698,106	1,808,293	668,934	226,219
TOUR model results	629,293	1,308,335	419,557	1,389,889	523,394	2,081,115	1,516,076	714,457	249,459

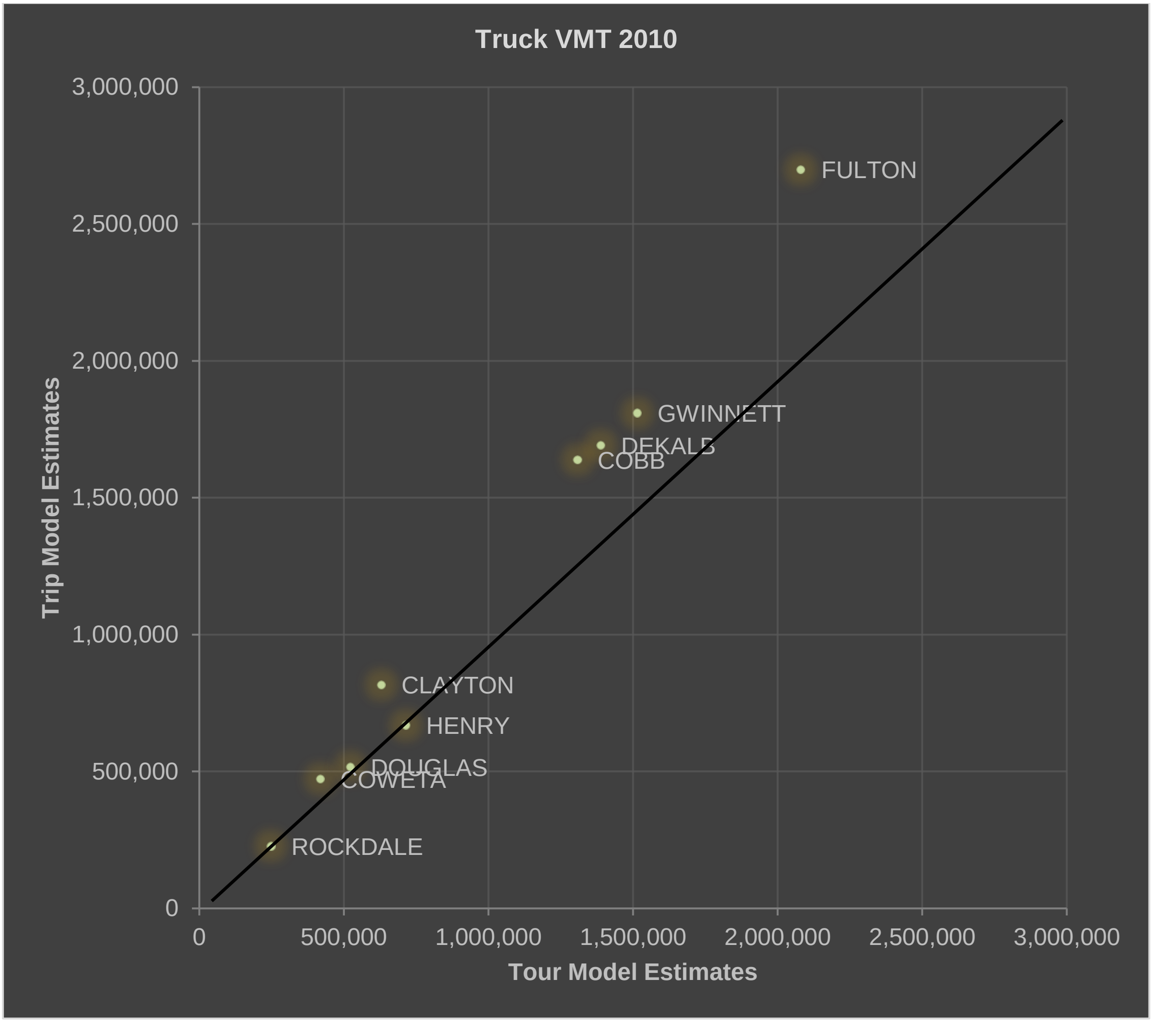


Figure 40: Truck Daily Vehicle Miles Traveled 2010 (Trip vs. Tour Model Results)

Table 75 through Table 78 show truck VMT comparisons between the two models by time of day (AM, MD, PM, and NT) and by area type (CBD/Very high density urban, High density urban, Medium density urban, Low density urban, Suburban, Exurban, and Rural). The trip model estimates higher truck VMT volumes for AM, MD, and PM for all the area types than the tour model. Higher estimates with the trip model are particularly in the following area types: High Density Urban, Medium Density Urban, and Low Density Urban. However, the tour model estimates higher truck VMT volumes than those of the trip model for NT for every area type.

The tour model produces higher estimates in the rural area types (Suburban, Exurban, and Rural).

Table 75: Truck VMT Comparison for AM Peak 2010 (ARC Trip Model vs. Tour Model)

		ARC Trip Model	Tour Model	
	Area Type	**Truck VMT**	**Truck VMT**	**Percent Overestimated w/ Trip model**
1	**CBD/Very High Density Urban**	39761	28571	0.39
2	**High Density Urban**	142805	82674	0.73
3	**Medium Density Urban**	293108	171398	0.71
4	**Low Density Urban**	396526	232422	0.71
5	**Suburban**	1320979	875817	0.51
6	**Exurban**	432673	287028	0.51
7	**Rural**	400102	279506	0.43

Table 76: Truck VMT Comparison for PM Peak 2010 (ARC Trip Model vs. Tour Model)

		ARC Trip Model	Tour Model	
	ATYPE	**Truck VMT**	**Truck VMT**	**Percent Overestimated w/ Trip model**
1	**CBD/Very High Density Urban**	39641	27779	0.43
2	**High Density Urban**	147530	82695	0.78
3	**Medium Density Urban**	308015	178136	0.73
4	**Low Density Urban**	417072	248826	0.68
5	**Suburban**	1413046	942783	0.50
6	**Exurban**	465819	345327	0.35
7	**Rural**	434893	361373	0.20

Table 77: Truck VMT Comparison for Mid-Day 2010 (ARC Trip Model vs. Tour Model)

		ARC Trip Model	Tour Model	
	ATYPE	Truck VMT	Truck VMT	Percent Overestimated w/ Trip model
1	CBD/Very High Density Urban	67426	42808	0.58
2	High Density Urban	240452	131519	0.83
3	Medium Density Urban	497385	299017	0.66
4	Low Density Urban	658094	421994	0.56
5	Suburban	2183982	1596562	0.37
6	Exurban	701570	597536	0.17
7	Rural	636729	612680	0.04

Table 78: Truck VMT Comparison for Night Time 2010 (ARC Trip Model vs. Tour Model)

		ARC Trip Model	Tour Model	
	ATYPE	Truck VMT	Truck VMT	Percent Under-estimated w/ Trip model
1	CBD/Very High Density Urban	35075	51047	-0.31
2	High Density Urban	119120	150683	-0.21
3	Medium Density Urban	259256	346367	-0.25
4	Low Density Urban	330806	489749	-0.32
5	Suburban	1086766	1832270	-0.41
6	Exurban	362217	723047	-0.50
7	Rural	321979	737955	-0.56

Table 79 shows the model forecast results for both trip-based model and tour-based model for year 2040. Compared to the trip based model, the tour model under-forecasts truck volume by 21.15% and truck VMT by 18.20% region wide. One interesting observation is that (when truck VMT is reviewed by time of day) NT truck VMT of the tour model is much higher than that of trip model by 63.02% while the other time of day results (AM, MD, and PM truck VMT) are much lower by 41.81%, 32.57%, and 35.28% respectively. Night time delay hours are expected to be 46.88% more with the tour model.

Table 79: Trip-based vs. Tour-based Model Performance Measure Comparison 2040

PERFORMANCE MEASURE: VMT VHT for 20 Counties	ARC Trip-based	ATL Tour-based	
VEHICLE VOLUME BY MODE			
SOV	379,999,895	378,581,408	-0.37%
HOV	99,675,973	104,240,304	4.58%
COMMERCIAL VEH	57,864,086	58,519,071	1.13%
TRUCK	46,315,479	36,518,076	-21.15%
TOTAL DAILY VEHICLE	583,855,433	577,858,859	-1.03%
VEHICLE MILES TRAVELED BY MODE			
SOV	148,831,783	148,526,641	-0.21%
HOV	38,870,042	40,363,456	3.84%
COMMERCIAL VEH	23,269,620	23,595,155	1.40%
TRUCK	19,506,484	15,991,685	-18.02%
TOTAL DAILY VMT	230,477,928	228,476,938	-0.87%
VEHICLE MILES TRAVELED BY TIME PERIOD			
AM VMT	54,462,150	52,772,913	-3.10%
MD VMT	65,316,578	62,353,521	-4.54%
PM VMT	74,197,126	73,352,502	-1.14%
NT VMT	36,502,073	39,998,002	9.58%
TOTAL DAILY VMT	230,477,928	228,476,938	-0.87%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD			
AM TRUCK VMT	4,294,023	2,498,782	-41.81%
MD TRUCK VMT	7,144,964	4,818,003	-32.57%
PM TRUCK VMT	4,553,870	2,947,117	-35.28%
NT TRUCK VMT	3,513,626	5,727,783	63.02%
TOTAL DAILY TRUCK VMT	19,506,484	15,991,685	-18.02%

Level of Service

Level of service (LOS) is a qualitative measure used to describe the operating conditions of

roadway (freeway, multilane highway, two-lane highway, and arterial) segments and intersections based on performance measures such as density, speed, travel time, maneuverability, delay, and safety. The level of service of a facility is designated with a letter, A to F, with A representing the best operating condition and F the worst. The Highway Capacity Manual is the most widely recognized source for determining level of service (LOS) and it uses a variety of single field measurable performance measures for level of service, depending on type of roadway. For freeways it is density in terms of equivalent passenger cars. For two-lane rural highways it is percent time delay. For arterial streets it is mean speed of through traffic. For an intersection it is mean delay.

Both ARC's trip-based model and the proposed tour-based model use daily volume to capacity ratio (V/C ratio) as an alternative for determining LOS for planning purposes. The breakpoints of V/C ratio were reviewed for later use. Table 80 is modified from GDOT's 'General Summary of Recommended Travel Demand Model Development Procedures for Consultants, MPOs and Modelers (2013).

Table 80: Level of Service V/C Ratio Breakpoints

	Average Level of Service				
	A	**B**	**C**	**D**	**E**
Proposed tour model		0.50	0.70	0.84	1.00
ARC trip-based model		0.50	0.70	0.84	1.00
GDOT models	0.30	0.50	0.70	0.85	1.00
All data sources	0.29	0.49	0.70	0.88	1.00
HCM 2010 & FDOT Q/LOS	0.27	0.48	0.65	0.87	1.00
Other Online Sources	0.43	0.58	0.80	0.90	1.00

Figure 42 and Figure 43 show the level of service of the roadway network for the Atlanta region (Figure 42) and its three most urban counties (Figure 43: Fulton, DeKalb, and Gwinnett) for year 2010 based on the daily volume to capacity (V/C) proposed above and using the proposed tour-based model. It appears that many of the roadways within urban counties such as Fulton, DeKalb, Cobb, and Gwinnett are suffering from heavy traffic congestion. More detailed analyses are needed in order to examine sub-regions by time of day and by functional class.

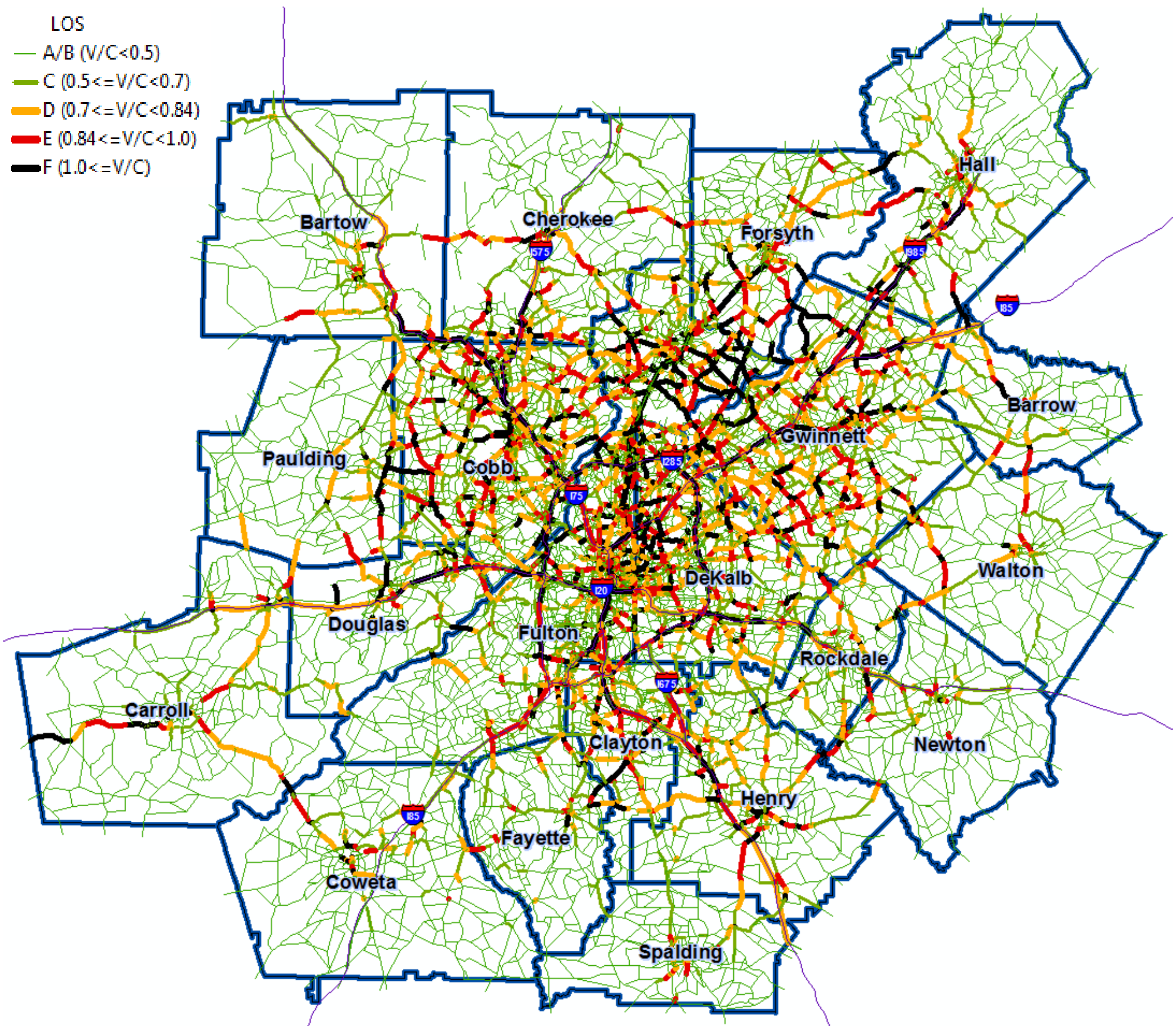


Figure 41: Level of Service 2010 with Tour-based model

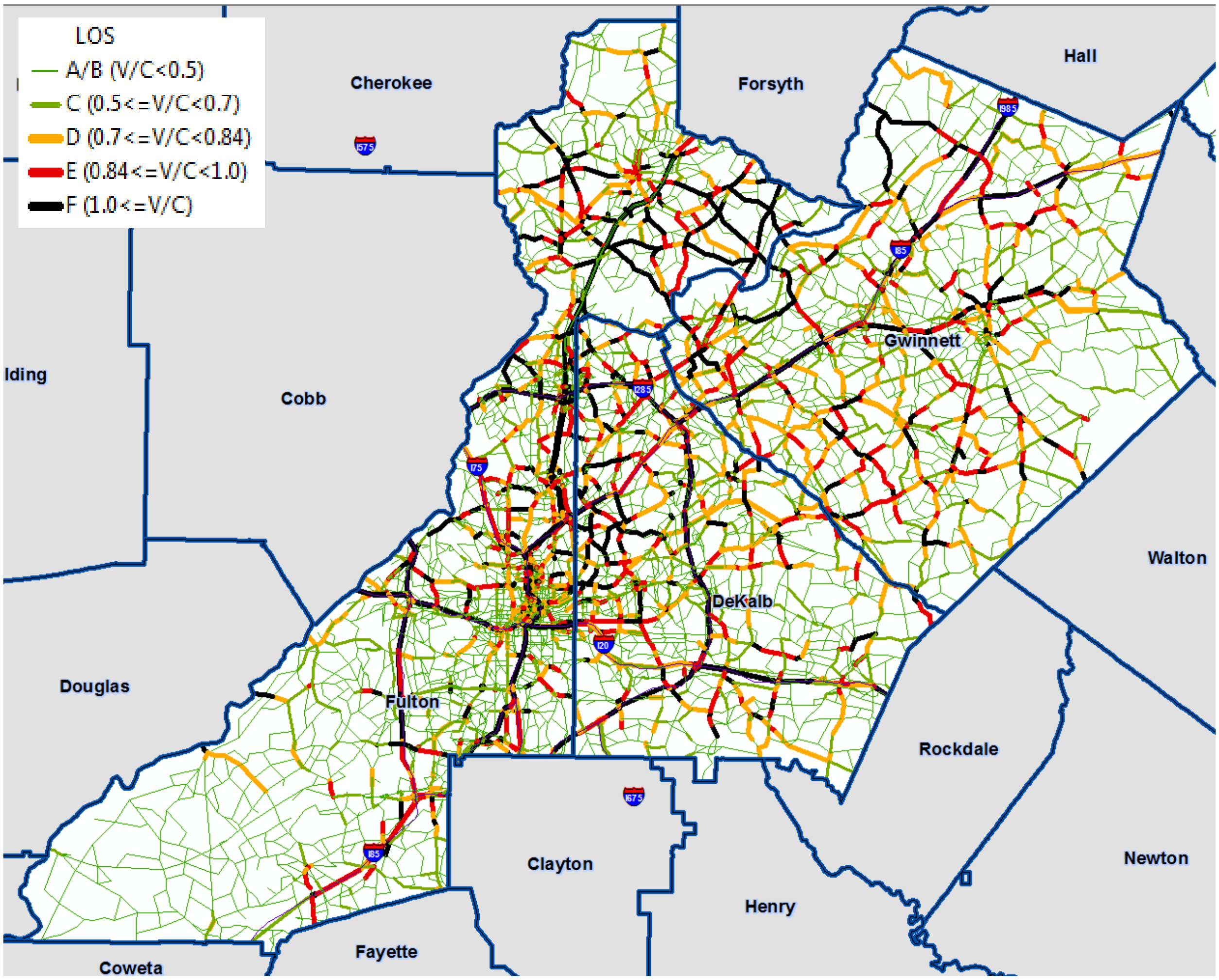


Figure 42: Level of Service 2010 for Three Major Urban Counties (Fulton, DeKalb, and Gwinnett) with Tour-based model

When the level of service/congestion is analyzed by different time of day at the link or corridor level, variation in truck traffic contributions to the congestion level at the roadway segment at different times of day can be revealed.

Figure 43 shows the level of service and truck volume share by time of day for the segment of I-285 South from model node #5252 to #5240, which covers 0.34 miles of a four lane facility. Total daily traffic volume is estimated as 85,770 and daily truck volume of 9,450 or 11.02% of this total. During the AM peak period (6:00 am – 10:00 am for Atlanta), 11.46% of the total traffic (16,010) is truck volume (1,834). During the MD period (10:00 am – 3:00 pm for Atlanta), 10.86% of the total traffic (25,686) is truck volume (2,789). During the PM peak period (3:00 pm – 7:00 pm for Atlanta), 5.52% of the total traffic (25,719) is truck volume (1,420). Noticeably, the NT period (7:00 pm – 6:00 am for Atlanta) shows the highest truck share which is 18.56% of the total traffic (18,355). These results suggest that a daily V/C should be avoided when determining roadway congestion level, since it varies so much throughout a day. The inset table in Figure 43 shows V/C ratio and LOS by time of day more clearly. Usually the hourly capacity is assumed to be the 10 percent of the daily capacity. The V/C ratios are calculated applying capacity factors as follows:

VC ratio AM= V_TOTAM / (AMCAPACITY * Capacity Factor)

VC ratio MD= V_TOTMD / (MDCAPACITY * Capacity Factor)

VC ratio PM= V_TOTPM / (PMCAPACITY * Capacity Factor)

VC ratio NT= V_TOTNT / (NTCAPACITY * Capacity Factor)

VC ratio (Daily) = V_TOTDAY / (CAPACITY * 10)

Capacity factors vary for each regional model and here are the capacity factors applied within the Atlanta MPO (ARC) and Birmingham MPO (RPCGB) models.

Capacity Factor	ARC	RPCGB
AM	4	2.22
MD	5	5.16
PM	4	2.92
NT	11	3.28

It seems that the segment suffers from congestion with LOS ‘F’. However, when V/C is analyzed by time of day, the congestion level of the roadway segment seems to be much milder.

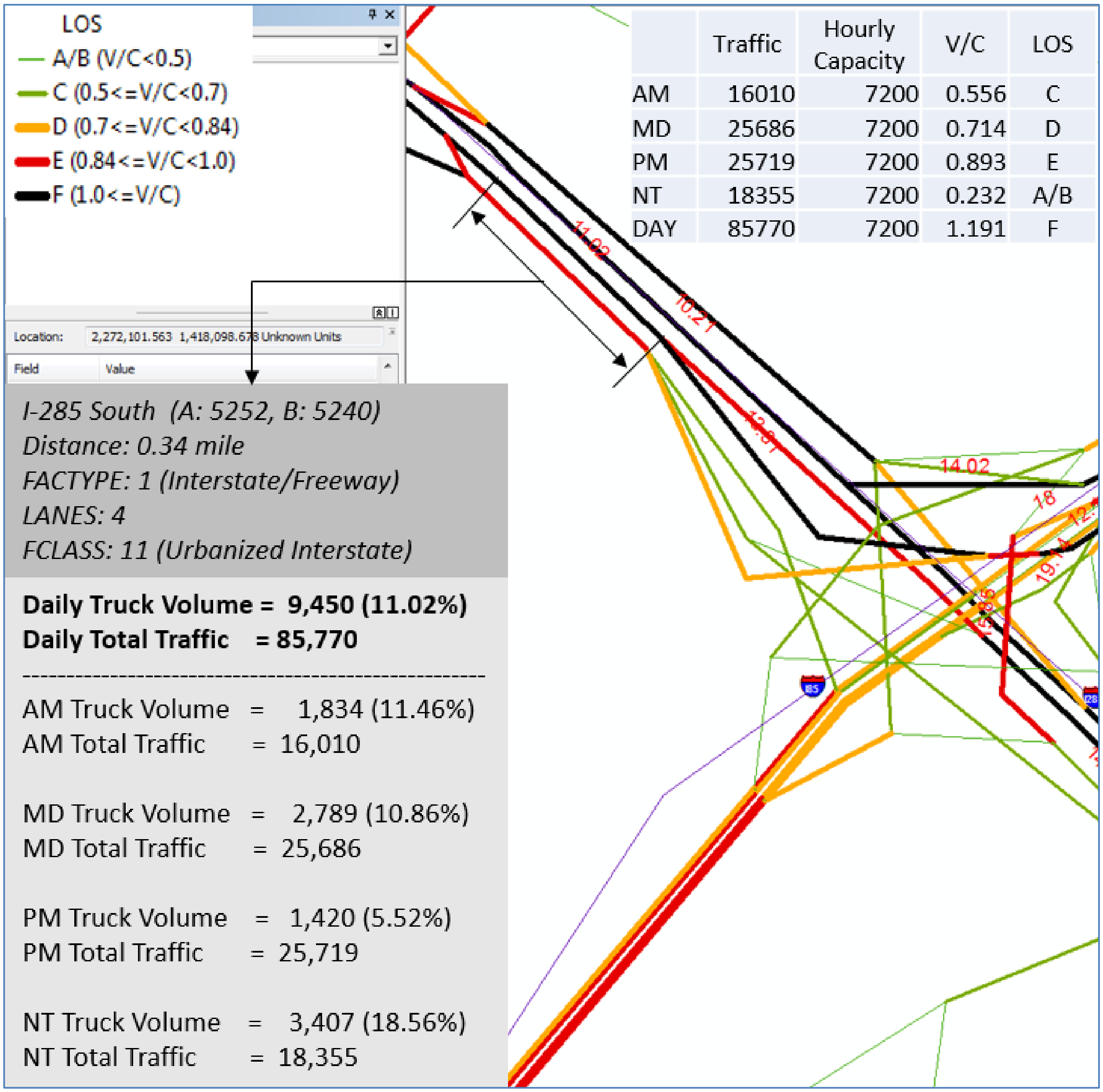
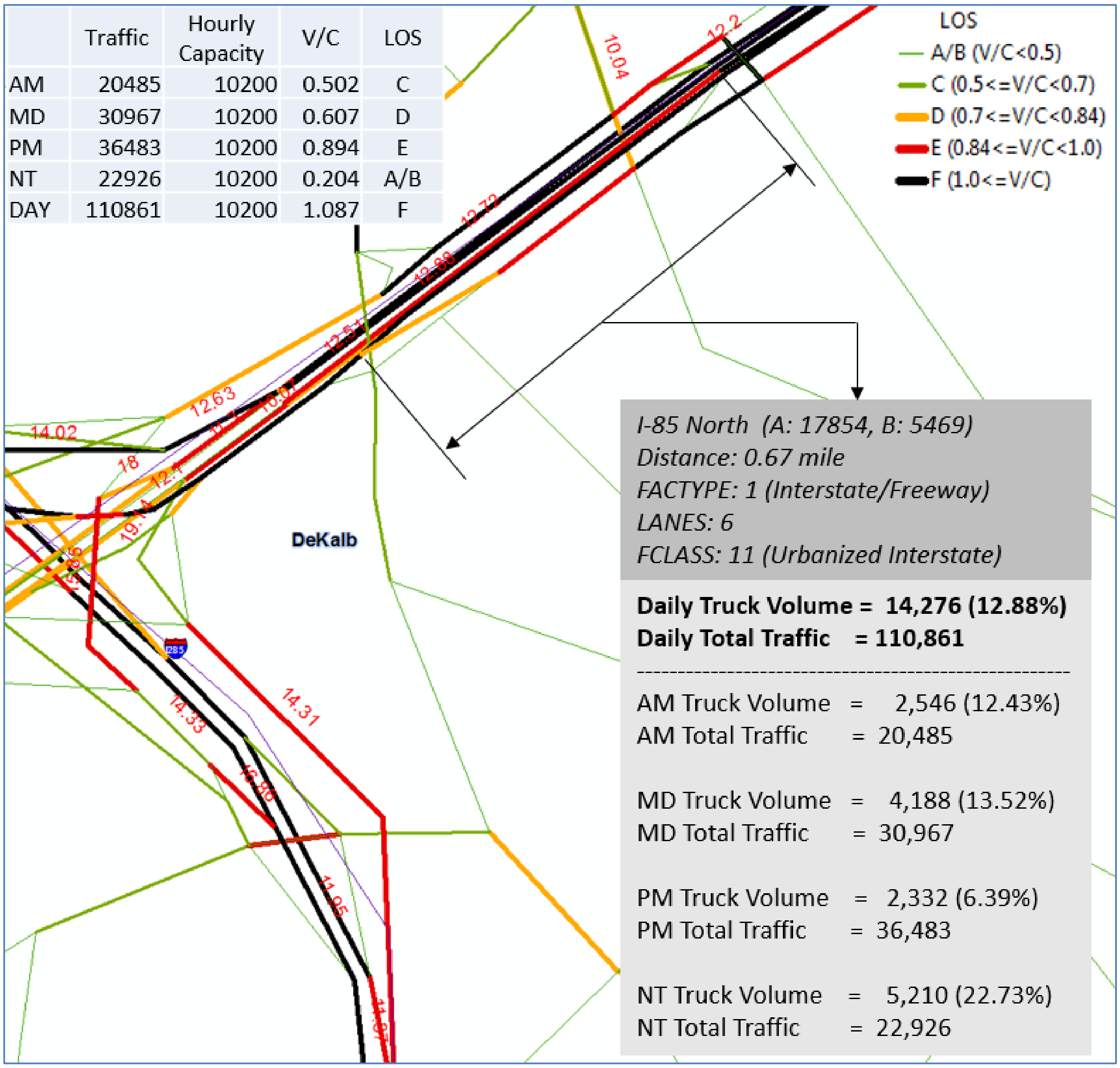


Figure 43: Level of Service and Truck Volume Share by Time of Day (I-285 South Segment from Node 5252 to Node 5240)

Figure 44 shows level of service and truck volume share by time of day for the segment of I-85 North from model node #17854 to #5469 which is a 0.67-mile and six-lane facility. Total daily traffic volume is estimated as 110,861 and daily truck volume takes about 12.88%, which is 14,276. For the selected roadway segment, the night time (NT) period also shows the highest truck share which is 22.73% of the total traffic of 22,926 during that period. The LOS level is mapped in this map based on daily traffic volume and daily roadway capacity. The daily V/C ratio of the selected segment indicates it has the LOS of 'F', but the LOS by each time of day are much milder: 'C' at AM peak, 'D' at mid-day, 'E' at PM peak, and 'A/B' at night time.



	Traffic	Hourly Capacity	V/C	LOS
AM	20485	10200	0.502	C
MD	30967	10200	0.607	D
PM	36483	10200	0.894	E
NT	22926	10200	0.204	A/B
DAY	110861	10200	1.087	F

Figure 44: Level of Service and Truck Volume Share by Time of Day (I-85 North Segment from Node 17854 to Node 5469)

As shown with these examples, the proposed model can be used for identifying major highway corridors of heavy truck use at various scales and developing appropriate congestion management strategies. Examples may include:

- Bottleneck analysis
- Development of alternative truck routes
- Development of alternative time management for truck movement
- Development of truck restriction areas
- Integration with crash and safety related database

Scenarios and the Tour-based Model

The Georgia DOT's statewide freight and logistics plan designates truck corridors with regard to oversize trucks. Figure 45 shows the three coding schemes that GDOT uses: Class A is for designated access routes for oversize trucks allowing single and twin trailers; Class C is used for designated access routes that only allow for oversize trucks that utilize twin trailers. These are routes with sharp turns that oversize (in terms of length) single trailer trucks cannot negotiate, but shorter, articulated twin trailer combinations can use; and Class D is for all Interstate routes. Oversize trucks are defined as trucks that have either longer dimensions than the standard five-axle semi-trailer, or are heavier than the 80,000-pound federal truck weight limit. Since freight movements coming from the eastern seaboards are expected to move along I-75 (leaving the Port of Savannah through I-16 and merging onto I-75 at Macon) and I-20, scenarios were developed to manifest potential truck volume changes along those corridors.

Figure 45: Georgia Designated Truck Corridors (Source: GDOT statewide freight and logistics plan)

Scenarios involve hypothetical truck volume changes for specific external stations: that is External Station #2087 for I-75 entering the model area from Savannah, GA and Florida, and Station #2078 for I-20 from Augusta, GA. Since the external station truck volumes (external.prn) are one of the key input files, manipulating the external station truck volumes can allow investigators to simulate how potential changes in these incoming truck volumes affect the dynamics of internal truck movements within the modeling area. For example we are expecting additional truck volume increases due to Panama Canal expansion for year 2040. With this expected future in mind we apply a set of hypothetical volume changes to those external stations where most canal impacts are likely to occur and simulate the model applications and evaluate the results. Specifically, the research team applied three hypothetical volume increases (30%, 50%, and 70%) to those selected external stations (#2087 and #2078). Table 81 shows the selected scenarios with corresponding scenario volumes applied.

Table 81: Selected Scenarios

SCENARIO	External Station	Tour-Model Forecast Volume (2040)	Hypothetical Increase	Scenario Volume (2040)	Truck Corridor
Scenario 1	ES-2087	29476	30% Increase	38319	I-75
Scenario 2	ES-2087	29476	50% Increase	44214	I-75
Scenario 3	ES-2087	29476	70% Increase	50109	I-75
Scenario 4	ES-2078	11639	30% Increase	15131	I-20
Scenario 5	ES-2078	11639	50% Increase	17459	I-20
Scenario 6	ES-2078	11639	70% Increase	19786	I-20

The following set of performance measures are used to evaluate the results for each scenario: (1) vehicle volume by mode, (2) vehicle miles traveled (VMT) by mode, (3) truck vehicle miles traveled by time period, (4) VMT per capita, VMT per household, VMT per job, (5) VHT per capita, VHT per household, VHT per job, (6) truck vehicle hours traveled (VHT) by time period, (7) daily delay hours, (8) average highway speeds, (9) daily fuel consumption by mode, (10) percent VMT by level-of-service. These performance measures are calculated and summarized by the 10 counties (Clayton, Cobb, Coweta, DeKalb, Douglas, Fulton, Gwinnett, Henry, Newton) located along the major truck corridors.

Scenario 1

With a 30% increase of truck volume at external station #2087, the total truck volume in the modeling area (20 counties) shows a 1.41% increase area wide, while Henry County shows the highest truck volume increase with 13.18% and Clayton County the second highest with a 6.70% increase; which seems to be reasonable since those counties are located between the external station and the metro core areas along I-75. The adjacent counties such as Fulton, DeKalb, and Rockdale Counties show some truck volume increases as well (2.45%, 1.43%, and 3.17% respectively). Table 82 shows the percent changes in performance measures at the county level with Scenario 1 compared to 2040 base results of the tour model.

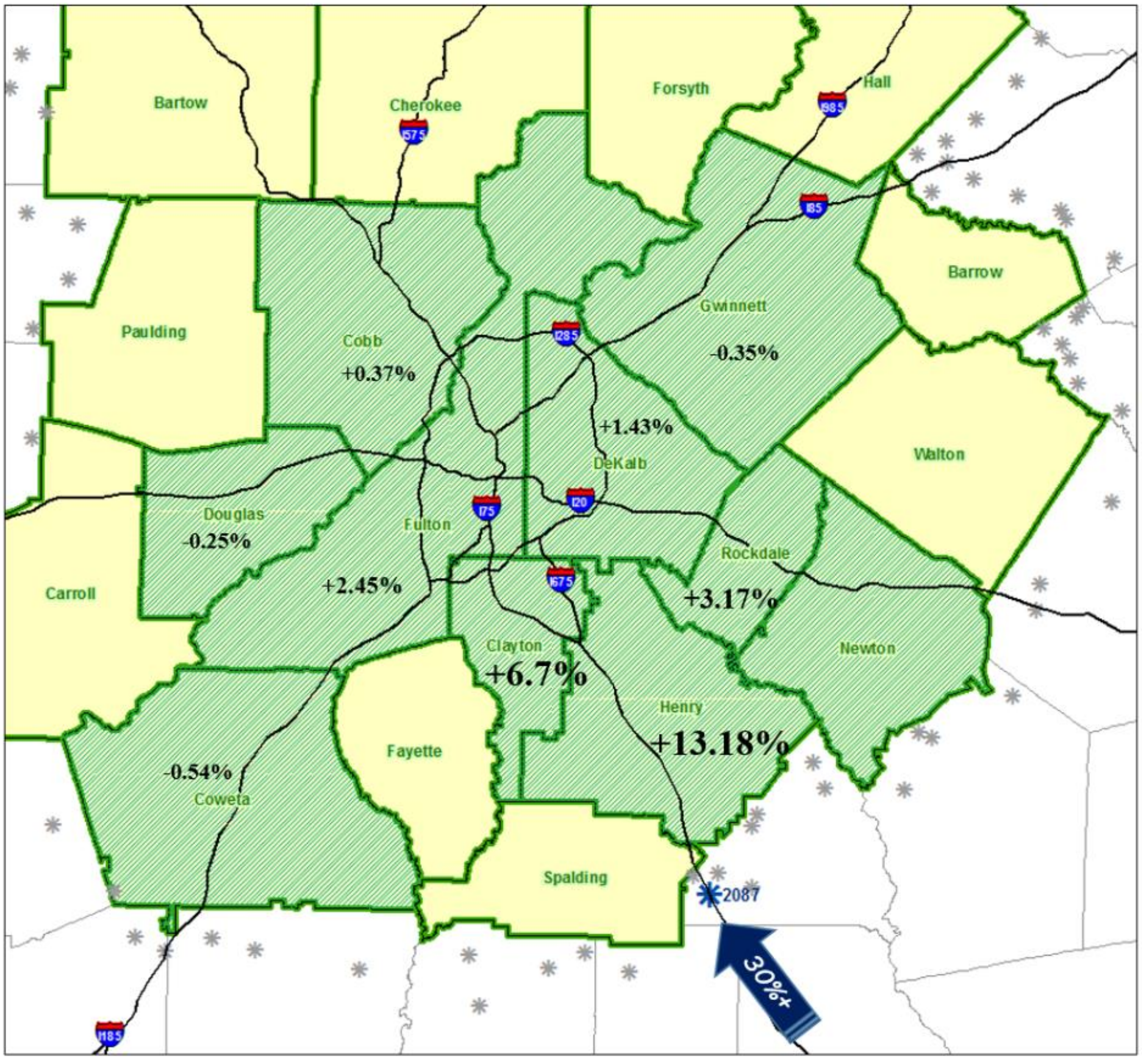


Figure 46: Percent Changes in County Truck Volume with Scenario 1

Table 82: Percent Changes in Performance Measures at County Level with Scenario 1

PERFORMANCE MEASURE: VMT VHT for	20 Counties	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE
VEHICLE VOLUME BY MODE										
TRUCK	1.41%	6.70%	0.37%	-0.54%	1.43%	-0.25%	2.45%	-0.35%	13.18%	3.17%
TOTAL DAILY VEHICLE	0.08%	0.38%	0.02%	-0.03%	0.06%	0.02%	0.09%	0.01%	0.92%	0.23%
VEHICLE MILES TRAVELED BY MODE										
TRUCK	1.94%	7.51%	0.48%	0.15%	1.82%	0.37%	1.82%	-0.38%	15.88%	2.95%
TOTAL DAILY VMT	0.12%	0.43%	0.03%	0.03%	0.08%	0.01%	0.08%	0.00%	1.32%	0.26%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD										
AM TRUCK VMT	2.23%	7.39%	0.53%	0.95%	2.02%	2.07%	2.20%	-0.05%	15.13%	3.33%
MD TRUCK VMT	2.26%	6.99%	1.18%	1.60%	1.85%	0.45%	2.20%	0.28%	15.21%	1.71%
PM TRUCK VMT	1.54%	6.83%	0.18%	-0.20%	1.58%	-0.12%	1.39%	-1.70%	15.77%	3.94%
NT TRUCK VMT	1.77%	8.38%	0.03%	-1.12%	1.81%	-0.07%	1.53%	-0.40%	16.79%	3.35%
TOTAL DAILY TRUCK VMT	1.94%	7.51%	0.48%	0.15%	1.82%	0.37%	1.82%	-0.38%	15.88%	2.95%
TRUCK (CONGESTED) VEHICLE HOURS TRAVELED BY TIME PERIOD										
AM TRUCK CONGESTED VHT	2.07%	6.89%	0.46%	0.59%	2.10%	1.94%	2.44%	-0.04%	15.98%	3.57%
MD TRUCK CONGESTED VHT	2.71%	6.11%	1.08%	1.48%	2.09%	0.32%	2.47%	-0.03%	20.75%	2.19%
PM TRUCK CONGESTED VHT	1.37%	6.04%	0.15%	-0.31%	1.83%	-0.05%	1.46%	-2.19%	17.72%	4.68%
NT TRUCK CONGESTED VHT	1.82%	7.49%	-0.22%	-1.77%	2.02%	-0.39%	1.50%	-0.49%	19.36%	3.77%
TOTAL DAILY TRUCK VHT	1.99%	6.64%	0.36%	-0.16%	2.00%	0.25%	1.93%	-0.76%	18.84%	3.53%
DAILY DELAY HOURS										
AM Delay	0.46%	1.57%	0.22%	0.04%	0.36%	0.21%	0.46%	0.23%	4.01%	0.91%
MD Delay	1.27%	2.85%	0.41%	0.91%	0.91%	1.11%	0.42%	-0.07%	16.15%	1.64%
PM Delay	0.25%	1.03%	0.19%	0.02%	0.35%	0.31%	0.14%	-0.31%	4.61%	1.48%
NT Delay	2.09%	6.18%	0.62%	-1.51%	0.89%	0.43%	0.97%	-0.11%	20.54%	2.73%
TOTAL DELAY	0.50%	1.55%	0.24%	0.09%	0.44%	0.38%	0.28%	-0.13%	6.98%	1.38%
DAILY FUEL CONSUMPTION BY CAR/TRUCK (GALLONS OF FUEL)										
TRUCK FUEL CONSUMPTION	1.94%	7.51%	0.48%	0.15%	1.82%	0.37%	1.82%	-0.38%	15.88%	2.95%
TOTAL FUEL CONSUMPTION	0.33%	1.31%	0.08%	0.05%	0.25%	0.07%	0.25%	-0.05%	3.76%	0.64%

Scenario 2

With a 50% increase of truck volume at external station #2087, the model shows 2.39% area wide truck volume increase. Similar to Scenario 1, counties most impacted from the volume changes are Henry (22.26%), Clayton (12.01%), Rockdale (5.30%), Fulton (3.82%), and DeKalb (2.32%). Accordingly, the other performance measures such as VMT, VHT, truck VMT, daily delay hours, and truck fuel consumption also highly increased in those counties.

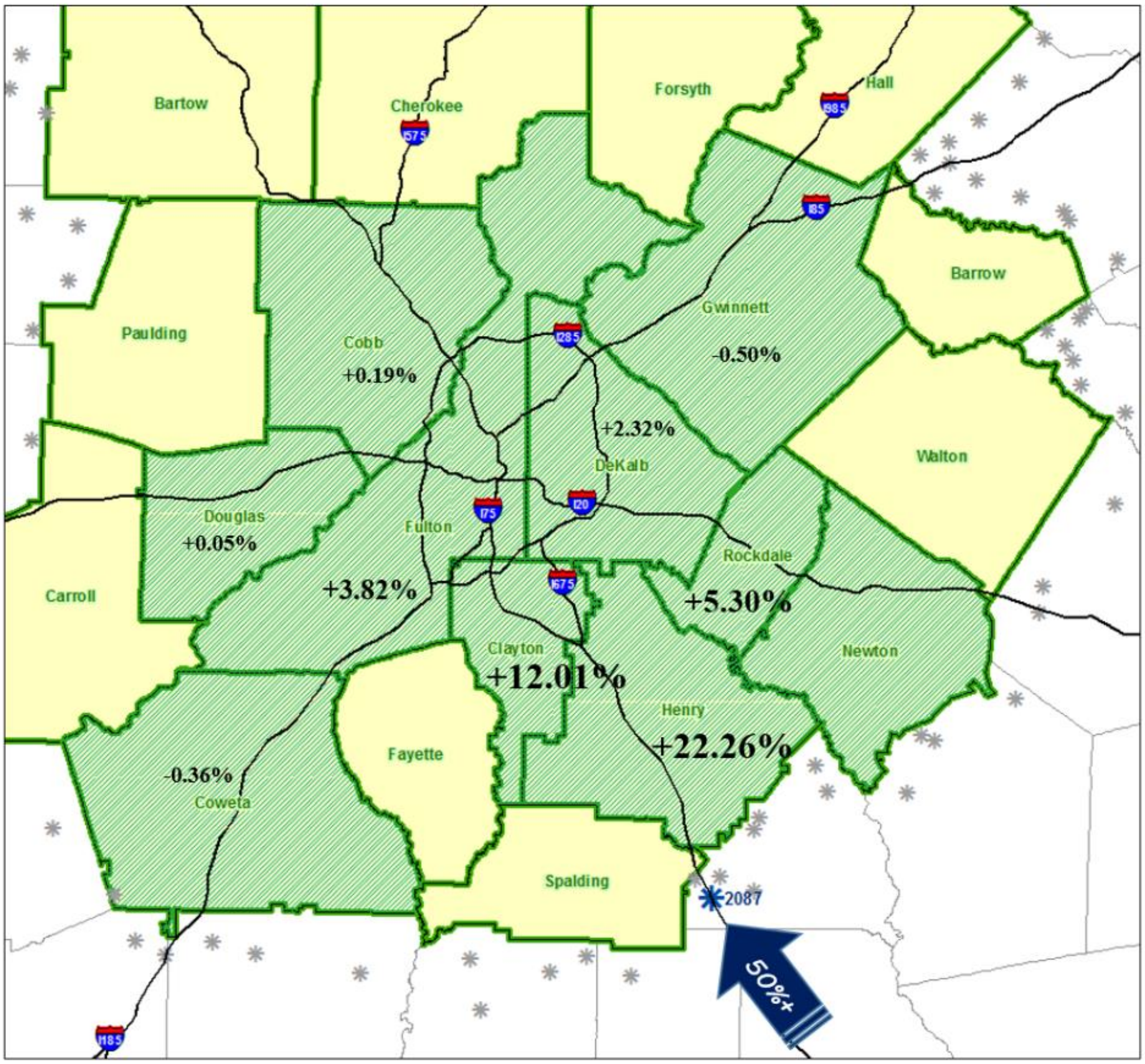


Figure 47: Percent Changes in County Truck Volume with Scenario 2

Table 83: Percent Changes in Performance Measures at County Level with Scenario 2

PERFORMANCE MEASURE: VMT VHT for	20 Counties	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE
VEHICLE VOLUME BY MODE										
TRUCK	2.39%	12.01%	0.19%	-0.36%	2.32%	0.05%	3.82%	-0.50%	22.26%	5.30%
TOTAL DAILY VEHICLE	0.15%	0.72%	0.05%	0.01%	0.10%	0.09%	0.15%	-0.01%	1.59%	0.40%
VEHICLE MILES TRAVELED BY MODE										
TRUCK	3.30%	13.36%	0.48%	0.47%	3.03%	0.81%	2.84%	-0.54%	26.75%	4.95%
TOTAL DAILY VMT	0.20%	0.78%	0.05%	0.07%	0.13%	0.04%	0.13%	-0.01%	2.26%	0.44%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD										
AM TRUCK VMT	3.72%	12.69%	1.65%	2.22%	3.19%	3.31%	3.35%	-0.12%	25.46%	4.91%
MD TRUCK VMT	3.44%	12.55%	1.03%	0.05%	3.52%	0.93%	2.96%	-0.57%	26.06%	5.24%
PM TRUCK VMT	2.65%	11.71%	-0.57%	-0.32%	2.97%	0.32%	2.36%	-1.42%	25.58%	5.24%
NT TRUCK VMT	3.32%	15.19%	0.02%	0.56%	2.58%	0.05%	2.73%	-0.27%	28.40%	4.54%
TOTAL DAILY TRUCK VMT	3.30%	13.36%	0.48%	0.47%	3.03%	0.81%	2.84%	-0.54%	26.75%	4.95%
TRUCK (CONGESTED) VEHICLE HOURS TRAVELED BY TIME PERIOD										
AM TRUCK CONGESTED VHT	3.57%	12.33%	1.40%	1.78%	3.21%	3.22%	3.76%	0.04%	27.30%	5.48%
MD TRUCK CONGESTED VHT	4.62%	11.37%	0.95%	-0.29%	4.01%	0.78%	3.31%	-0.90%	40.43%	6.50%
PM TRUCK CONGESTED VHT	2.62%	11.12%	-0.80%	-0.72%	3.27%	0.72%	2.62%	-1.59%	29.65%	6.43%
NT TRUCK CONGESTED VHT	3.55%	14.10%	-0.34%	-0.07%	2.74%	-0.41%	2.71%	-0.29%	33.42%	4.93%
TOTAL DAILY TRUCK VHT	3.60%	12.30%	0.20%	0.01%	3.32%	0.76%	3.04%	-0.76%	33.61%	5.85%
DAILY DELAY HOURS										
AM Delay	0.83%	2.46%	0.52%	0.48%	0.60%	0.61%	0.82%	0.32%	6.53%	1.54%
MD Delay	2.43%	5.88%	0.89%	0.37%	1.47%	1.04%	0.65%	-0.18%	33.69%	4.76%
PM Delay	0.54%	1.81%	0.06%	0.24%	0.58%	0.55%	0.45%	-0.15%	7.75%	2.34%
NT Delay	3.74%	9.46%	0.78%	0.00%	1.99%	0.31%	1.95%	0.10%	35.02%	4.01%
TOTAL DELAY	0.96%	2.66%	0.30%	0.31%	0.73%	0.61%	0.61%	-0.03%	12.64%	2.43%
DAILY FUEL CONSUMPTION BY CAR/TRUCK (GALLONS OF FUEL)										
TRUCK FUEL CONSUMPTION	3.30%	13.36%	0.48%	0.47%	3.03%	0.81%	2.84%	-0.54%	26.75%	4.95%
TOTAL FUEL CONSUMPTION	0.57%	2.35%	0.09%	0.13%	0.43%	0.17%	0.39%	-0.07%	6.36%	1.07%

Scenario 3

With a 70% increase of truck volume at external station #2087, the model shows 3.31% area wide truck volume increase. Similar to Scenario 1 and 2, counties most impacted from the volume changes are Henry (31.09%), Clayton (16.28%), Rockdale (7.47%), Fulton (5.18%), and DeKalb (3.81%). Accordingly, the other performance measures such as VMT, VHT, truck VMT, daily delay hours, and truck fuel consumption also greatly increased in those counties.

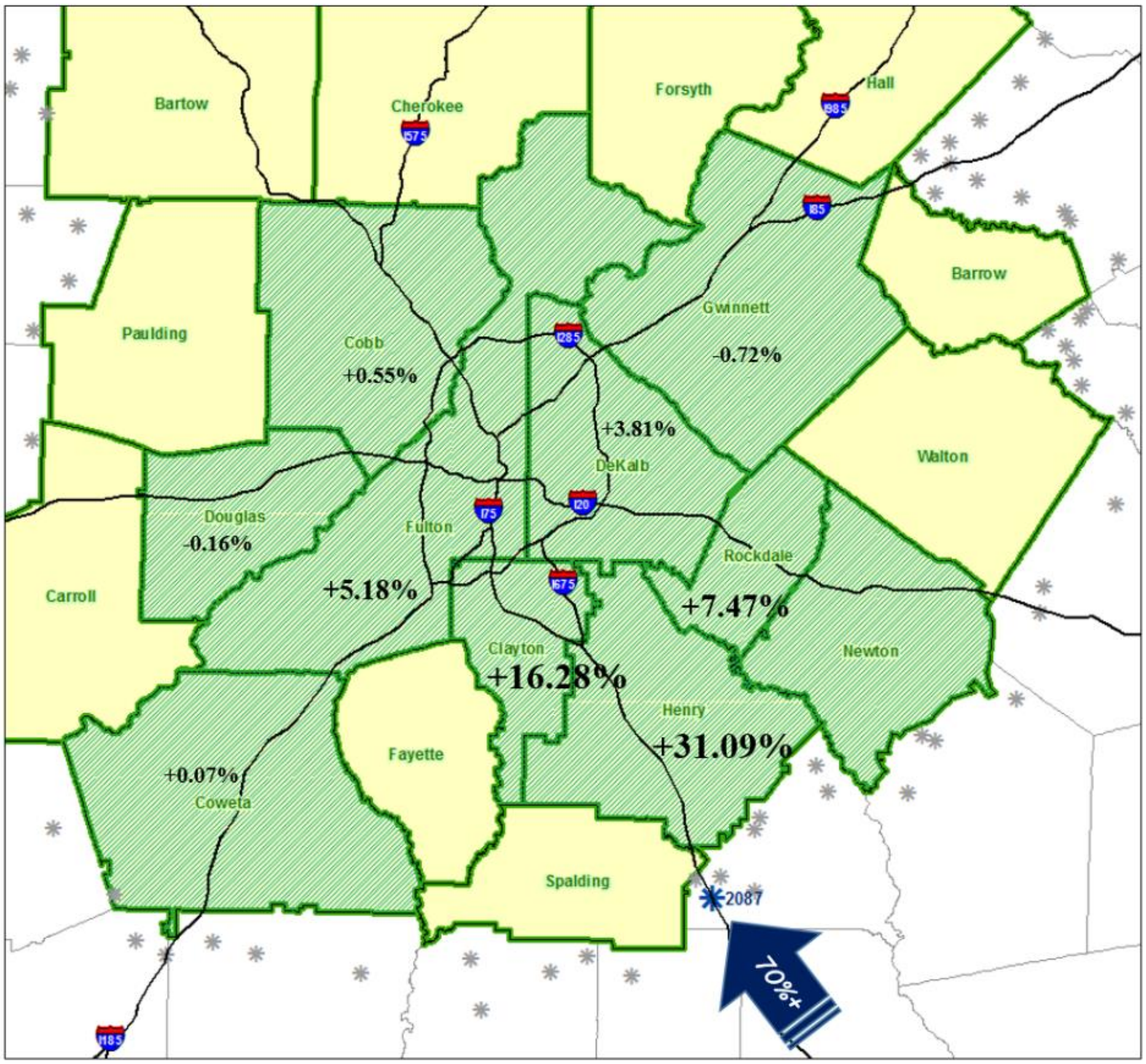


Figure 48: Percent Changes in County Truck Volume with Scenario 3

Table 84: Percent Changes in Performance Measures at County Level with Scenario 3

PERFORMANCE MEASURE: VMT VHT for	20 Counties	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE
VEHICLE VOLUME BY MODE										
TRUCK	3.31%	16.28%	0.55%	0.07%	3.81%	-0.16%	5.18%	-0.72%	31.09%	7.47%
TOTAL DAILY VEHICLE	0.24%	0.94%	0.11%	0.05%	0.19%	0.09%	0.31%	-0.01%	2.29%	0.59%
VEHICLE MILES TRAVELED BY MODE										
TRUCK	4.65%	18.39%	0.72%	0.80%	4.76%	1.09%	3.96%	-0.76%	37.71%	6.90%
TOTAL DAILY VMT	0.29%	1.03%	0.08%	0.09%	0.21%	0.05%	0.22%	-0.02%	3.24%	0.63%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD										
AM TRUCK VMT	5.36%	18.49%	2.14%	1.46%	4.48%	3.03%	4.55%	0.85%	36.81%	7.75%
MD TRUCK VMT	4.80%	16.85%	1.16%	2.88%	5.14%	1.45%	4.47%	-0.49%	36.34%	6.11%
PM TRUCK VMT	3.93%	16.65%	-0.04%	0.85%	4.32%	1.08%	3.57%	-1.77%	36.08%	5.36%
NT TRUCK VMT	4.58%	20.61%	0.07%	-1.12%	4.82%	0.11%	3.42%	-1.21%	40.01%	8.13%
TOTAL DAILY TRUCK VMT	4.65%	18.39%	0.72%	0.80%	4.76%	1.09%	3.96%	-0.76%	37.71%	6.90%
TRUCK (CONGESTED) VEHICLE HOURS TRAVELED BY TIME PERIOD										
AM TRUCK CONGESTED VHT	5.38%	18.17%	2.03%	0.47%	4.59%	2.22%	5.23%	1.02%	41.01%	8.95%
MD TRUCK CONGESTED VHT	7.07%	15.12%	1.11%	3.46%	5.96%	1.19%	5.03%	-0.80%	62.61%	7.54%
PM TRUCK CONGESTED VHT	4.13%	15.31%	-0.24%	0.13%	4.76%	1.06%	4.25%	-2.15%	44.07%	6.59%
NT TRUCK CONGESTED VHT	4.99%	19.25%	-0.31%	-2.04%	5.06%	-0.51%	3.37%	-1.35%	47.89%	8.81%
TOTAL DAILY TRUCK VHT	5.40%	16.92%	0.53%	0.40%	5.11%	0.77%	4.42%	-0.98%	50.19%	7.90%
DAILY DELAY HOURS										
AM Delay	1.25%	3.35%	0.84%	-0.09%	0.99%	0.25%	1.19%	0.57%	9.81%	2.37%
MD Delay	3.80%	7.35%	1.12%	2.20%	2.23%	1.47%	1.19%	-0.21%	53.06%	5.90%
PM Delay	0.86%	2.48%	0.29%	0.47%	0.83%	0.57%	0.73%	-0.19%	11.61%	2.53%
NT Delay	5.18%	13.06%	0.86%	-1.08%	3.11%	0.89%	2.50%	-0.52%	50.35%	6.85%
TOTAL DELAY	1.48%	3.58%	0.55%	0.50%	1.11%	0.59%	0.96%	0.00%	19.19%	3.03%
DAILY FUEL CONSUMPTION BY CAR/TRUCK (GALLONS OF FUEL)										
TRUCK FUEL CONSUMPTION	4.65%	18.39%	0.72%	0.80%	4.76%	1.09%	3.96%	-0.76%	37.71%	6.90%
TOTAL FUEL CONSUMPTION	0.81%	3.19%	0.15%	0.20%	0.68%	0.22%	0.58%	-0.10%	9.02%	1.50%

Scenario 4

With a 30% increase of truck volume at external station #2078, the total truck volume in the modeling area (20 counties) shows 0.74% increase area wide, while Newton County shows highest truck volume increase of 11.67% and Rockdale County hits the second with 6.54% increase, which seems to be reasonable since those counties are located between the external station and the Atlanta metro core areas along I-20. The adjacent counties such as DeKalb, Fulton, Henry, and Clayton, Counties show some truck volume increases as well (2.23%, 0.69%, 0.53%, and 0.26% respectively).

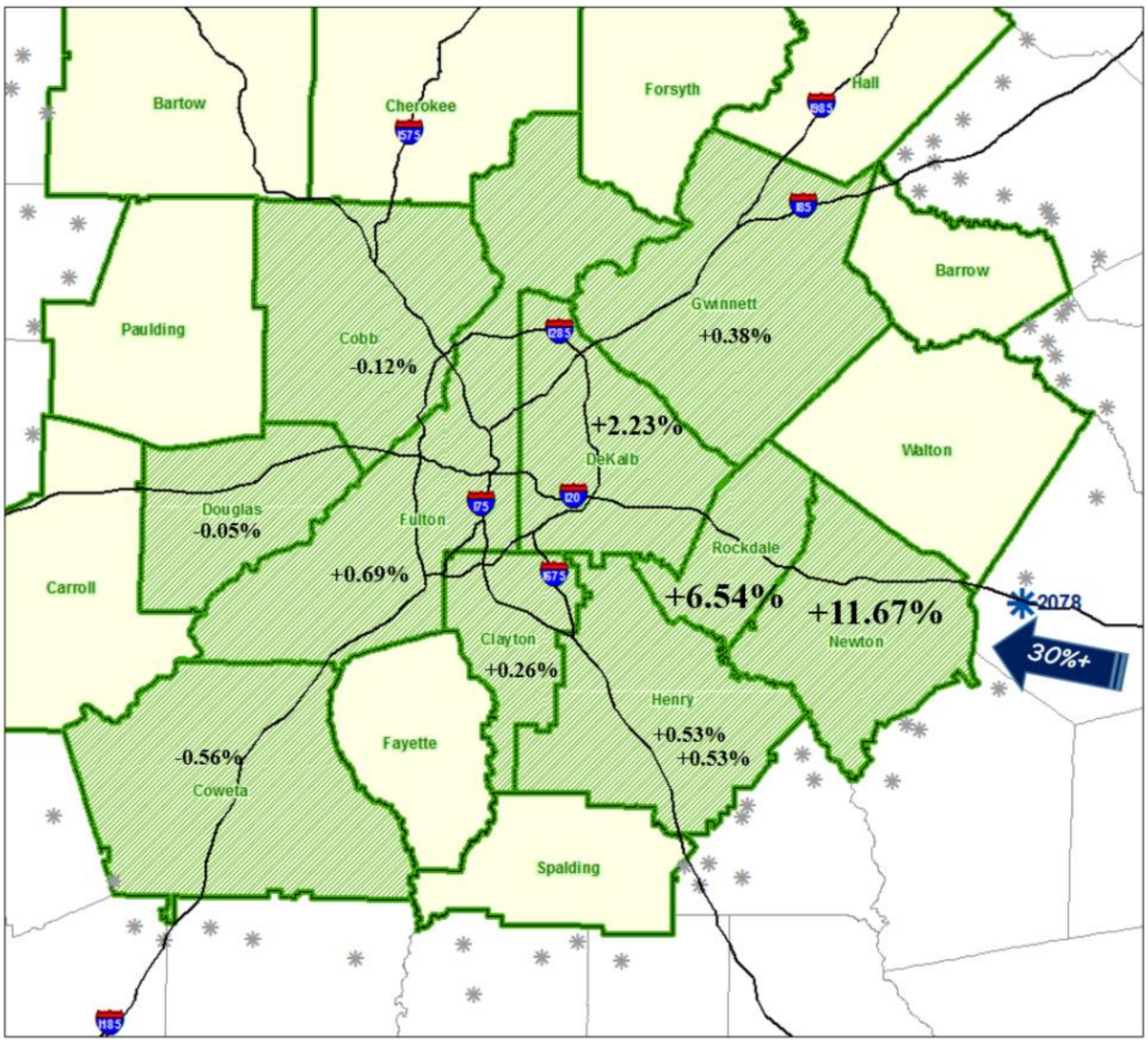


Figure 49: Percent Changes in County Truck Volume with Scenario 4

Table 85: Percent Changes in Performance Measures at County Level with Scenario 4

PERFORMANCE MEASURE: VMT VHT for	20 Counties	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE	NEWTON
VEHICLE VOLUME BY MODE											
TRUCK	0.74%	0.26%	-0.12%	-0.56%	2.23%	-0.05%	0.69%	0.38%	0.53%	6.54%	11.67%
TOTAL DAILY VEHICLE	0.08%	0.05%	0.02%	-0.04%	0.09%	-0.01%	0.13%	0.04%	0.07%	0.39%	0.89%
VEHICLE MILES TRAVELED BY MODE											
TRUCK	0.81%	0.44%	-0.04%	-0.05%	2.39%	0.17%	0.45%	0.40%	0.48%	6.98%	13.10%
TOTAL DAILY VMT	0.06%	0.07%	-0.02%	0.00%	0.08%	-0.01%	0.05%	0.05%	0.06%	0.48%	1.00%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD											
AM TRUCK VMT	1.11%	0.81%	0.37%	-0.48%	2.61%	1.41%	0.53%	0.11%	1.49%	8.09%	13.59%
MD TRUCK VMT	1.06%	-0.12%	0.46%	1.32%	2.32%	0.94%	0.97%	1.17%	-0.36%	6.59%	11.55%
PM TRUCK VMT	0.07%	0.53%	-0.99%	-0.67%	2.02%	-0.42%	-0.11%	-1.30%	1.57%	5.34%	12.69%
NT TRUCK VMT	0.84%	0.73%	-0.18%	-0.71%	2.53%	-0.62%	0.27%	0.76%	0.26%	7.79%	14.39%
TOTAL DAILY TRUCK VMT	0.81%	0.44%	-0.04%	-0.05%	2.39%	0.17%	0.45%	0.40%	0.48%	6.98%	13.10%
TRUCK (CONGESTED) VEHICLE HOURS TRAVELED BY TIME PERIOD											
AM TRUCK CONGESTED VHT	1.03%	0.45%	0.26%	-0.81%	2.78%	1.75%	0.66%	0.32%	1.75%	7.85%	10.83%
MD TRUCK CONGESTED VHT	1.05%	-0.15%	0.29%	1.50%	2.55%	1.30%	1.19%	1.28%	-0.79%	6.30%	8.57%
PM TRUCK CONGESTED VHT	-0.25%	0.81%	-1.14%	-1.22%	2.22%	-0.68%	-0.09%	-2.01%	2.38%	4.88%	10.57%
NT TRUCK CONGESTED VHT	0.73%	0.72%	-0.35%	-1.02%	2.57%	-0.85%	0.20%	0.95%	0.24%	6.95%	12.74%
TOTAL DAILY TRUCK VHT	0.61%	0.44%	-0.29%	-0.28%	2.51%	0.17%	0.47%	0.08%	0.68%	6.38%	10.75%
DAILY DELAY HOURS											
AM Delay	0.21%	0.39%	0.16%	-0.18%	0.27%	0.11%	0.06%	0.29%	1.01%	1.59%	1.81%
MD Delay	0.52%	1.42%	-0.05%	1.31%	1.24%	1.12%	0.12%	0.59%	-0.59%	4.43%	3.63%
PM Delay	-0.06%	0.26%	-0.21%	-0.22%	0.20%	-0.16%	0.04%	-0.33%	0.95%	1.12%	2.08%
NT Delay	0.66%	-0.89%	-0.37%	-0.84%	1.40%	-0.52%	0.76%	0.60%	0.50%	7.63%	14.84%
TOTAL DELAY	0.11%	0.36%	-0.10%	0.00%	0.38%	0.04%	0.08%	-0.03%	0.72%	1.89%	2.86%
DAILY FUEL CONSUMPTION BY CAR/TRUCK (GALLONS OF FUEL)											
TRUCK FUEL CONSUMPTION	0.81%	0.44%	-0.04%	-0.05%	2.39%	0.17%	0.45%	0.40%	0.48%	6.98%	13.10%
TOTAL FUEL CONSUMPTION	0.14%	0.12%	-0.02%	-0.01%	0.32%	0.02%	0.09%	0.09%	0.13%	1.39%	2.72%

Scenario 5

With a 50% increase of truck volume at external station #2078, the model shows 1.14% area wide truck volume increase. Similar to Scenario 4, counties most impacted from the volume changes are Newton (19.61%), Rockdale (10.98%), and DeKalb (3.21%). Accordingly, the other performance measures such as VMT, VHT, truck VMT, daily delay hours, and truck fuel consumption increase significantly in those counties. Table 86 shows the percent changes in performance measures at the county level with Scenario 5 compared to 2040 base result of the tour model.

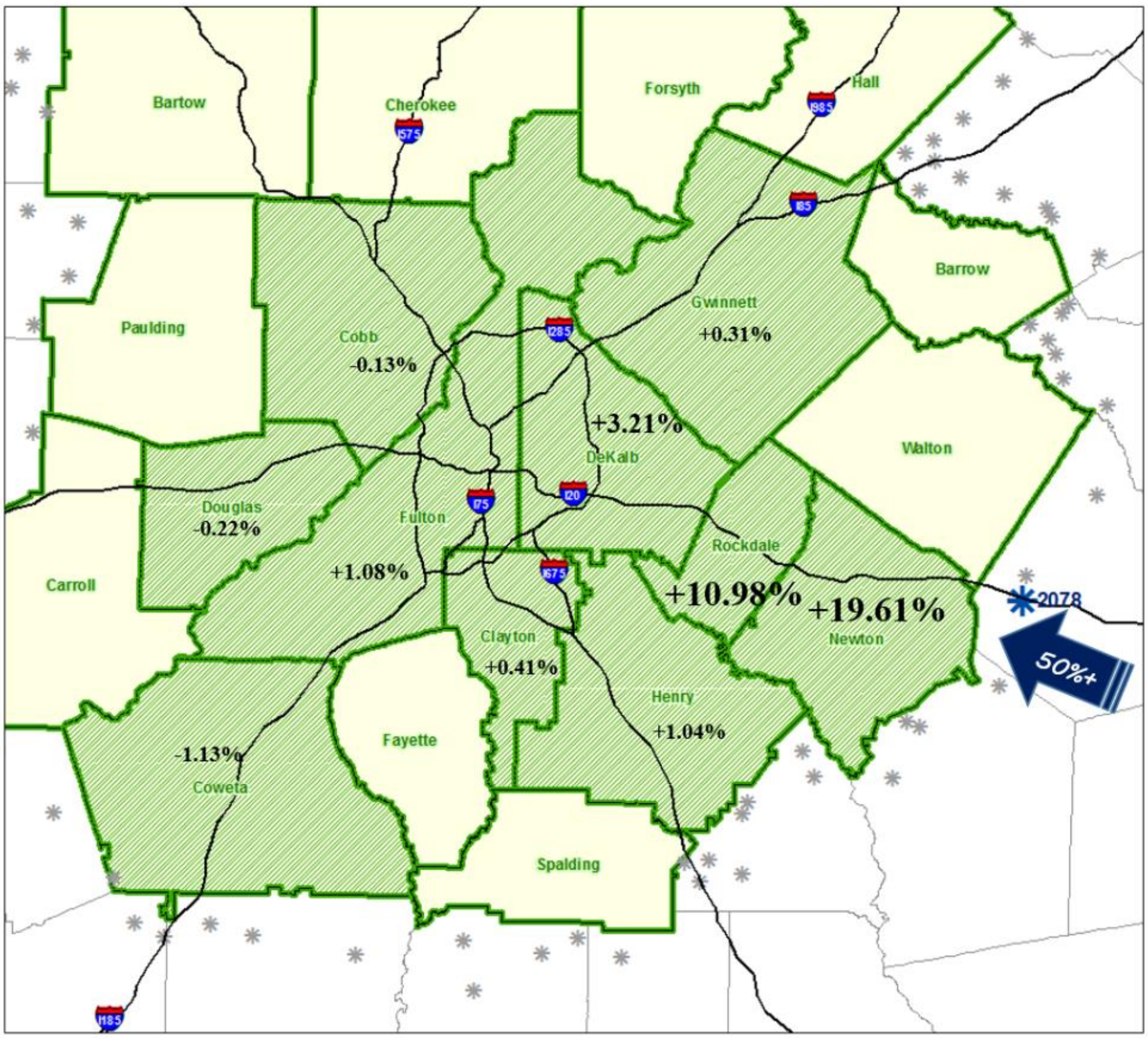


Figure 50: Percent Changes in County Truck Volume with Scenario 5

Table 86: Percent Changes in Performance Measures at County Level with Scenario 5

PERFORMANCE MEASURE: VMT VHT for	20 Counties	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE	NEWTON
VEHICLE VOLUME BY MODE											
TRUCK	1.14%	0.41%	-0.13%	-1.13%	3.21%	-0.22%	1.08%	0.31%	1.04%	10.98%	19.61%
TOTAL DAILY VEHICLE	0.08%	0.07%	0.02%	-0.09%	0.12%	0.01%	0.07%	0.03%	0.14%	0.65%	1.46%
VEHICLE MILES TRAVELED BY MODE											
TRUCK	1.26%	0.56%	0.00%	-0.20%	3.54%	0.19%	0.68%	0.38%	0.81%	11.78%	21.99%
TOTAL DAILY VMT	0.08%	0.08%	0.01%	-0.02%	0.12%	0.00%	0.05%	0.06%	0.12%	0.81%	1.68%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD											
AM TRUCK VMT	1.68%	0.64%	0.64%	-0.99%	3.66%	2.19%	1.04%	0.30%	2.44%	11.61%	21.19%
MD TRUCK VMT	1.72%	0.56%	0.54%	1.24%	3.59%	0.76%	1.41%	1.46%	0.23%	11.63%	21.02%
PM TRUCK VMT	0.49%	0.13%	-1.10%	-0.81%	3.09%	-0.43%	0.23%	-1.14%	1.27%	10.31%	19.93%
NT TRUCK VMT	1.09%	0.74%	-0.18%	-0.79%	3.68%	-0.68%	0.10%	0.30%	0.44%	12.83%	24.11%
TOTAL DAILY TRUCK VMT	1.26%	0.56%	0.00%	-0.20%	3.54%	0.19%	0.68%	0.38%	0.81%	11.78%	21.99%
TRUCK (CONGESTED) VEHICLE HOURS TRAVELED BY TIME PERIOD											
AM TRUCK CONGESTED VHT	1.57%	0.43%	0.52%	-1.91%	4.09%	2.04%	1.14%	0.56%	3.06%	11.32%	16.57%
MD TRUCK CONGESTED VHT	1.65%	0.49%	0.49%	1.46%	3.68%	0.78%	1.48%	1.69%	0.02%	10.93%	16.77%
PM TRUCK CONGESTED VHT	0.20%	0.35%	-1.15%	-1.66%	3.10%	-0.58%	0.37%	-1.68%	2.08%	9.69%	16.06%
NT TRUCK CONGESTED VHT	0.88%	0.70%	-0.35%	-1.66%	3.55%	-0.97%	-0.04%	0.45%	0.52%	11.74%	21.83%
TOTAL DAILY TRUCK VHT	1.03%	0.51%	-0.19%	-0.76%	3.55%	0.06%	0.71%	0.20%	1.14%	10.91%	18.32%
DAILY DELAY HOURS											
AM Delay	0.41%	0.59%	0.18%	-0.29%	0.51%	0.21%	0.30%	0.50%	1.47%	2.26%	3.23%
MD Delay	0.60%	0.54%	0.47%	0.93%	1.20%	0.85%	-0.12%	0.97%	-0.05%	8.02%	7.50%
PM Delay	0.04%	0.10%	-0.14%	-0.22%	0.29%	-0.05%	0.08%	-0.18%	1.12%	2.37%	2.96%
NT Delay	0.74%	-0.12%	0.01%	-1.33%	2.05%	-0.58%	0.26%	0.13%	0.35%	12.59%	26.65%
TOTAL DELAY	0.23%	0.27%	0.02%	-0.12%	0.51%	0.10%	0.11%	0.14%	1.00%	3.37%	4.87%
DAILY FUEL CONSUMPTION BY CAR/TRUCK (GALLONS OF FUEL)											
TRUCK FUEL CONSUMPTION	1.26%	0.56%	0.00%	-0.20%	3.54%	0.19%	0.68%	0.38%	0.81%	11.79%	21.99%
TOTAL FUEL CONSUMPTION	0.22%	0.14%	0.00%	-0.05%	0.47%	0.03%	0.11%	0.09%	0.24%	2.34%	4.56%

Scenario 6

With a 70% increase of truck volume at external station #2078, the model shows 1.56% area wide truck volume increase. Similar to Scenario 4 and 5, counties mostly impacted from the volume changes are Newton (27.95%), Rockdale (15.14%), and DeKalb (4.43%). Accordingly, the other performance measures such as VMT, VHT, truck VMT, daily delay hours, and truck fuel consumption also increased significantly in those counties.

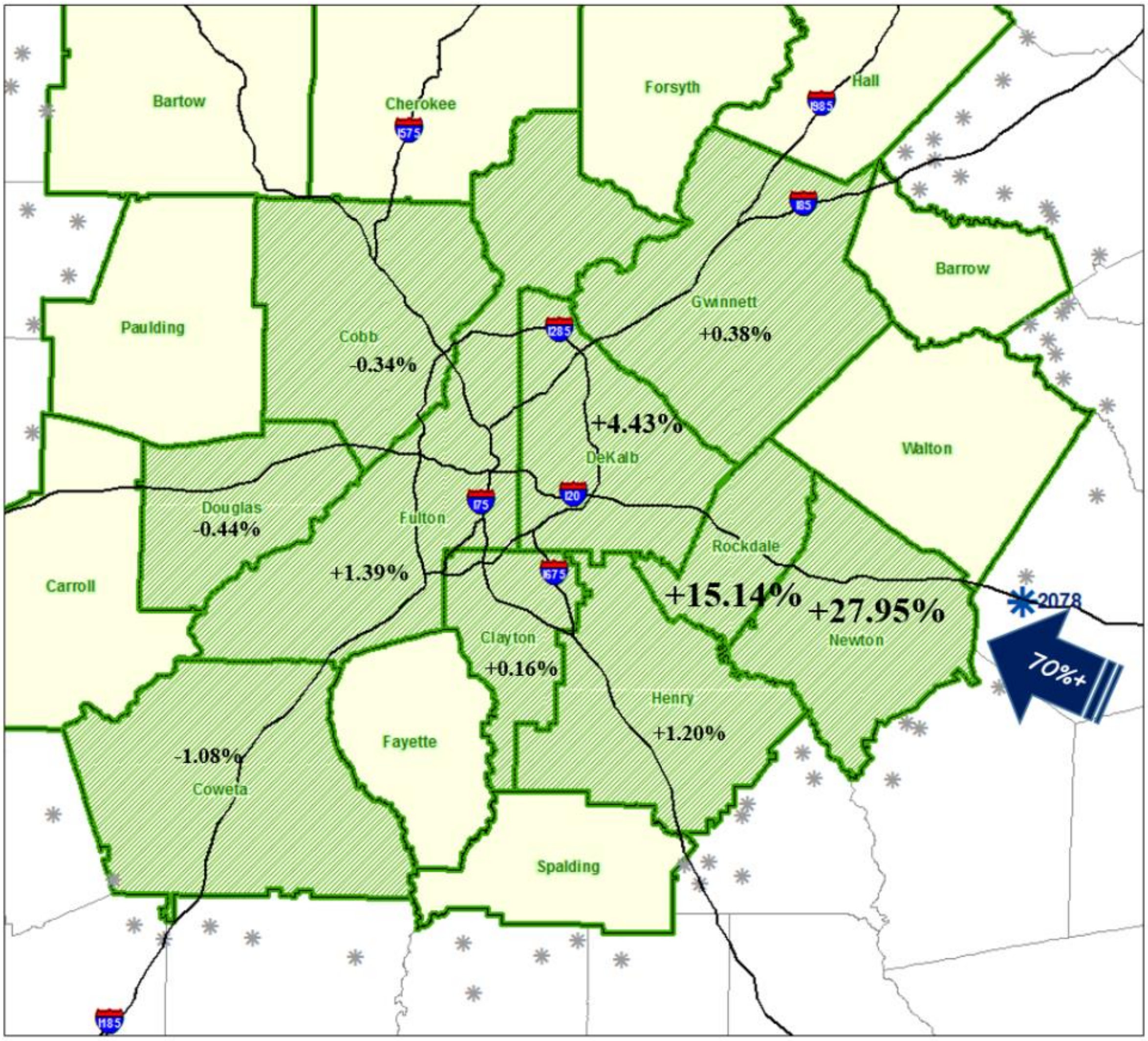


Figure 51: Percent Changes in County Truck Volume with Scenario 6

Table 87: Percent Changes in Performance Measures at County Level with Scenario 6

PERFORMANCE MEASURE: VMT VHT for	20 Counties	CLAYTON	COBB	COWETA	DEKALB	DOUGLAS	FULTON	GWINNETT	HENRY	ROCKDALE	NEWTON
VEHICLE VOLUME BY MODE											
TRUCK	1.56%	0.16%	-0.34%	-1.08%	4.43%	-0.44%	1.39%	0.38%	1.20%	15.14%	27.95%
TOTAL DAILY VEHICLE	0.09%	0.12%	0.01%	-0.07%	0.12%	-0.01%	0.04%	0.06%	0.21%	0.92%	2.03%
VEHICLE MILES TRAVELED BY MODE											
TRUCK	1.76%	0.41%	-0.20%	0.04%	5.05%	0.28%	0.82%	0.46%	0.93%	16.33%	31.22%
TOTAL DAILY VMT	0.11%	0.09%	-0.01%	0.00%	0.15%	-0.01%	0.05%	0.07%	0.18%	1.12%	2.37%
TRUCK VEHICLE MILES TRAVELED BY TIME PERIOD											
AM TRUCK VMT	2.36%	0.57%	0.95%	1.96%	4.30%	3.54%	1.32%	0.30%	2.65%	14.96%	30.45%
MD TRUCK VMT	1.89%	-0.25%	0.32%	1.15%	5.16%	-0.43%	1.19%	0.93%	-0.17%	15.34%	29.66%
PM TRUCK VMT	1.15%	-0.33%	-0.83%	-1.45%	4.24%	0.12%	0.27%	-0.17%	1.43%	14.07%	30.18%
NT TRUCK VMT	1.70%	1.31%	-0.86%	-0.84%	5.77%	-0.24%	0.54%	0.47%	0.94%	19.09%	33.33%
TOTAL DAILY TRUCK VMT	1.76%	0.41%	-0.20%	0.04%	5.05%	0.28%	0.82%	0.46%	0.93%	16.33%	31.22%
TRUCK (CONGESTED) VEHICLE HOURS TRAVELED BY TIME PERIOD											
AM TRUCK CONGESTED VHT	2.19%	0.10%	0.89%	1.87%	4.94%	3.43%	1.45%	0.29%	3.58%	14.39%	24.65%
MD TRUCK CONGESTED VHT	1.66%	-0.50%	0.18%	0.79%	5.12%	-0.75%	1.35%	0.87%	-0.32%	14.59%	24.65%
PM TRUCK CONGESTED VHT	0.85%	-0.35%	-0.99%	-2.16%	4.25%	-0.23%	0.32%	-0.51%	2.45%	13.37%	25.15%
NT TRUCK CONGESTED VHT	1.46%	1.22%	-1.04%	-1.82%	5.67%	-0.78%	0.54%	0.57%	1.12%	17.85%	31.15%
TOTAL DAILY TRUCK VHT	1.48%	0.16%	-0.33%	-0.56%	4.97%	0.01%	0.86%	0.29%	1.40%	15.21%	26.96%
DAILY DELAY HOURS											
AM Delay	0.50%	0.58%	0.33%	0.17%	0.66%	0.69%	0.27%	0.46%	1.61%	3.20%	4.26%
MD Delay	0.59%	1.65%	0.20%	0.21%	1.44%	-0.13%	0.00%	0.48%	0.07%	11.22%	10.45%
PM Delay	0.19%	0.31%	-0.16%	-0.37%	0.42%	-0.07%	0.13%	0.06%	1.48%	3.44%	4.74%
NT Delay	1.41%	0.20%	-0.03%	-1.20%	3.29%	0.43%	0.78%	0.42%	1.08%	18.83%	40.40%
TOTAL DELAY	0.36%	0.51%	0.01%	-0.17%	0.69%	0.17%	0.16%	0.22%	1.29%	4.85%	7.20%
DAILY FUEL CONSUMPTION BY CAR/TRUCK (GALLONS OF FUEL)											
TRUCK FUEL CONSUMPTION	1.76%	0.41%	-0.20%	0.04%	5.05%	0.28%	0.82%	0.46%	0.93%	16.33%	31.22%
TOTAL FUEL CONSUMPTION	0.30%	0.13%	-0.03%	0.00%	0.65%	0.04%	0.12%	0.12%	0.31%	3.24%	6.46%

Scenarios with ARC's Trip-based Model

Unlike the proposed tour-based truck model, the current ARC trip-based model does not directly use the external station truck volumes (external.prn) as an input file. Instead, the model uses proportions of external and through traffic volume (parameters\externals.dbf) which sum up to 1.0 for each external station. The following equation is applied to every external station:

1.00 = PCTINTWK + PCTINTNW + PCTNINTW + PCTNINTN + CAREE + COMIE
+ COMEE + MTKIE + MTKEE + HTKIE + HTKEE

The variables involved are as follows:

PCTINTWK: Proportion of IE passenger car work (interstate)
PCTINTNW: Proportion of IE passenger car non-work (interstate)
PCTNINTW: Proportion of IE passenger car work (non-interstate)
PCTNINTN: Proportion of IE passenger car non-work (non-interstate)
CAREE: Proportion of EE passenger car
COMIE: Proportion of IE commercial vehicle
COMEE: Proportion of EE commercial vehicle

MTKIE:	Proportion of IE medium duty truck
MTKEE:	Proportion of EE medium duty truck
HTKIE:	Proportion of IE heavy duty truck
HTKEE:	Proportion of EE heavy duty truck

In order to apply the similar scenarios as used with the tour model, the proportions of the four variables (MTKIE, MTKEE, HTKIE, and HTKEE) have been modified by applying scenario factors of 1.3 (30% increase), 1.5 (50% increase), and 1.7 (70% increase) and the proportions normalized to make them sum to 1.0 for each external station. Although these are not exactly the same controllable values which have been incorporated in the tour model, the results may be used to produce a set of performance measures to simulate how potential changes in external and through truck volumes to the modeling area affect the dynamics of internal truck movements within the modeling area for comparison with the results obtained from the Tour-based model as reported in the previous section.

Table 88: Selected Scenarios and External Truck Shares

External Station	PCINTWK	PCINTNW	PCNINTW	PCNINTN	CAREE	COMIE	COMEE	MTKIE	MTKEE	HTKIE	HTKEE
2078	0.1852	0.2419	0.0000	0.0000	0.3030	0.0341	0.0026	0.0349	0.0090	0.0985	0.0908
Scenario 1	0.1731	0.2261	0.0000	0.0000	0.2832	0.0319	0.0024	0.0424	0.0109	0.1197	0.1103
Scenario 2	0.1659	0.2166	0.0000	0.0000	0.2714	0.0305	0.0023	0.0469	0.0121	0.1323	0.1220
Scenario 3	0.1592	0.2080	0.0000	0.0000	0.2605	0.0293	0.0022	0.0510	0.0132	0.1440	0.1327
2087	0.2368	0.3094	0.0000	0.0000	0.1978	0.0078	0.0006	0.0133	0.0034	0.0731	0.1578
Scenario 4	0.2204	0.2880	0.0000	0.0000	0.1841	0.0073	0.0006	0.0161	0.0041	0.0885	0.1910
Scenario 5	0.2107	0.2753	0.0000	0.0000	0.1760	0.0069	0.0005	0.0178	0.0045	0.0976	0.2106
Scenario 6	0.2018	0.2637	0.0000	0.0000	0.1686	0.0066	0.0005	0.0193	0.0049	0.1059	0.2286

Similar to the scenarios with the tour model, the research team applied three hypothetical volume increases (30%, 50%, and 70%) to those selected external stations (#2087 and #2078), and the same set of performance measures has been developed in order to evaluate the results for each scenario, which include: (1) vehicle volume by mode, (2) vehicle miles traveled (VMT) by mode, (3) truck vehicle miles traveled by time period, (4) VMT per capita, VMT per household, VMT per job, (5) VHT per capita, VHT per household, VHT per job, (6) truck vehicle hours traveled (VHT) by time period, (7) daily delay hours, (8) average highway speeds, (9) daily fuel consumption by mode, (10) Percent VMT by level-of-service, etc. The performance measures were calculated and summarized by county. The results are included in Appendix.

Findings

In this section, the research team attempted to show different results using both current ARC trip-based model and the newly developed tour-based model. Although it is not the intent of this study to demonstrate that the tour-based model structure is superior to the trip-based structure based on empirical validation (due to some significant gaps in the observed or reported data), it should be self-evident that modeling discrete tours is more realistic than modeling zonal averages. The model works in a manner closer to the way travel decisions are made in the real world. More empirical evidence is needed and will be provided once tour-based truck modeling approaches get better data to support them, and become more popular and implemented in planning processes.

SECTION V. PLANNING APPLICATION: Birmingham

Application of the Tour-Based Freight Model in Birmingham

For this study, the Regional Planning Commission of Greater Birmingham (RPC-GB) year 2035 planning model was used as a base for comparison with the new tour-based freight model. The RPC 2035 model is a traditional 4-step trip-based model that has been calibrated to 2008 traffic volumes. The RPC model does not explicitly include a freight model, rather it generates truck trips by applying a standard factor to overall vehicle trip productions. The RPC model also does not classify trucks into subgroups (such as those used in the FHWA 13-bin vehicle classification system) nor does it distinguish between medium and heavy trucks and general commercial vehicles.

The new tour-based freight model of the Birmingham region offers several potential improvements over the existing model. First, it provides classification of trucks into medium and heavy vehicles. This allows for more detailed analysis of truck travel patterns, particularly long-haul vs. local movements. Second, the new tour-based freight model was developed using actual GPS data provided by ATRI, thus the model predicts the truck traffic closely to the observed data.

The Birmingham tour based freight model was built on the RPC year 2035 regional planning model dataset. Although RPC has since created a 2040 model with updated analysis zones, the tour based freight model was developed using the 2035 models and therefore all comparisons are made using it.

Issues with Transfer of the Proposed Modeling Framework

There were several issues encountered when transferring from RPC's current trip-based model to the tour-based freight model. First, the-tour based model was developed using ATRI's 2010 truck GPS database, which was built on a 999 traffic analysis zone (TAZ) system. Although RPCGB's 2035 model was built on the same 999 TAZ system, the model was developed using 2008 socioeconomic and traffic data, which meant the results would not be directly comparable to the tour-based model. Moreover, the RPC model did not include any time-of-day (TOD) component. To address these issues for this study, RPC's 2035 model was redeveloped using 2010 socioeconomic and traffic data. Also, a TOD model was inserted into the 2035 modeling so that outputs could be directly compared with the tour-based model.

RPC has recently developed a year 2040 planning model based on 2010 census data, which necessitated the expansion of the MPA (metropolitan planning area). As a result, the number of traffic analysis zones (TAZ's) was increased from 999 to 1934. The 2040 model also includes a TOD component. The newly developed tour-based freight model can be modified for the new 1934 zone system, however the main truck data source, the ATRI database, was built on an older 999 zone system and therefore an equivalency table will be needed between old and new TAZ systems. An attempt was made to develop such a table as part of this project, but the conversion from the 999 zone system to the 1934 zone system was not straightforward and necessitated a zone by zone evaluation that required more effort than was available for this study. It is recommended that this conversion be performed as part of future applications of the tour-based model.

Comparisons of Model Outputs

The RPC trip-based model and the new tour-based model were run and the results were compared across a variety of outputs. Some of the key findings are presented in the following sections.

Vehicle Miles Traveled by Mode and Time Period

Total VMT across the network was compared for each model. VMT by mode is presented in Table 89. Overall VMT across the network as well as the modal split of VMT were similar across the two models. However, the trip-based model tended to overestimate truck VMT, which may be a result of the truck factor applied to productions to generate truck trips.

Table 89: Vehicle Miles Traveled (VMT) by Mode

Vehicle Miles Traveled by Mode	Trip Base Model	Tour Based Model
SOV VMT	22,601,310	24,233,649
HOV VMT	3,052,640	3,617,879
TRUCK VMT	2,552,040	1,511,619
Total Daily VMT	28,205,990	29,363,147

Overall VMT by time of day shows the trip-based model generating slightly more VMT during the daytime but less during the night, as shown in Table 90. This effect is particularly pronounced when looking specifically at truck VMT in Table 91, where the trip-based model significantly overestimated daytime truck VMT but underestimated nighttime truck VMT. While much of the overestimation of truck VMT during the daytime is related to the general overestimation of truck VMT in the trip-based model, this discrepancy between daytime and nighttime truck VMT is significant and was found in the Atlanta model as well. The finding that the existing trip-based models are underestimating nighttime truck traffic will have significant impacts to the planning process.

Table 90: Vehicle Miles Traveled (VMT) by Time Period

Vehicle Miles Traveled by Time Period	Trip Base Model	Tour Based Model
AM VMT	4,578,625	4,492,435
MD VMT	9,916,877	9,798,449
PM VMT	6,270,139	6,637,723
NT VMT	7,440,349	8,434,540
Total Daily VMT	**28,205,990**	**29,363,147**

Table 91: Truck VMT by Time Period

Truck Vehicle Miles Traveled by Time Period	Trip Base Model	Tour Based Model
AM Truck VMT	508,074	119,122
MD Truck VMT	2,687,053	467,740
PM Truck VMT	378,950	246,216
NT Truck VMT	400,964	678,541
Total Daily Truck VMT	**2,552,040**	**1,511,619**

Truck Volumes

Comparisons were also made between truck volumes generated by each model. Figure 52 shows truck volumes on the regional network as generated by the new tour-based model. As expected, the heaviest truck volumes were found in the major freight corridors, including I-65, I-20/59, I-459, and US 280. As was found in the comparison of truck VMT, the trip-based model generated significantly higher daily truck volumes than did the tour-based model (see Figure 53). This is likely the result of the method used to generate truck trips in the trip-based model, and the fact that the trip-based model does not classify trucks by type or differentiate them from general commercial vehicles. Figure 54 through Figure 56 compare truck volumes for the AM, Mid-Day, and PM peak periods and show the same patterns as were found with truck VMT, which is that the trip-based model consistently generates higher truck volumes than the tour-based model did.

Figure 57 presents a comparison of truck volumes for night-time hours, and shows that the tour-based model generates higher truck volumes during the overnight hours. This mirrors the findings found in the comparisons of truck VMT and suggest that the existing trip-based model has been significantly underestimating night-time truck traffic.

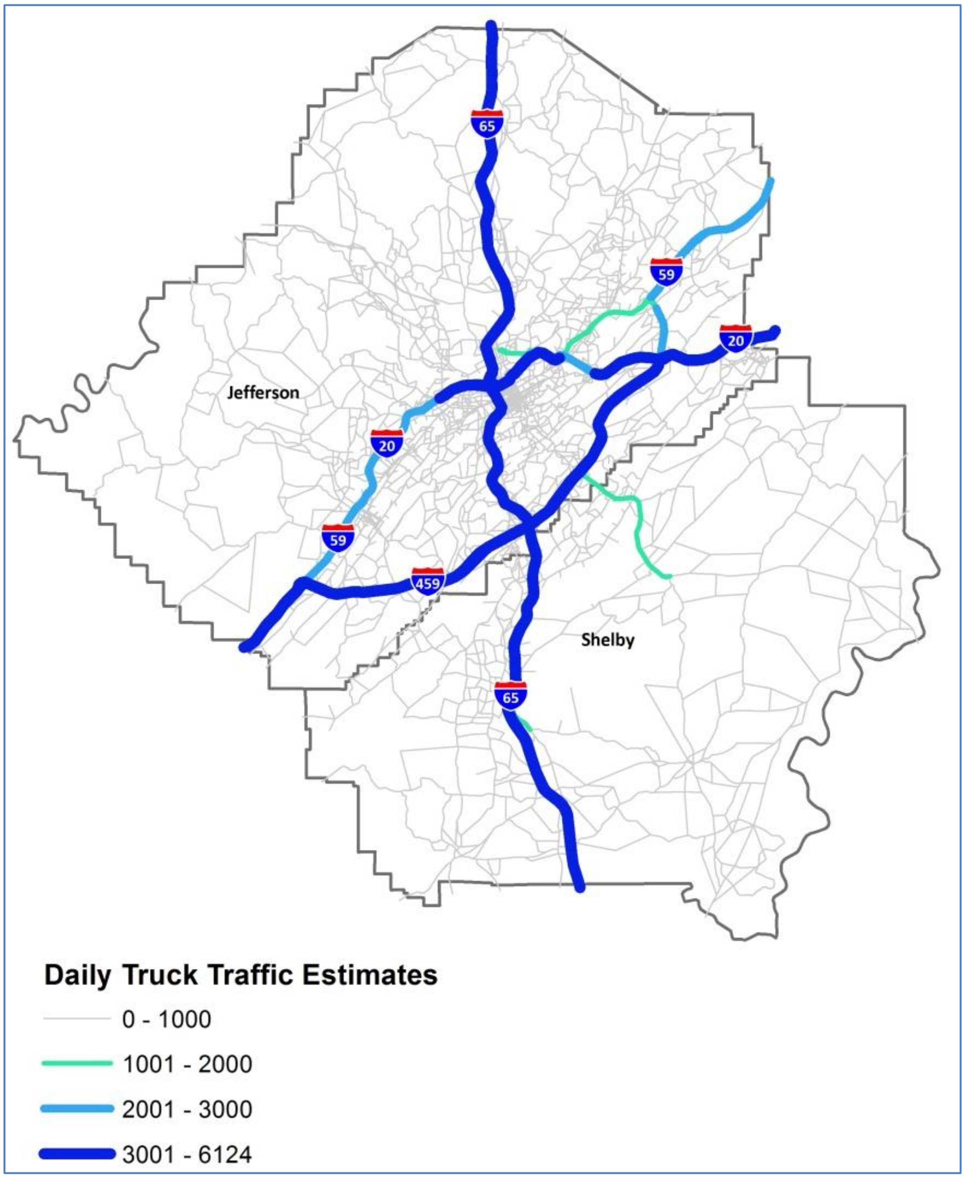


Figure 52: Daily truck volumes (tour-based model)

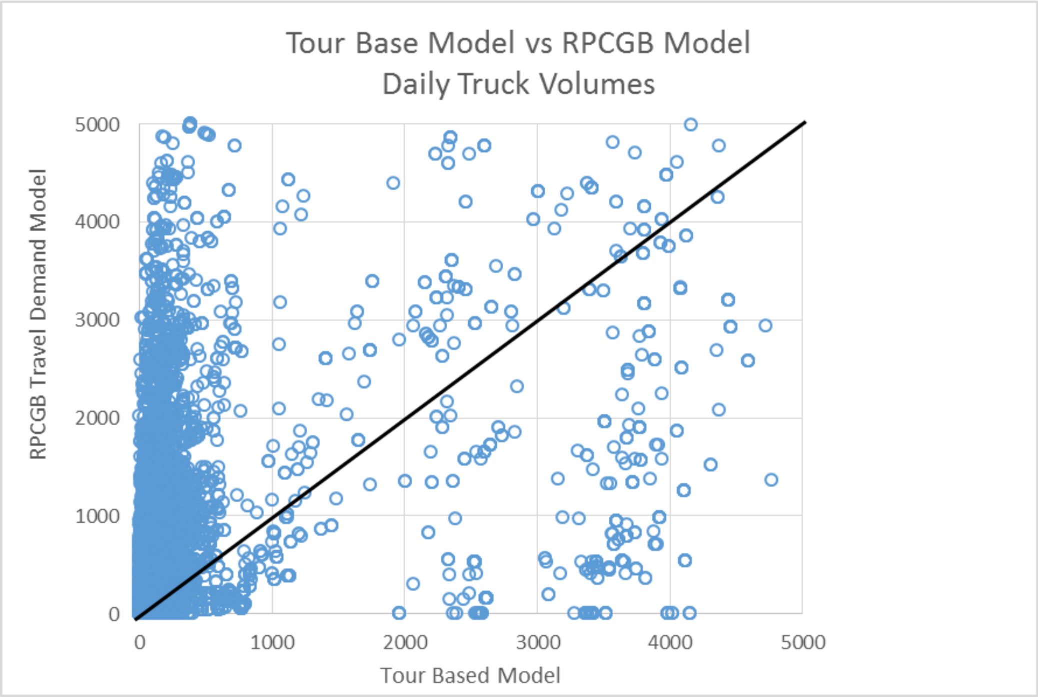


Figure 53: Daily truck volumes (trip-based vs. tour-based model)

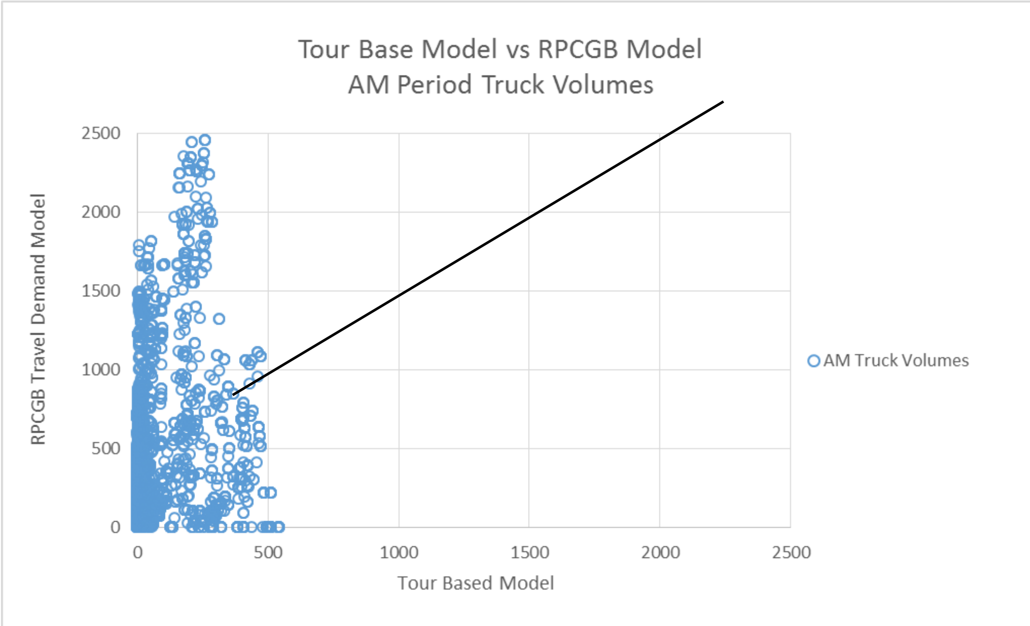


Figure 54: Trip-based vs. tour-based link volume comparison (AM Peak)

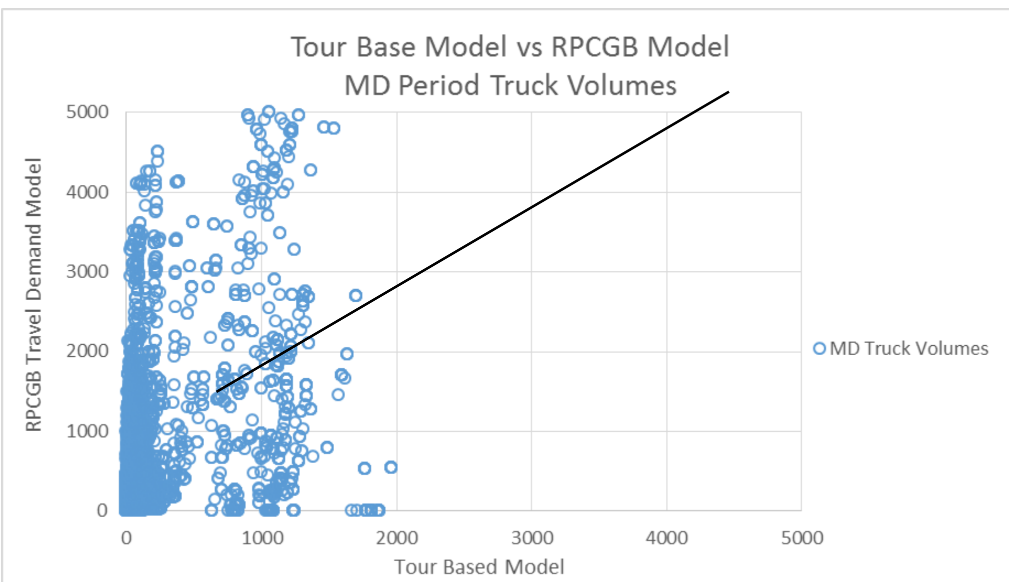


Figure 55: Trip-based vs. tour-based link volume comparison (Mid-Day Peak)

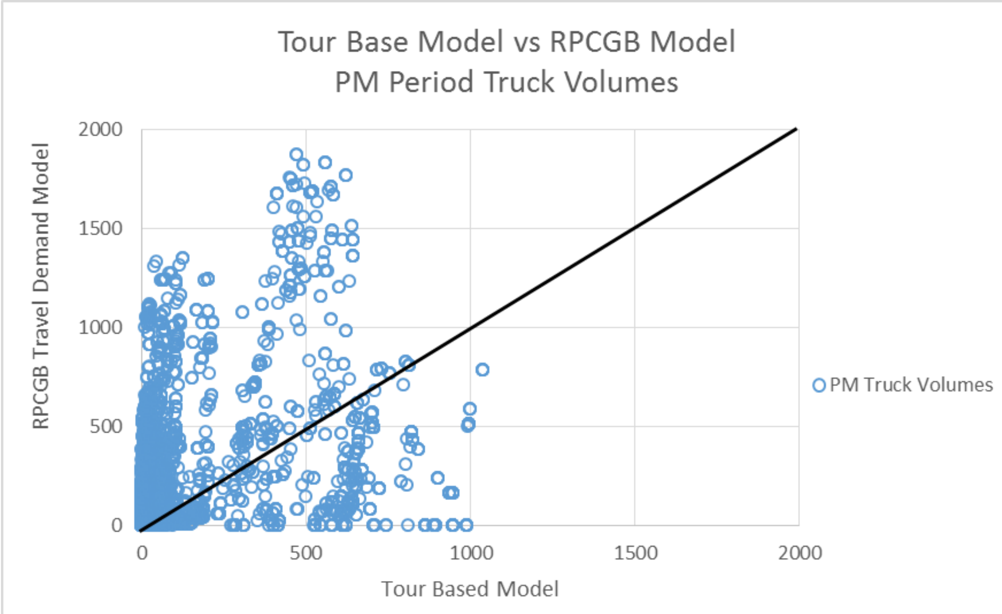


Figure 56: Trip-based vs. tour-based link volume comparison (PM Peak)

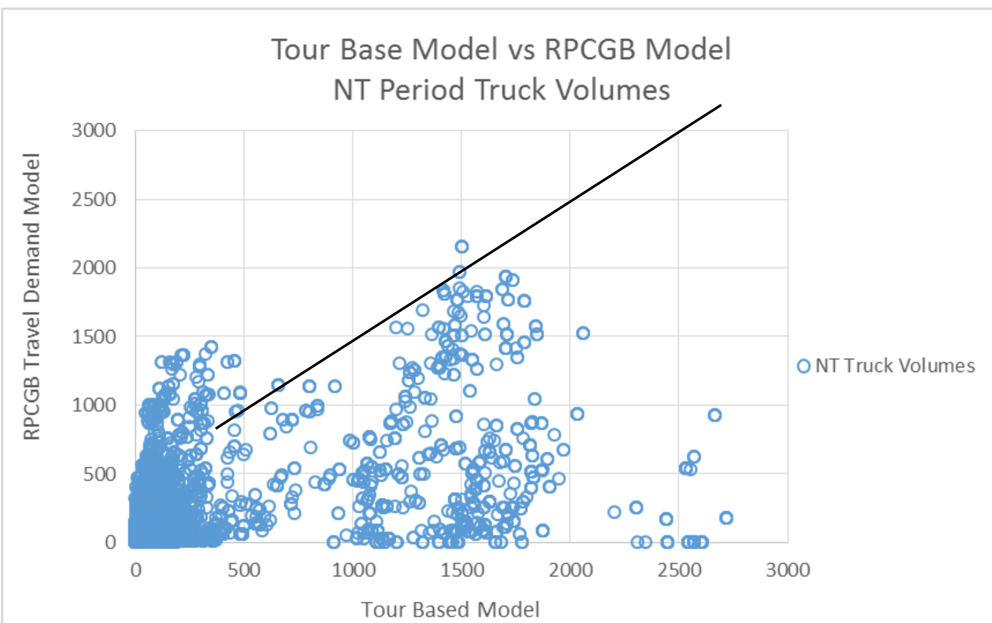


Figure 57: Trip-based vs. tour-based link volume comparison (Night)

Truck VMT by Area Type

Truck VMT was summarized by area type as shown in Table 92. The results show that the trip-based model consistently overestimated truck VMT in urban areas, but underestimated it in rural areas when it is compared to the tour-based model. As mentioned before, RPC's trip-based model does not distinguish between medium and heavy trucks and general commercial vehicles. Therefore, truck VMT in the trip based model presents commercial vehicle and/or delivery truck predictions in urban areas, while the tour-based model reports only medium and heavy truck traffic VMT.

Table 92: Daily Truck VMT by Area Type

Area Type	Trip Base Model	Tour Based Model	Percent Difference
	Truck VMT Daily	Truck VMT Daily	
Central Business District Major	146,297	25,502	82.57%
Central Business District Minor	58,207	16,778	71.18%
Central Business District Fringe	48,154	9,843	79.56%
Urban Stable	325,679	71,647	78.00%
Urban Activity Center	630,894	193,234	69.37%
Urban Growth	1,013,902	638,063	37.07%
Transitioning to Urban	164,124	247,062	-33.57%
Rural Developed	100,239	221,584	-54.76%
Rural Undeveloped	64,545	87,905	-26.57%

Area Type	Description Density Range
Central Business District Major	Greater or equal to 20.00
Central Business District Minor	15.00 to 20.00
Central Business District Fringe	12.00 to 15.00
Urban Stable	8.00 to 12.00
Urban Activity Center	5.00 to 8.00
Urban Growth	1.00 to 5.00
Transitioning to Urban	0.50 to 1.00
Rural Developed	0.25 to 0.50
Rural Undeveloped	Less than 0.25

Findings

There were several key findings resulting from the study that will have direct application to the planning and modeling process in Birmingham:

- The current RPC models overestimate truck volumes and truck VMT, particularly during daytime hours. The tour-based freight model will provide more accurate projections of truck volumes and VMT.

- Despite the fact that the RPC trip-based model overestimates daily truck volumes and VMT, it appears to underestimate truck volumes during nighttime hours. The tour-based model indicates that a greater proportion of truck traffic occurs at night than has currently been assumed.

- The RPC trip-based model also appears to underestimate truck traffic in rural areas. A change to the tour-based model may yield more accurate projections for rural and urban areas.

The research team recommends further study to refine the tour-based freight model and understand its implications for the planning process in Birmingham:

- Modify the tour-based model to run with RPC's current year 2040 model. This will require expanding it to run on the new 1934 TAZ network and developing conversion tables to map the truck model and ATRI data to the new zone system. Since the new RPC 2040 model already includes a TOD component, this should provide a better framework to compare model outputs and test the impacts on the long range planning process.

- Test the new tour-based model with different planning scenarios and compare the outputs to current trip-based model projections. For the Birmingham Region, these scenarios could include:

    - Testing the impacts of the proposed Northern Beltline
    - Testing the impacts of a relocation of I-20/59 through downtown
    - Testing the impacts of the completion of I-22 on freight movements through the Birmingham area
    - Modeling the impacts of freight growth in the I-20/59 corridor.

SECTION V. RECOMMENDATION

Lessons Learned

The project provides a framework for MPOs and DOTs to build freight demand models that account for truck touring behavior, and it demonstrates how GPS-derived truck movement data can support freight forecasts. The project also provides a series of lessons learned, both about steps to improve tour-based freight models and limitations that still have to be addressed in other modeling approaches. The lessons relate to data availability and analysis, as well as model construction. The primary lessons learned are summarized as follows:

1. **Freight Modeling Remains Underutilized in Most MPOs:** MPOs should be able to perform independent freight demand modeling activities for traffic forecasting. MPO freight modeling is important not only because of freight's rapidly increasing share of total roadways traffic, but also because of freight's unique travel patterns compared with passengers. Even though modeling can help MPOs to more accurately develop plans with future truck volumes, 64% of the MPOs surveyed stated that they do not model freight movement. Of those that do, lack of data remains one of the primary obstacles in developing freight demand models, and more MPO respondents say that they are seeking to improve their data sources than realize any other modeling improvements. Despite this need, only 19% of the MPOs surveyed which have a trip-based freight model also employed GPS-derived data in their model. It is very important to implement data sources that are accurate and accessible for more MPOs to adopt freight modeling.

2. **Tour-Based Freight Modeling Retains a Theoretical Advantage over Trip-Based Modeling:** Tour-based modeling is theoretically more robust than trip-based modeling because it accounts for distribution channels and trip-chaining behavior to more

realistically capture the vehicle movements and motor carriers' decision making. Since tour-based models can capture truck travel behavior more accurately, they provide more reliable results. However, due to their intense processing and data requirements, only a few MPOs in the US use tour-based freight models. Many MPO respondents expressed the need for more truck data to support their freight modeling. Better data might also allow more MPOs to forecast freight demand, including via emerging sophisticated methods like tour-based models.

3. **Tour-Based Truck Movement Models Capture Underlying Freight Movement Relationships More Completely than Conventional Models:** Though the differences in the total truck volumes projected by the trip-based and tour-based freight models remain small, it is observed that there is a significant variation between these two types of models in terms of truck volumes by route and by time of day. It is hard to determine one model's forecasting superiority to the other due to the lack of reasonable observed truck data, which can specify the model more accurately. However, the tour-based model's stronger theoretical foundation and the GPS data inputs show that the tour-based freight demand model likely assigns the truck volumes more realistically. Comparing tour-based results with the existing freight models can provide potential improvements and directions for future research. The distinct differences between the truck traffic estimation results of the two models emphasize the necessity of supporting the decision-making with well- developed models.

4. **GPS-Derived Truck Movement Data Is a Viable Data Source:** GPS-derived truck data is used in a small minority of MPO freight models, but it can provide detailed truck travel diary data for disaggregate freight models, including tour-based freight models.

However, GPS data itself can be computationally intensive due to the required data quantity and the need for complex algorithms for processing raw data.

5. **The Data Analysis Revealed Important Socio-Demographic, Descriptive, and Temporal Characteristics of Truck Movement:** The analyses of GPS truck sample data, which is employed by the tour-based freight demand modeling in this study, have revealed several important travel patterns of trucks, which are listed as following:

    - **Socio-Demographic:** In addition to the socio-demographic variables that are often included in the four-step personal travel demand modeling, such as population and households, truck tour generation is highly associated with specific categories of employment, including (1) wholesale employment, (2) finance, insurance, real estate employment, and (3) transportation, communication, utilities employment. The identified truck zones will have very different tour generation patterns and need to be addressed based on each employment type's prevalence. The difference between truck tour and passenger travel trip generation reemphasizes the need for modeling trucks independently, rather than applying truck trip rates to total personal demand model result. This study also highlights the importance of having suitable stratifications of employment by zone and the availability of Census data to help with that task.
    - **Descriptive:** More than half of trucks touring in Atlanta and Birmingham metro area have intermediate stops during one tour. This pattern shows that trip chaining behavior is a common phenomenon and needs to be adequately addressed in freight demand modeling. The number of intermediate stops made by trucks varies by tour type, which reflects the need to employ different trip-

chaining models (models to determine the number of intermediate stops and their locations) by tour endpoints, such as Internal-External (I/X), Internal-Internal (I/I) and External-External (X/X). The variation also illustrates the advantage of using a tour-based rather than a trip-based model.

- **Temporal:** Truck tours follow different time distributions and have different peak hours from passenger tours, indicating the need to separate truck modeling from passenger travel demand modeling. Several factors, including tour O-D direct travel time, accessibility to employment at the tour origin and destination, whether the tour origin is urban or rural, and whether the tour is round-trip, have been identified to significantly affect the start time of truck tours. This manifests the necessity of employing tour-based truck modeling instead of trip-based modeling, so that different tours can modeled to start at different time of day according to its unique characteristics.

6. **Improving Truck Movement Data Will Have Limited Impact if Pursued in Isolation from Broad Modeling and Data Improvements:** Sophisticated freight demand models should be approached holistically in terms of data and data forecasting improvements for the explanatory variables. The ability to add explanatory relationships relies on available and accurate data for independent variables at the right geographical scales. Moreover, no model can consistently forecast a dependent variable any more accurately than the forecasted independent variables. Likewise, GPS-derived truck movement data greatly improved data availability for modelers, but it does not obviate the need for improvements in other modeling data. A particular challenge in the models as applied remains when data is obtained at the TAZ level. Moreover, data needs to be detailed enough. For example, employment data by detailed sectors is preferable to the total

employment data in a TAZ (or even the commonly-used retail/non-retail split of employment). A final process that requires attention is the identification of special generator truck zones, which should be as complete and objective as possible.

7. **GPS Data Processing Should Carefully Preserve Data Completeness and Representativeness:** GPS-derived truck data must be processed prior to its use, but the processing should not degrade the data's representativeness. Increasing the size of sample truck data is particularly important to better represent the entire truck population. While it is sometimes necessary to use the existing model to scale up the sample data, it is more ideal to use observed data. Scaling up based on observed data makes the tour-based model's accuracy independent of the existing model's accuracy.

8. **Tour-Based Modeling Can Provide Forecast Data for Numerous Planning Functions:** This research's primary objective is developing a tour-based truck network model framework utilizing truck GPS data and using this framework for MPO applications in the Atlanta and Birmingham metropolitan areas. The model can also serve applications including—
    - Truck traffic volume forecasting in conjunction with observed multi-stop truck travel behavior,
    - Analysis at various geographic levels (e.g., MPO, county, TAZ, etc.) and comparisons of relative magnitudes of a region's truck traffic by sub-areas, area types, and highway functional classifications including urban and rural interstates, major and minor arterials, collectors, and local roads,
    - Intercity and inter-regional corridor level studies to identify the relative size of interstate truck flows from major origins and destinations,

- Truck traffic impact studies on detour routes resulting from potential roadway projects,
- Scenario planning with performance measure comparison.

Tour-Based vs. Trip-Based Models

Advantages

Tour-based freight demand models present several advantages compared to traditional trip-based models. The primary advantage is that tour-based models more precisely match the travel behavior that they model. This benefit has several different components.

- **Tour-based models account for fundamental differences between passenger and cargo transportation:** Tour-based models can more accurately forecast truck movements than models that account for each trip separately because many truck trips are parts of tours. Trip-based models, which were developed for passenger vehicles, are often mismatched to correctly describe freight behavior since passenger and cargo vehicles behave inherently differently.
- **Tour-based models capture freight decision making dynamics:** Tour-based models better capture freight carriers' delivery strategy better than trip-based models. For example, Ruan et al. (2012) believe that tour-based models can provide more details about a carriers' distribution strategy, distribution channels, and item bundling than trip-based models. While tour-based models include fewer details than logistics models, they nonetheless incorporate more supply chain decision characteristics than traditional models.
- **Tour-based models lay the foundation for other model improvements:** Tour-based models lay the groundwork for future changes that will more completely capture complex

freight movement decisions. Modeling evolves progressively, meaning that each improvement builds the technical skills required for the next improvement. One of the improvements that tour-based models may prepare for are tour-based micro simulation models. Many tour-based models generate and distribute tours at the TAZ level. Conversely, micro simulation models each freight agency separately. Tour-based micro simulation models similar to Hunt and Stefan's (2007) Calgary model can simulate different freight related decision making, expense, and value-of-time dynamics for each truck generated.

Challenges

When using the proposed model, there are several limitations that should be evaluated. Limitations are primarily related to the nature of modeling. More sophisticated models allay modeling's inherent challenges without eliminating them altogether. Specifically—

1. **Modeling can be no more accurate than the relationships that are Included:** Models usually posit that a dependent variable (e.g., truck travel) depends on a variety of independent variables at a certain geographical scale (e.g., population and employment data at the TAZ level). A model is accurate to the extent that the independent variables accurately and completely forecast the dependent variable, and inaccuracies will appear to the extent that the relationships are incomplete, important independent variables are omitted, and present or forecasted independent variable data is inaccurate or unavailable. A tour-based truck model models truck behavior more precisely than conventional models. Moreover, GPS truck data strengthens the model by enhancing dependent variable precision. However, the model remains dependent on the relationships being modeled. No single model addition or data improvement can be a panacea.

2. **The dependent variable forecasts (e.g., Truck Travel) can be no more accurate than the independent variable forecasts (e.g., Population, Employment):** Inaccurate independent variable forecasts will not accurately and consistently forecast the dependent variable even with perfectly sophisticated models. Therefore, it is necessary to improve forecasting across the board while improving model's sophistication.

3. **While the two previous limitations are Inherent to all models, there are also many particular limitations that modelers can encounter when applying a tour-based truck model:** These tour-based truck models encountered several limitations as applied. The lack of data drove several challenges. For example, data unavailability prevented the models from generating truck trips in a fully disaggregate fashion, which would have required an inventory of all trucks. Instead, in this project, the models used a zonal aggregate model of the number of tour starts. It is common that unavailable data requires modelers to alter the model or process the available data that fits the model, often at the cost of forecasting robustness.

GPS Data

Advantages

GPS truck movement data can serve many types of freight or passenger travel demand models, including tour-based models. As such, GPS movement data is not only valuable for its role in tour-based freight models. Some of the greatest advantages over other types of freight data include—

- **Data Availability:** GPS devices provide precise and comprehensive data without burdening the companies whose data is being reported. Many passenger travel demand models rely on self-report travel diaries to explain where and when a person has traveled. While travel diaries may also provide truck information, truck movement data is very hard to obtain because commercial freight companies are reluctant to share their private operational information for fear of revealing trade secrets and because of the burden that travel diaries can impose on drivers. GPS data can eliminate driver burden, although it is not sufficient to assuage all privacy concerns. Carefully scrubbing data to cover company and driver identity can help alleviate concerns and encourage data sharing.

- **Data Disaggregation:** GPS data has the potential to provide more detailed trip information than roadside truck counts, which cannot provide details on specific truck types or trips, and more complete information than travel demand diaries, which depend on drivers taking the time to fill in at each destination. GPS data can provide detailed movement information with exact times, locations, and speeds following specific vehicles across an operational area.
- **Data Reliability:** GPS data can produce more reliable truck movement information than travel diaries because it does not depend on driver memory or effort. Trips can only be omitted if the satellite connection is lost or if there is an equipment malfunction, whereas travel diaries may omit trips when the driver forgets or is too busy to record them. Moreover, GPS data provides more precise time and speed information, which may often be rounded in travel diaries for convenience.
- **Adaptability to Other Uses:** GPS data can support other transportation initiatives besides travel demand models. For example, researchers have used GPS truck movement data to develop roadway performance measures in Washington state (McCormack et al. 2010), Georgia (Southworth and Gillette 2011), U.S. interstate highways (Federal Highway Administration 2006), the United Kingdom (Hudson and Rhys-Tyler 2004), Australia (Greaves and Figliozzi 2008), and South Africa (Joubert and

Axhausen 2011). GPS data can also be combined with truck weight to assist in pavement management, or input into truck emissions models (Greaves and Figliozzi 2008).

Challenges

This project confirms several challenges of using GPS data, though in most cases we were able to overcome them.

- **Obtaining Proprietary Movement Data:** Whereas past studies have approached trucking companies to directly request data, this project used GPS data assembled and processed by the American Transportation Research Institute (ATRI). Many companies are reluctant to share movement data due to privacy concerns. Obtaining anonymized data from a central source ensured uniform formatting, made the sample more representative of all trucks, and eased legal hurdles with obtaining proprietary movement data.
- **Lack of Commodity and Truck Characteristics Data:** GPS data determines a truck's precise location and speed and set time intervals. However, GPS data does not reveal the commodities that a truck is carrying nor the vehicle class. More detailed information on truck characteristics including truck classification and commodities carried would make GPS data more useful for modeling.
- **Identifying Tour Endpoints:** GPS data must be analyzed to identify trip start and end points, since they are not marked as such in trip diaries. The analysis used in this project identified tour starts by comparing adjacent records until the first records showing movement out of a travel analysis zone were located. The tour ends were identified when the truck returned to the zone where it had begun, or at midnight. It is important to adjust identification algorithms and when possible check manually for best results.

- **Lost and Inaccurate Data:** The GPS data included inconsistencies in the start/end locations and the time stamps. For example, some trucks were recorded as moving from one zone to another without the passage of any time. In these cases, the preceding and subsequent records were examined to locate the error. Trucks with unreasonably recorded or implicit speeds were dropped. Data processing reduced the total number of records but produced better data for each day.

Differences between Old and New Models

Atlanta Regional Commission

The tour-based freight model for Atlanta includes several improvements compared with past models.

- **Tour Component:** The new model can account for touring behavior, which the old model could not. Adding tour behavior was one of the project's primary motivations since it more realistically imitates truck behavior and improves forecasting as described previously
- **Improved Calibration:** The new model is based on GPS data, which is more accurate than the truck movement data that past metro Atlanta freight models have used. Because the Atlanta Regional Commission did not have data tracking specific truck movements, it had instead used an innovative calibration technique called "adaptable assignment" to iteratively assign trucks to roads based on roadside counts. The GPS data provides a more complete, reliable, and disaggregate database for use in the tour-based model or the conventional freight demand model.
- **Through Trips:** The Atlanta Regional Commission's existing freight travel demand model was hampered in its ability to estimate through trips due to the lack of detailed truck movement data. Therefore, the existing model relied on a look-up table that calculated the probability of a through trip by facility type and truck size. The GPS data

improves through trip calculation by basing through trip calculations on vehicle-specific truck movement records.

Regional Planning Commission of Greater Birmingham

The Birmingham tour-based model benefits from many of the same advantages as the Atlanta model, including—

- **Tour Component:** The new model can more closely mimic truck trip behavior since it includes truck tours. The previous planning models simply estimated truck trips by multiplying total trip productions by a standard factor. It is believed the new tour-based model provides more accurate modeling of truck trips.
- **Vehicle Classification:** The previous model was not able to differentiate between trucks and general commercial traffic. The new model separates these two trip types.
- **Time of Day:** The existing Birmingham freight travel demand model did not forecast the time of day at which trucks would travel. This makes it difficult to load roads and predict actual congestion since it is unknown how truck trips will be distributed throughout the day. The new Birmingham model includes four time-of-day designations for morning peak, mid-day, evening peak, and nighttime.

Further Study

The research team encountered several aspects of freight modeling that merit further study, namely the following.

Truck Types: It is recommended to develop methodologies and GPS data sources that distinguish and stratify different truck types (e.g., medium vs. heavy, short- vs. long-haul) to permit more precise modeling based on truck characteristics. A shortcoming of this project that should be addressed in future studies is the distinction between medium and heavy truck trips. This project was unable to estimate trips by these categories because the GPS data was not stratified by truck type. This distinction is important for air quality planning, since majority of medium trucks (i.e., single-unit vehicles with 2-3 axles) have gasoline engines, while almost all heavy trucks (i.e., multi-axle tractor-trailer combinations) have diesel engines. It should be possible for the GPS data to be stratified by truck type (or related data) without compromising the confidentiality that is necessary for data collection.

Precise Origin and Destination Locations: Tour-based model can benefit from truck origins and destinations coded in latitude and longitude rather than aggregated at the TAZ level, which was the level of GPS data precision in this project. Moreover, more precise external station geocoding can improving modeling accuracy. Finally better data on the universe of trucks in the study area and truck sampling rates will allow for disaggregate trip generation and will improve how the GPS truck movement sample is scaled up.

Intermediate Stops: It can be useful to analyze the sequence of intermediate stops and associated land uses at the stop locations to understand true regional economic activities and commodity movements. Stop location land use can best be viewed in conjunction with localized logistics information. In the models used in this study, only internal-to-internal (I/I) tours were analyzed for intermediate stops because trips with an external component did not have complete origin and destination zone information.

Round-Trip Tours: This project did not investigate round-trip tours (i.e., tours that begin and end in the same zone) due to limited resources. Future research should examine round-trip tours more carefully. It may be necessary to enhance the tour main destination choice model (or impose a separate model) to estimate the likelihood that a truck tour will return to its starting point.

Time of Day: With the Atlanta tour based model, the time of day model investigated the use of different coefficients and different variables for the midday, PM peak, and night periods (the utility of the AM peak period is defined as zero, by convention). Upon further reflection, it might be more promising to stratify the variables and/or coefficients by PM peak vs. midday/night (jointly). As for the Birmingham model, the time of day model should be validated with traffic counts, once truck count data by hour becomes available.

Complete Truck Inventory: Future models can benefit from a zone-level inventory of trucks, perhaps using state registration data with adjustments to account for trucks are garaged and registered in different locations. A truck inventory would enable a true disaggregate logit tour frequency model.

Through Trips: The Atlanta Regional Commission's existing freight travel demand model was hampered in its ability to estimate through trips by the lack of observed truck movement data. Lack of data was especially problematic during the model's expansion from 13 counties to 20 counties since there was not sufficient data to build an X/X trip tables for the larger region. Therefore, the X/X trip tables for the 20-county region were extrapolated based on the assumption that through trips in the 20-county region would be similar to those in the 13-county region. The tour-based freight model uses GPS data, which calculates through trips based on newer and more complete vehicle-specific truck movement records. The proposed models did not handle through truck movements (X/X movements) in the same manner as other truck tours.

Through trucks were estimated conventionally, as trips between pairs of external stations. Conventional estimation omits the possibility of trip chaining into tours. In reality, the GPS data indicates that X/X movements are more complex. Some are actually tours and may make a brief stop in the analysis area. The available data does not reveal whether the internal stops are related to goods movement or unrelated (e.g., to buy fuel or food). Some X/X movements enter and leave the area via the same external station. These behaviors are inconsistent with conventional modeling techniques and raise the question as to whether X/X trips with internal stops should be considered one X/X tour or a pair of X/I and I/X tours. Through movements are a relatively large share of total truck volumes, especially in Birmingham, which means that improving through trips can significantly affect model function.

Overestimated Volumes on Small and Rural Roads: The Birmingham tour-based model overestimates truck volumes on lower-volume roads, especially in rural areas. This bears further investigation. The truck counts at the cordon should be verified more in detail.

Local and Regional Difference: Researchers should also work with practitioners to implement tour-based truck models with GPS data in different settings to overcome local and regional characteristics. Tour-based models and GPS data have not yet been adopted as widely as their theoretical benefits and practical advantages might indicate. These two models provide a foundation for other MPOs and DOTs to use GPS-derived truck data in freight demand models, and they identified and proposed solutions to challenges that organizations might encounter in implementing such a model. Cooperation among researchers and practitioners can widely disseminate the model and lessons that this research provides.

Multiple New Applications: Finally, researchers should examine the usefulness of the proposed models for a wide range of applications, including impacts on air quality models, traffic congestion forecasts, and investment decisions. The tour-based truck model with GPS-derived data has been shown to be feasible for MPOs and DOTs, and lessons have been identified to improve the models. While this study begins to compare the new models with legacy models, it addresses a small number of the potential applications and only a few of the settings. Research and practice can both explore the differences in application between tour-based and conventional models as planners gain experience in tour-based modeling. Understanding these differences can produce recommendations for making tour-based models more useful for air quality, congestion, decision making, and other functions.

REFERENCES

Allen, W. (2011, May). *Tour-Based Model for a Small Area*. Presented at the 11th National Transportation Planning Applications Conference.

Ambrosini, C., & Routhier, J.-L. (2004). Objectives, methods and results of surveys carried out in the field of urban freight transport: an international comparison. *Transport Reviews*, *24*(1), 57–77.

American Transportation Research Institute. (2012). *Freight Performance Measures » ATRI*. Retrieved February 24, 2014, from http://atri-online.org/2012/02/28/freight-performance-measures/

Armoogum, J., & Madre, J. L. (1997). Accuracy of data and memory effects in home based surveys on travel behaviour. In *76th Annual Meeting of the Transportation Research Board, Washington, DC*.

Bassok, A., McCormack, E. D., Outwater, M. L., & Ta, C. (2011). Use of truck GPS data for freight forecasting. In *Transportation Research Board 90th Annual Meeting*. Retrieved from http://trid.trb.org/view.aspx?id=1092809

Beagan, D. F., Fischer, M. J., & Kuppam, A. R. (2007). *Quick response freight manual II*. Retrieved from http://trid.trb.org/view.aspx?id=859168

Blonn, J., Dresser, C., Rungjang, K., Guo, J. Y., & Adams, T. M. (2007). Freight Planning at Small MPOs: Current Practices and Challenges. In *Proc., 2007 Mid-Continent Transportation Research Symposium*. Retrieved from http://ctre.iastate.edu/pubs/midcon2007/BlonnFreight.pdf

Bradley, M., Bowman, J. L., & Griesenbeck, B. (2010). SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. *Journal of Choice Modelling*, *3*(1), 5–31. doi:10.1016/S1755-5345(13)70027-7

Bricka, S., & Bhat, C. R. (2006). Comparative analysis of global positioning system-based and travel survey-based data. *Transportation Research Record: Journal of the Transportation Research Board*, *1972*(1), 9–20.

Bronzini, M. (2006). *New Data Sources*. Retrieved from http://onlinepubs.trb.org/onlinepubs/archive/Conferences/FDM/Bronzini.pdf

CA DOT. (2013, November 5). California Statewide Freight Forecasting Model (CSFFM). Retrieved from http://freight.its.uci.edu/sites/default/files/csffm_presentations/2011/Kickoff%20Meeting%20-%20REVISED.pdf

Cambridge Systematics. (1997). Inc. NCHRP Report 388: A Guidebook for Forecasting Freight Transportation Demand. *Transportation Research Board, Washington DC*.

Cambridge Systematics. (2009). *Maryland Statewide Freight Plan*. Retrieved from http://www.mdot.maryland.gov/Office_of_Planning_and_Capital_Programming/Freight_Planning/Documents/Freight_Plan_Final.pdf

Cambridge Systematics. (2010). *Freight-demand Modeling to Support Public-sector Decision Making* (No. NCFRP 8). Transportation Research Board. Retrieved from http://onlinepubs.trb.org/onlinepubs/ncfrp/ncfrp_rpt_008.pdf

Cambridge Systematics, National Cooperative Highway Research Program, & Transportation Officials. (2008). *Forecasting statewide freight toolkit* (Vol. 606). Transportation Research Board. Retrieved from http://books.google.com/books?hl=en&lr=&id=Q7bYgoUpkO4C&oi=fnd&pg=PA1&dq=Forecasting+Statewide+Freight+Toolkits.+National+Cooperative+Highway+Research+Program+Report++606&ots=ORJro0gXh6&sig=UHPudJbJzoRJxqqUr2lTnl4b8qQ

Chicago Metropolitan Agency for Planning. (n.d.). *Agent-Based Economic Extension to Mesoscale Freight Model* (Draft). Retrieved from http://www.cmap.illinois.gov/documents/10180/98867/201309_FreightForecasting.pdf/65715463-b04d-4a54-bbb5-5fd9efb9f747

Chow, J. Y. J., Yang, C. H., & Regan, A. C. (2010). State-of-the art of freight forecast modeling: lessons learned and the road ahead. *Transportation*, *37*(6), 1011–1030. doi:10.1007/s11116-010-9281-1

Chow, J. Y., Yang, C. H., & Regan, A. C. (2010). State-of-the art of freight forecast modeling: lessons learned and the road ahead. *Transportation*, *37*(6), 1011–1030.

Cohen, O. (2007, May 8). *Microsimulation of Intra-Urban Commercial Vehicle and Person Movements*. Presented at the 11th National Transportation Planning Applications Conference.

Daly, A. (1982). Estimating choice models containing attraction variables. *Transportation Research Part B: Methodological*, *16*(1), 5–15. doi:10.1016/0191-2615(82)90037-6

De Jong, G., Gunn, H., & Walker, W. (2004). National and international freight transport models: An overview and ideas for future development. *Transport Reviews*, *24*(1), 103–124.

Donnelly et al. (2008). *Atlanta Freight Modeling, External Truck Flows* (Prepared by Parsons Brinckerhoff for ARC).

Du, J., & Aultman-Hall, L. (2007). Increasing the accuracy of trip rate information from passive multi-day GPS travel datasets: Automatic trip end identification issues. *Transportation Research Part A: Policy and Practice*, *41*(3), 220–232.

Eatough, C. J., Brich, S. C., & Demetsky, M. J. (1998). *A methodology for statewide intermodal freight transportation planning*. Retrieved from http://trid.trb.org/view.aspx?id=497083

Federal Highway Administration. (2006). *Freight Performance Measurement: Travel Time in Freight-Significant Corridors*. Retrieved from http://ops.fhwa.dot.gov/Freight/freight_analysis/perform_meas/fpmtraveltime/index.htm

Federal Highway Administration. (2007). *Quick Response Freight Manual I and II. Freight Management and Operations* (No. FHWA-HOP-08-010 (2007)).

Ferguson, M., Maoh, H., Ryan, J., Kanaroglou, P., & Rashidi, T. H. (2012). Transferability and enhancement of a microsimulation model for estimating urban commercial vehicle movements. *Journal of Transport Geography*, *24*, 358–369.

Figliozzi, M. A., Kingdon, L., & Wilkitzki, A. (2007). Analysis of freight tours in a congested urban area using disaggregated data: characteristics and data collection challenges. *Analysis*, *12*, 1–2007.

Fischer, M. J., & Han, M. (2001). *Truck trip generation data*. Retrieved from http://trid.trb.org/view.aspx?id=715869

Fischer, M., Outwater, M., Cheng, L., Ahanotu, D., & Calix, R. (2005). Innovative Framework for Modeling Freight Transportation in Los Angeles County, California. *Transportation Research Record: Journal of the Transportation Research Board*, *1906*(-1), 105–112. doi:10.3141/1906-13

Gliebe, J., Cohen, O., & Hunt, J. D. (2007). Dynamic choice model of urban commercial activity patterns of vehicles and people. *Transportation Research Record: Journal of the Transportation Research Board*, *2003*(1), 17–26.

Gliebe, J., Smith, C., & Shabani, K. (2013, September 19). *Tour-based and Supply Chain Modeling for Freight in Chicago*. Retrieved from http://www.cmap.illinois.gov/documents/10180/98867/20130919_PeerExch_Gliebe_CMAP_ACE_FreightModel_PanelMeetingV04.pdf/bedc1a2c-c8a3-4eba-90ad-95edae1a34eb

Gonzalez-Feliu, J., Pluvinet, P., Serouge, M., & Gardrat, M. (2013). GPS-based data production in urban freight distribution. *Global Positioning Systems: Signal Structure, Applications and Sources of Error and Biases*, 1–20.

Gray, J. (2005). *Town Hall Discussion: Gaps and Shortcomings in Current Practice*. Retrieved from http://www.trb.org/Publications/Blurbs/159983.aspx

Greaves, S. P., & Figliozzi, M. A. (2008). *Commercial Vehicle Tour Data Collection Using Passive GPS Technology: Issues and Potentioal Applications*. Institute of Transport and Logistics Studies. Retrieved from http://web.cecs.pdx.edu/~maf/Conference_Proceedings/COMMERCIAL%20VEHICLE%20TOUR%20DATA%20COLLECTION%20USING%20PASSIVE%20GPS%20Technology.pdf

Guensler, R. L., Li, H., Ogle, J. H., Axhausen, K. W., & Schönfelder, S. (2006). Analysis of Commute Atlanta Instrumented Vehicle GPS Data: Destination Choice Behavior and Activity Spaces. Presented at the Transportation Research Board 85th Annual Meeting. Retrieved from http://trid.trb.org/view.aspx?id=777196

Guo, J. Y., & Wittwer, E. (2009). *Best Practices in Freight Planning*. Retrieved from http://trid.trb.org/view.aspx?id=890427

Holguin-Veras, J., & Patil, G. R. (2007). Integrated origin-destination synthesis model for freight with commodity-based and empty trip models. *Transportation Research Record: Journal of the Transportation Research Board*, *2008*(1), 60–66.

Holguín-Veras, J., & Thorson, E. (2000). An investigation of the relationships between the trip length distributions in commodity-based and trip-based freight demand modeling. *Transportation Research Record*, *1707*, 37–48.

Holguin-Veras, J., & Wang, Q. (2008). Investigation of attributes determining trip chaining behavior in hybrid microsimulation urban freight models. *Transportation Research Record: Journal of the Transportation Research Board*, *2066*(1), 1–8.

Horowitz, A. J. (2006). *Statewide travel forecasting models* (Vol. 358). Transportation Research Board. Retrieved from http://books.google.com/books?hl=en&lr=&id=O6uDMCF9ATUC&oi=fnd&pg=PA13&dq=NCHRP+SYNTHESIS+358&ots=lRp5YnTLrD&sig=hPz7rFJYf3qoBXP50vGDRoYGxIc

Hudson, M., & Rhys-Tyler, G. (2004). Using GPS data to calculate the length and variability of freight vehicle journey times on motorways. Retrieved from http://digital-library.theiet.org/content/conferences/10.1049/cp_20040007

Hunt, J. D., Donnelly, R., Abraham, J. E., Batten, C., Freedman, J., Hicks, J., … Upton, W. J. (2001). Design of a statewide land use transport interaction model for Oregon. In *Proceedings of the 9th World Conference for Transport Research, Seoul, South Korea* (p. 19). Retrieved from http://www.wgianalytics.com/landuse/docs/other/Oregon_OG2D_WCTR.pdf

Hunt, J. D., & Gregor, B. J. (2008). Oregon Generation 1 Land Use–Transport Economic Model Treatment of Commercial Movements: Case Example. In *Transportation Research Board Conference Proceedings*. Retrieved from http://trid.trb.org/view.aspx?id=863313

Hunt, J. D., & Stefan, K. J. (2007). Tour-based microsimulation of urban commercial movements. *Transportation Research Part B: Methodological*, *41*(9), 981–1013.

IHS Global Insights. (n.d.). *Transearch*. Retrieved May 5, 2013, from http://www.ihs.com/products/global-insight/industry-analysis/commerce-transport/database.aspx

Iowa Department of Transportation, & Iowa State University Center for Transportation Research and Education. (2008). Retrieved from http://ctre.iastate.edu/Research/statemod/dev_guid.pdf

Jones, C., Murray, D. C., & Short, J. (2005). *Methods of Travel Time Measurement in Freight-Significant Corridors*. American Transportation Research Institute. Retrieved from http://atri-online.org/research/results/Freight%20Performance%20Measures%20TRB%20for%20atri-online.pdf

Joubert, J. W., & Axhausen, K. W. (2011). Inferring commercial vehicle activities in Gauteng, South Africa. *Journal of Transport Geography*, *19*(1), 115–124.

Kawamura, K., Shin, H.-S., McNeil, S., & Ogard, L. (2005). *Business and Site Specific Trip Generation Methodology for Truck Trips*. Midwest Regional University Transportation Center, College of Engineering, Department of Civil and Environmental Engineering, University of Wisconsin, Madison. Retrieved from http://www.utc.uic.edu/research/reports/UTCWP-08-01-TTG.pdf

KIM, H., PARK, D., KIM, C., & KIM, Y. (2011). A Tour-Based Approach to Destination Choice Modeling Incorporating Agglomeration and Competition Effects. In *Proceedings of the Eastern Asia Society for Transportation Studies* (Vol. 8). Retrieved from http://www.dasan93.co.kr/upload/resear/resear1_12924153145.pdf

Knudson, B., Hunt, J., Weidner, T., Bettinard, A., & Wardell, E. (2011). Effective Modeling Analysis: A Case Study Using the Oregon Statewide Integrated Model for the Oregon Freight Plan. Presented at the 2011 TRB Transportation Planning Applications Conference. Retrieved from http://www.oregon.gov/ODOT/TD/TP/docs/Statewide/EffModeling.pdf

KRCU. (2011, August 18). Panama Canal expansion could increase shipping traffic on Mo. waterways. Retrieved from http://m.news.stlpublicradio.org/?utm_referrer=https%3A%2F%2Fwww.google.com%2F#mobile/1900

Kuppam, A., Lemp, J., Beagan, D., Livshits, V., Vallabhaneni, L., & Nippani, S. (2013, May 7). *Development of a Tour-Based Truck Travel Demand Model using Truck GPS Data*. Presented at the 14th National Transportation Planning Applications Conference.

Retrieved from http://pressamp.trb.org/aminteractiveprogram/EventDetails.aspx?ID=29013

Kuzmyak, J. R. (2008). NCHRP Synthesis of Highway Practice 384: Fore casting Metropolitan Commercial and Freight Travel. *Transportation Research Board of the National Academies, Washington, DC*.

Lahsene, J. S. (2005). Introduction, Policy Direction, and Megatrends. In *Conference Proceedings 40*. Retrieved from http://www.trb.org/Publications/Blurbs/159983.aspx

Liao, C.-F. (2010, September 14). *Fusing Public and Private Truck Data to Support Regional Freight Planning and Modelin*. Presented at the TRB SHRP 2 Symposium, Washington, D.C. Retrieved from http://www.menet.umn.edu/~cliao/SHRP2_2010_LIAO.pdf

Lindsey, C. L. (2008). A framework for integrating freight into MPO transportation planning. Retrieved from http://smartech.gatech.edu/handle/1853/24606

Logendran, R., Peterson, C., & Northwest, T. (2006). *Urban commodity flow data collection and analysis using Global Positioning Systems*. Transportation Northwest, Department of Civil Engineering, University of Washington. Retrieved from http://ntl.bts.gov/lib/25000/25100/25132/TNW2006-04.pdf

Ma, X., McCormack, E. D., & Wang, Y. (2011). Processing Commercial Global Positioning System Data to Develop a Web-Based Truck Performance Measures Program. *Transportation Research Record: Journal of the Transportation Research Board*, *2246*(1), 92–100.

Marshall, C. (2013). *CBRD » Motorway Database » M6*. Retrieved February 21, 2014, from http://www.cbrd.co.uk/motorway/m6

McCormack, E., & Hallenbeck, M. E. (2006). ITS devices used to collect truck data for performance benchmarks. *Transportation Research Record: Journal of the Transportation Research Board*, *1957*(1), 43–50.

McCormack, E., Ma, X., Charles, K., Currarei, A., & Duane, W. (2010). (No. WA-RD 748.1). Retrieved from http://www.wsdot.wa.gov/research/reports/fullreports/748.1.pdf

McCormack, E. (2011). Developing Transportation Metrics from Commercial GPS Truck Data. Retrieved from http://trid.trb.org/view.aspx?id=1105195

Memphis Area MPO. (n.d.). *Memphis Urban Area Long Range Transportation Plan (LRTP): Direction 2040. Appendix G: Travel Demand Model Documentation*. Retrieved from http://www.memphismpo.org/sites/default/files/public/documents/lrtp-2040/appendix-g-tdm-final.pdf

Moving Ahead for Progress in the 21st Century, USC § 1202. Retrieved from from http://www.gpo.gov/fdsys/pkg/PLAW-112publ141/pdf/PLAW-112publ141.pdf

Mysore, V. (2013, May 5). *Florida Statewide Multi - Modal Freight Model*. Presented at the 14th TRB Application Conference. Retrieved from http://www.trbappcon.org/2013conf/presentations/363_mysore_TRB%20Application%20Conference-FL%20SW%20Freight%20Model.pdf

NCDOT. (2009). *NC Truck NetworkModel Development Research* (Prepared for the NC Department of Transportation). Retrieved from http://www.ncdot.gov/doh/preconstruct/tpb/research/download/2006-09FinalReport.pdf

NCHRP. (2008). *NCHRP Report 606: Forecasting Statewide Freight Toolkit* (No. Report 606). Retrieved from http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_606.pdf

Ortuzar, J. de, & Willumsen, L. G. (1994). *Modelling transport*. Retrieved from http://trid.trb.org/view.aspx?id=410941

Outwater, M., Smith, C., Wies, K., Yoder, S., Sana, B., & Chen, J. (2013a). Tour based and supply chain modeling for freight: integrated model demonstration in Chicago. *Transportation Letters-the International Journal of Transportation Research*, *5*(2), 55–66. doi:10.1179/1942786713Z.0000000009

Outwater, M., Smith, C., Wies, K., Yoder, S., Sana, B., & Chen, J. (2013b). Tour based and supply chain modeling for freight: integrated model demonstration in Chicago. *Transportation Letters*, *5*(2), 55–66.

PBSJ, et al. (2009). Southwest Georgia Interstate Study. Technical Memorandum Truck Trip Table Development. Retrieved from https://www.yumpu.com/en/document/view/8261052/technical-memorandum-truck-trip-table-development-georgia-

Pearson, D. (2001). Global Positioning System (GPS) and travel surveys: Results from the 1997 Austin household survey. In *Eighth Conference on the Application of Transportation Planning Methods, Corpus Christi, Texas*.

Pendyala, R. M., Shankar, V. N., & McCullough, R. G. (2000). Freight travel demand modeling: synthesis of approaches and development of a framework. *Transportation Research Record: Journal of the Transportation Research Board*, *1725*(1), 9–16.

Pennsylvania Department of Transportation. (2007). Development of the Pennsylvania Statewide Commodity-Based Freight Model. Presented at the 11th TRB National Transportation Planning Applications Conference.

Pluvinet, P., Gonzalez-Feliu, J., & Ambrosini, C. (2012). GPS data analysis for understanding urban goods movement. *Procedia-Social and Behavioral Sciences*, *39*, 450–462.

Polak, J., & Han, X. L. (1997). Iterative Imputation Based Methods for Unit and Item Non-Response in Travel Surveys. In *th Meeting of the International Association of Travel Behaviour Research, Austin, Texas*.

Proussaloglou, K., Popuri, Y., Tempesta, D., Kasturirangan, K., & Cipra, D. (2007). Wisconsin passenger and freight statewide model: case study in statewide model validation. *Transportation Research Record: Journal of the Transportation Research Board*, *2003*(1), 120–129.

Prozzi, J., Mani, A., & Harrison, R. (2006). Development of sources and methods for securing truck travel data in Texas. *Texas Department of Transportation*.

Prozzi, J., Wong, C., & Harrison, R. (2004). *Texas truck data collection guidebook*. Retrieved from http://trid.trb.org/view.aspx?id=849364

Regan, A. C., & Garrido, R. A. (2001). Modelling freight demand and shipper behaviour: state of the art, future directions. *Travel Behaviour research–The Leading Edge. Pergamon, London*, 185–215.

Regional Planning Association, & Cambridge Systematics. (2010). *Travel Demand Model Documentation and User's Guide*. Retrieved from http://www.chcrpa.org/TPO_reorganized/Plans_and_Programs/LRTP/LRTP_2035/LRTP_2035_Final/VOLUME%203%20TRAVEL%20DEMAND%20MODEL%20DOCUMENTATION%20AND%20USER'S%20GUIDE.pdf

Resource Systems Group, Inc. (n.d.). *Florida Statewide Freight Model*. Retrieved March 21, 2014, from http://www.rsginc.com/node/302

Richardson, A. J. (2000). Measurement error problems in surveys of motor vehicle usage. *Road and Transport Research*, *9*(4), 3–10.

Richardson, A. J., Ampt, E. S., & Meyburg, A. H. (1995). *Survey methods for transport planning*. Eucalyptus Press Melbourne. Retrieved from http://www.geog.ucsb.edu/~deutsch/geog111_211a/code_books/Survey_Methods_For_Transport_Planning.pdf

Ritchie, S. (2013). *California Statewide Freight Forecasting Model* (pp. 1–25). Retrieved from http://freight.its.uci.edu/sites/default/files/csffm_presentations/2013/November/Caltrans%20Presentation%20November%205,%202013.pdf

Ruan, M., Lin, J. J., & Kawamura, K. (2011, January). *Modeling Commercial Vehicle Daily Tour Chaining*. 90th Transportation Research Board Annual Meeting, National Research Council.

Ruan, M., Lin, J. J., & Kawamura, K. (2012). Modeling urban commercial vehicle daily tour chaining. *Transportation Research Part E: Logistics and Transportation Review*, *48*(6), 1169–1184.

Russo, F., & Carteni, A. (2004). *A Tour-Based Model for the Simulation of Freight Distribution*. Association for European Transport.

Samimi, A., Mohammadian, A., & Kawamura, K. (2010, October). *Behavioral Paradigms for Modeling Freight Travel Decision-Making*. Presented at the International Conference on Travel Behaviour Research, Jaipur, India.

Sharman, B. W., & Roorda, M. J. (2011). Analysis of Freight Global Positioning System Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2246*(1), 83–91.

Shen, H. (2005). Evaluation of Practice Today: Florida's Statewide Model. Transportation Research Board. Retrieved from http://www.trb.org/Publications/Blurbs/159983.aspx

Smith, C., & Shabani, K. (2013, July 11). *FSUTMS Webinar: Exploring Freight Modeling*. Retrieved from http://www.fsutmsonline.net/images/uploads/webinar_videos/FDOT_Freight_Modeling_Webinar_-Only_Slides.pdf

Southworth, F. (1982a). *An urban goods movement model: framework and some results* (p. 165 184).

Southworth, F. (1982b). *Logistic demand models for urban goods movements* (UMTA NY 06-0087 82 2) (p. 189 204). Urban Mass Transportation Administration.

Southworth, F. (2002). Freight transportation planning: models and methods. In *Transportation Systems Planning: Methods and Applications*. CRC Press.

Southworth, F. (2011). Intermodal Transportation: Moving Freight in a Global Economy. In *Freight Flow Models*. Washington, DC: Eno Foundation.

Southworth, F. (2014). *On the Creation of Spatially Disaggregated Commodity Flow Matrices: An Overview of U.S. Studies (Draft)*. Oak Ridge, TN: Oak Ridge National Laboratory.

Southworth, F. & Gillette, J. (2011). *Trucking in Georgia: Freight Performance Measures* (No. 10-16). Georgia Department of Transportation. Retrieved from http://www.utc.gatech.edu/sites/default/files/files/pdf/2011_gti_01.pdf

Spear, B. (2005). State Modeling in Urban Areas: State of the Practice. In *Transportation Research Board, Conference Proceedings 40*. Retrieved from http://www.trb.org/Publications/Blurbs/159983.aspx

Stewart, R. D. (2012). *Multimodal Freight Transportation Within the Great Lakes-Saint Lawrence Basin*. Transportation Research Board. Retrieved from http://books.google.com/books?hl=en&lr=&id=phru3disrnAC&oi=fnd&pg=PP1&dq=Multimodal+Freight+Transportation+Within+the+Great+Lakes-Saint+Lawrence+Basin.+&ots=tq8QQIzPyK&sig=z_R90EvvZk-oLxAcanCVi7TzzF0

Tavasszy, L. A., Ruijgrok, K., & Davydenko, I. (2012). Incorporating logistics in freight transport demand models: state-of-the-art and research opportunities. *Transport Reviews*, *32*(2), 203–219.

TDOT. (2005). *Tennessee Long Range Transportation Plan: 10 Year Strategic Investment Program* (Final Report). Retrieved from http://www.tdot.state.tn.us/plango/pdfs/plan/SIP.pdf

Transportation Research Board. (2007). *Metropolitan Travel Forecasting: Current Practice and Future Direction. Special Report 288* (pp. Washington, D.C.). Retrieved from http://www.trb.org/Main/Blurbs/158933.aspx

Turnquist, M. A. (2006). Characteristics of effective freight models. *Freight Demand Modeling*, 11.

VHB. (2006). *Determination of the State of Practice in Metropolitan Area Travel Forecasting: Findings of the Survey of Metropolitan Planning Organizations*. Retrieved from ttp://onlinepubs.trb.org/onlinepubs/reports/vhb-2007-final.pdf

Virginia Department of Transportation. (2012). *Virginia Transportation Modeling Program*. Retrieved from http://www.virginiadot.org/projects/vtm/statewide.asp

Vleugel, J. M., & Janic, M. (2004). Route choice and the impact of'logistic Routes'. In *The 3rd International Conference on City Logistics*. Retrieved from http://trid.trb.org/view.aspx?id=758623

Wagner, D. P. (1997). Lexington area travel data collection test: GPS for personal travel surveys. *Final Report, Office of Highway Policy Information and Office of Technology Applications, Federal Highway Administration, Battelle Transport Division, Columbus*.

Wang, Q., & Holguin-Veras, J. (2010, September 15). *A Tour-based Urban Freight Transportation Model Based on Entropy Maximization*. Presented at the SHRP2 Innovations in Freight Demand Modeling and Data Symposium.

Wheeler, N., & Figliozzi, M. (2011). Multicriteria Freeway Performance Measures for Trucking in Congested Corridors. *Transportation Research Record: Journal of the Transportation Research Board*, *2224*(1), 82–93.

Wies, K. (2012). *An Agent-based Computational Economic (ACE) extension to CMAP's Mesoscale Freight Model* (White Paper). Chicago Metropolitan Agency for Planning. Retrieved from http://www.cmap.illinois.gov/documents/10180/15705/AdvModelSymposium-ACE_08-31-2012_final.pdf/f9d5ddb3-185c-4c0c-8f5f-93684bbdcac4

Wigan, M. & Southworth, F. (2005). What's wrong with freight models? *PROCEEDINGS OF ETC 2005, STRASBOURG, FRANCE 18-20 SEPTEMBER 2005-TRANSPORT POLICY AND OPERATIONS-FREIGHT AND LOGISTICS-FREIGHT MODELLING II*. Retrieved from http://trid.trb.org/view.aspx?id=846410

Wisetjindawat, W., Sano, K., Matsumoto, S., & Raothanachonkun, P. (2007). Micro-simulation model for modeling freight agents interactions in urban freight movement. In *CD Proceedings, 86th Annual Meeting of the Transportation Research Board, Washington DC* (pp. 21–25). Retrieved from http://www.researchgate.net/publication/228729495_Micro-simulation_model_for_modeling_freight_agents_interactions_in_urban_freight_movement/file/79e4151159d44a3219.pdf

Wolf, J., & Lee, M. (2008). Synthesis of and statistics for recent GPS-enhanced travel surveys. In *8th International Conference on Survey Methods in Transport, Annecy*. Retrieved from http://www.isctsc.let.fr/papiers/workshop%20final%20version/58%20A2%20wolf%20and%20lee.pdf

Wolf, J., Loechl, M., Thompson, M., & Arce, C. (2003). Trip rate analysis in GPS-enhanced personal travel surveys. *Transport Survey Quality and Innovation*, *28*, 483–498.

Yokota, T., & Tamagawa, D. (2012). Route Identification of Freight Vehicle's Tour Using GPS Probe Data and its Application to Evaluation of on and off Ramp Usage of Expressways. *Procedia-Social and Behavioral Sciences*, *39*, 255–266.

Zmud, J. P., & Arce, C. H. (2000). *Item nonresponse in travel surveys: Causes and solutions*. Retrieved from http://trid.trb.org/view.aspx?id=686581