Global Positioning System-based Truck Modelling for Regional Travel Demand Forecasting

Submission Date: August 1, 2014
Word Count: 6,247 words (excluding tables and figures)
3 Tables and 2 Figures

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ABSTRACT

Freight movement complexity and a lack of truck trip data limits freight modelling’s practicality and application. Most publicly available truck movement data is reported at higher geographical levels than detailed analysis and modelling require. 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 departments of transportation (DOT) and other proprietary data sources. Commercially available commodity flow databases (e.g., Global Insight’s TRANSEARCH) are excessively expensive, and this data set also provides aggregate information on commodity shipments between selected major cities. However, this data set provides limited information on shipments into smaller geographies. Freight transportation surveys such as roadside/intercept surveys, focus and stakeholder group surveys, and commodity flow surveys are time-consuming and requires a great amount of labor to geocode the trip origins and destinations.

This study shows a truck modelling effort utilizing real-time global positioning system (GPS) truck data with a belief that GPS-based databases may provide detailed and disaggregate data for regional freight modelling. Eight weeks of GPS data for 5,000 different trucks in 2011 (two weeks in four seasons) for the Atlanta and Birmingham metropolitan planning organizations (MPO) was collected and incorporated with other datasets. Notably, GPS data can provide detailed origin-destination (O-D) information, routes and corridors, operating speeds, travel times, and flows. This study explores various possible ways that a GPS-based truck movement data can contribute to freight demand forecasts at the state and regional levels.
INTRODUCTION

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 metropolitan planning organizations (MPO) are becoming increasingly interested in structuring formal freight transportation planning procedures.

In general, freight modelling is largely limited 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 modelling. 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 departments of transportation (DOT) and other proprietary data sources. Commercially available commodity flow databases (e.g., Global Insight’s TRANSEARCH) are excessively expensive, and only provide aggregate information on commodity shipments between selected major cities and limited information on shipments into smaller geographies. Freight transportation surveys such as roadside/intercept surveys, focus and stakeholder group surveys, and commodity flow surveys are time-consuming and require a great amount of labor to geocode the trip origins and destinations.

Global positioning system (GPS) -based truck travel data may lower the hurdle of the lack of detailed and disaggregated truck travel data, so that regional planning organizations can develop freight-demand models in conjunction with travel demand forecasting models more easily. Incorporated with other existing data, GPS data provide detailed origin-destination (O-D) 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 modelling, and collaboration of MPO freight planning activities within the statewide freight planning framework.

LITERATURE REVIEW

Cities and states are facing the continuing increase of global trade and concomitant rises in domestic freight flows. The freight volume is projected to increase by 75% between 2005 and 2020 and freight value by 300% in the same period (1). The great projected increase in freight stresses the importance of performing freight demand modelling. 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 (2). 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) (3).

While it is not uncommon to scale up projected passenger travel demand to account for freight demand at a very basic level, freight modelling 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 modelling and forecasting techniques because of the ways in which they differ, regarding several fundamental characteristics as follows (4–6).

Lindsey finds that the limited availability of data is one of the large challenges to effective freight modelling that metropolitan planning organizations face (7). Likewise, the Transportation Research
Board determined the lack of truck data within and beyond MPO boundaries to be a major obstacle in MPO freight modelling (3). Generally, meager data are available for modelling because most of the data needed for freight modelling 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 (8). 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 (9). To advance, Lindsey suggests regional-level data collection and standardizing data format (7).

Figliozi find that few transportation planners in major developing countries use “analytical urban freight tour models” largely because disaggregate truck data is rarely available to planners” (10, 11). When disaggregate truck data is available, it is possible to use the disaggregate data to analyze the freight movement, revealing the relationship between trip length and empty trips, trip speed, and movement (10). 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 (12).

Most freight models are derived from passenger demand models. Therefore, as a group they assume that freight and passenger movement respond similarly under given conditions (13). However, 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 (14).

Urban freight modelling faces several obstacles to accurate modelling that are not encountered in regional freight modelling. 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” (15). Urban trucking involves daily multi-stop tours that are not so 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/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.

**SURVEY**

As part of the project, a survey was delivered to 50 state Department of Transportation (DOTs) and 381 MPOs. Out of the targeted agencies, 44% of DOTs (22 agencies) and 39.4% of MPOs (150 agencies) responded. The survey explicitly distinguished freight modelling from freight study and definitions were provided to survey respondents prior to questions being completed. Freight study was 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 modelling 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 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>
<thead>
<tr>
<th>Table 1 DOTs’ and MPOs’ freight study/model/performance measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freight Study</td>
</tr>
<tr>
<td>Yes</td>
</tr>
</tbody>
</table>
Freight demand is often forecast via 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 modeling (31% of the DOT respondents and 48% of the MPO respondents) is still more common than commodity-based modeling (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>
<thead>
<tr>
<th>Topic</th>
<th>Agency</th>
<th>Description</th>
<th>Number (Percent of Respondents)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecasting Method</td>
<td>DOT</td>
<td>In-house model</td>
<td>4 (31%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Contractor-built model</td>
<td>7 (54%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trend extrapolation</td>
<td>1 (8%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other</td>
<td>1 (8%)</td>
</tr>
<tr>
<td></td>
<td>MPO</td>
<td>In-house model</td>
<td>14 (32%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Contractor-built model</td>
<td>18 (41%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trend extrapolation</td>
<td>1 (2%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other</td>
<td>11 (25%)</td>
</tr>
<tr>
<td>Freight model last updated</td>
<td>DOT</td>
<td>Within the last year</td>
<td>6 (46%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Between 1 and 2 years ago</td>
<td>3 (23%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Between 2 and 5 years ago</td>
<td>2 (15%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Between 5 and 10 years ago</td>
<td>1 (8%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>More than 10 years ago</td>
<td>1 (8%)</td>
</tr>
<tr>
<td></td>
<td>MPO</td>
<td>Within the last year</td>
<td>10 (23%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Between 1 and 2 years ago</td>
<td>15 (35%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Between 2 and 5 years ago</td>
<td>9 (21%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Between 5 and 10 years ago</td>
<td>7 (16%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>More than 10 years ago</td>
<td>2 (5%)</td>
</tr>
<tr>
<td>Modelling method</td>
<td>DOT</td>
<td>Vehicle-based</td>
<td>4 (31%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Commodity-based</td>
<td>3 (23%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hybrid</td>
<td>6 (46%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other</td>
<td>0 (0%)</td>
</tr>
<tr>
<td></td>
<td>MPO</td>
<td>Vehicle-based</td>
<td>20 (48%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Commodity-based</td>
<td>7 (17%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hybrid</td>
<td>8 (19%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other</td>
<td>7 (17%)</td>
</tr>
</tbody>
</table>
The survey results also reveal current truck movement data sources. Publicly available data developed by state or federal governments 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 two out of nine DOTs and seven out of thirty seven MPOs who answered that they have vehicle-based model 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. Agencies which had used GPS data in a freight model addressed that they obtained the GPS data from the American Transportation Research Institute (ATRI).

Many of the primary obstacles in modelling freight were well understood: insufficient funding, insufficient staffing, competing tasks, lack of specialized knowledge, 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.

MODEL FRAMEWORK

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 1990s trucking’s increasingly important role in air quality conformance, traffic congestion, and economic growth have all grown the attention paid to estimating truck movement separately. Nearly all truck models still use the conventional aggregate four-step methodology, which pays 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.

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 used an establishment survey to develop a commercial tour model as part of the Ohio Statewide Model (16). Ruan, Lin, and Kawamura used similar data to develop a truck trip chaining model for Texas (17). Russo and Carteni, and Wang and Holguin-Veras described research approaches to address this problem (18, 19). Samimi, Mohammadian, and Kawamura 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 (20). Outwater et al. describe a proof-of-concept study for a tour-based and logistics supply chain model for the Chicago area (21).

Perhaps the most directly relevant prior research was documented by Kuppam et al. in a presentation at the May 2013 TRB Planning Applications Conference (22). Kuppam et al. described a tour-based truck model developed for the Phoenix area based on truck GPS data. That model includes components for tour generation, stop generation, tour completion, stop purpose, stop location, and stop time period. The model is a series of connected logit models leading to a set of trips that can be conventionally assigned to a network.

This model’s framework builds upon the work of Kuppam et al. and the innovative model for Brunswick, GA, by Allen (22, 23). Truck movements are modelled as individual tours, which may or may not daily return to the starting point and which may have intermediate stops. A series of logit models is applied and Monte Carlo simulation identifies the tour’s main destination zone, the number of intermediate stops, stop locations, and the tour’s starting time period. Some simplifying assumptions similar to Allen’s Brunswick model are made to increase tractability (23). 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 with “real world” applications.
Although GPS data provide excellent information, they must be used with caution because they represent an unknown sample of the universe of truck trips. Moreover, data confidentiality requirements prevent information about vehicle type and ownership from being shared. 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 1 illustrates the components of the proposed model structure. Each component is described in more detail below.

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Figure 1 Model structure

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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 modelling 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.

**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 socio-economic variables used by the Atlanta Regional Commission (ARC), such as employment in eight categories, population, households, university enrollment, land area, zone type, truck zone, etc. Output from the truck generation model was used to scale ATRI GPS truck data by using expansion factors. Next, the tour records were summarized by the zone of the tour main origin. Then, a Cube script was written to calculate these ARC variables 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. Several adjustments were made 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, as described later. The destination choice submodel uses a logit form to calculate the probability of each destination.

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 of stops 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 = 10am – 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.

GPS DATA PROCESSING

A FoxPro program was used to process truck GPS data. The ATRI data comes from four months in 2011: February, May, July, and October. Only the dates in each month that were weekdays were identified, 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 eight sets of input files were concatenated for processing. Some GPS records span a multi-day period. Multi-day records spanning a
period other than midnight over two consecutive days were deleted. Speed in miles per hour was
calculated as a function of change in distance over change in time.

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. The intent is to
determine when trucks start (from the origin) and stop moving (at the destination). If the truck’s first
record shows a speed below two miles per hour, the logical variable ‘STOPPED’ was set to ‘true,’ and the
‘STATUS’ column value is replaced with ‘F’. The record showing a truck’s first movement 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. Based on the STATUS variable, the cleaned truck
records were turned into trip records which must have legitimate origin and destination zone information.
For example, trip records for the selected truck (Truck ID: 0014827042235482023992) contain 23 truck
trips generated out of 224 truck records.

A second FoxPro program was used to convert 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. For example, Tour 1 of the selected truck 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. 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. 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. 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.

APPLICATION

Figure 2 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’s trip-based model overestimates for morning (i.e., AM), evening (i.e., PM) and midday
(i.e., MD), and underestimates for night (i.e., NT).
Table 3 shows truck vehicle miles traveled (VMT) comparisons between the two models by time of day (AM, MD, PM, and NT) and by area type (central business district - 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 nighttime (i.e., NT) for every area type. The tour model produces higher estimates in the rural area types (suburban, exurban, and rural).

Table 3: Truck VMT Comparison for 2010 (ARC Trip Model vs. Tour Model)

<table>
<thead>
<tr>
<th>Number</th>
<th>Time</th>
<th>Area Type</th>
<th>ARC Trip Model - Truck VMT</th>
<th>Tour Model - Truck VMT</th>
<th>Percent Overestimated with Trip model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AM</td>
<td>CBD/Very High Density Urban</td>
<td>39,761</td>
<td>28,571</td>
<td>39%</td>
</tr>
<tr>
<td>2</td>
<td>AM</td>
<td>High Density Urban</td>
<td>142,805</td>
<td>82,674</td>
<td>73%</td>
</tr>
<tr>
<td>3</td>
<td>AM</td>
<td>Medium Density Urban</td>
<td>293,108</td>
<td>171,398</td>
<td>71%</td>
</tr>
<tr>
<td>4</td>
<td>AM</td>
<td>Low Density Urban</td>
<td>396,526</td>
<td>232,422</td>
<td>71%</td>
</tr>
<tr>
<td>5</td>
<td>AM</td>
<td>Suburban</td>
<td>1,320,979</td>
<td>875,817</td>
<td>51%</td>
</tr>
<tr>
<td>6</td>
<td>AM</td>
<td>Exurban</td>
<td>432,673</td>
<td>287,028</td>
<td>51%</td>
</tr>
<tr>
<td>7</td>
<td>AM</td>
<td>Rural</td>
<td>400,102</td>
<td>279,506</td>
<td>43%</td>
</tr>
<tr>
<td>1</td>
<td>PM</td>
<td>CBD/Very High Density Urban</td>
<td>39,641</td>
<td>27,779</td>
<td>43%</td>
</tr>
<tr>
<td>2</td>
<td>PM</td>
<td>High Density Urban</td>
<td>147,530</td>
<td>82,695</td>
<td>78%</td>
</tr>
<tr>
<td>3</td>
<td>PM</td>
<td>Medium Density Urban</td>
<td>308,015</td>
<td>178,136</td>
<td>73%</td>
</tr>
<tr>
<td>4</td>
<td>PM</td>
<td>Low Density Urban</td>
<td>417,072</td>
<td>248,826</td>
<td>68%</td>
</tr>
<tr>
<td>5</td>
<td>PM</td>
<td>Suburban</td>
<td>1,413,046</td>
<td>942,783</td>
<td>50%</td>
</tr>
<tr>
<td>6</td>
<td>PM</td>
<td>Exurban</td>
<td>465,819</td>
<td>345,327</td>
<td>35%</td>
</tr>
<tr>
<td>7</td>
<td>PM</td>
<td>Rural</td>
<td>434,893</td>
<td>361,373</td>
<td>20%</td>
</tr>
</tbody>
</table>
In this section, the research team attempted to show different results using both current ARC trip-based model and newly developed tour-based model. Although it is not a matter to show 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 modelling discrete tours is more realistic than modelling 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 modelling approaches get better data to support them, and become more popular and implemented in planning processes. This said, the finding that the tour model's assignment was closer to the reported traffic counts than the trip based model's assignment suggests that the tour model's O/D table is at least as accurate, and founded on a more satisfying theoretical approach.

Model choice should depend on the policy goals. Both trip-based and tour-based models suffer from the same problem: a severe lack of data describing the existing goods movement system. In this study, GPS data was valuable, but it lacked key data components (e.g., truck size) and involved too small a sample for direct O-D expansion.

CONCLUSION

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 modelling approaches. The lessons relate to data availability and analysis, as well as model construction. The primary lessons learned are summarized as follows:

**Freight Modelling Remains Underutilized in Most MPOs:** MPOs should be able to perform independent freight demand modelling activities for traffic forecasting. MPO freight modelling 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 modelling 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 modelling 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 modelling.

**Tour-Based Freight Modelling Retains a Theoretical Advantage over Trip-Based Modelling:** Tour-based modelling is theoretically more robust than trip-based modelling because it more realistically captures vehicle movements and motor carriers’ decision making. However, due to their intense processing and data requirements, only a few MPOs use tour-based freight models. Many MPO respondents expressed the need for more truck data to support their freight modelling.

**Tour-Based Truck Movement Models Likely Capture Underlying Freight Movement Relationships More Completely than Conventional Models:** There is a significant variation between trip-based and tour-based models in terms of truck volumes by route and by time of day. It is hard to determine one model’s forecasting superiority due to the lack of validating truck data. However, the tour-based model’s stronger theoretical foundation and the GPS data findings 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.

**GPS-Derived Truck Movement Data Is a Viable Data Source:** GPS-derived truck data can provide detailed truck travel diary data for disaggregate freight models, including tour-based freight models. However, GPS data is computationally intensive due to the required data quantity and the need for complex algorithms for processing raw data.

**The Data Analysis Revealed Important Socio-Demographic, Descriptive, and Temporal Characteristics of Truck Movement:** The analyses of GPS truck sample data 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 modelling, such as population and households, truck tour generation is highly associated with specific categories of employment, including (a) wholesale employment; (b) finance, insurance, real estate employment; and (c) 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 modelling 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 modelling. 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 modelling from passenger travel demand modelling. 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 modelling instead of trip-based modelling, so that different tours can modeled to start at different time of day according to its unique characteristics.
Improving Truck Movement Data Will Have Limited Impact if Pursued in Isolation from Broad Modelling 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 modelling 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.

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.

Tour-Based Modelling 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 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.

ACKNOWLEDGEMENTS

The authors would like to thank and acknowledge the contributions of Mr. William G. Allen and Dr. Frank Southworth, and Peter Hylton and Fangru Wang, who are PhD students at the Georgia Institute of Technology, for their contributions to this project. This research was supported by the U.S. Department of Transportation and Georgia Department of Transportation through the National Center for Transportation Systems Productivity and Management.
REFERENCES


2. KRCU. Panama Canal expansion could increase shipping traffic on Mo. waterways. Aug 18, 2011.


