URBAN LOGISTICS DECISIONS MODELLING FRAMEWORK FOR SHIPMENT SCHEDULING, STOP DURATION AND VEHICLE ROUTING

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ABSTRACT

Freight transportation models based on the conventional four-step modelling paradigm are aggregate in nature and cannot account for freight-specific phenomena such as the relationship between different agents and logistics decisions, such as shipment bundling. This paper presents a conceptual framework of the FRELODE urban logistics decisions model that forms one component of a larger agent-based commercial vehicle travel model currently under development by University of Toronto researchers. This modelling framework accepts a list of shipments by carrier as input and applies these shipments to the transportation network. Component decisions include: 1) shipment scheduling and shipment size, 2) vehicle selection, 3) tour generation, 4) tour start time, and 5) stop duration models. The FRELODE modelling framework is designed to be completely estimated using passively-collected GPS data. Operational shipment scheduling and stop duration models have been estimated and are discussed. This paper concludes with a brief discussion on policy decisions that be analyzed using this framework.

Keywords: GPS, tour-based freight model, urban commercial travel model

INTRODUCTION

Forecasting future commercial travel demand is an important activity for governments, who need to prioritize infrastructure improvements in a budget constrained environment and to formulate policies that encourage efficient commercial vehicle travel while minimizing externalities such as congestion and pollution. The majority of freight models used in practice are derived from the "four-step" modelling procedure used to model passenger flows. Multiple authors (e.g. Holguin-Veras & Thorson, 2000; Hensher & Figliozzi, 2007; Samimi et al, 2010) have argued that the four-step modelling procedure is not suitable for freight transportation. Particular deficiencies of using four-step models to forecast commercial vehicle travel include that these models cannot represent the following behaviour.

1. Decisions about freight travel can be made by multiple firms and different actors (e.g. shippers, carriers, receivers and freight-forwarders) are likely responsible for different aspect of shipment planning (Boerkamps et al, 2000; Liedtke et al, 2009; Roorda et al, 2010; de Jong et al, 2012).

2. Four-step models use a single model structure for movement of all commodities in spite of a wide variety between the logistics associated with different commodities, for example agricultural goods compared with computer chips. (Wang & Holguin-Veras, 2008).

3. Shipments are not independent from one another as firms optimize their supply chains through supplier selection, shipment frequency, use of consolidation and distribution centres and consolidation of multiple tours on a single vehicle (Hensher & Puckett, 2005). For example, surveys conducted in Denver and in Calgary reported an average of 4.97 and 5 stops per tour, respectively (Holguin-Veras & Patil, 2005; Hunt & Stefan, 2007).

4. Services are not included in commodity-based four-step models, which first estimate origins and destinations of commodities that are then shipped. Hunt and Stefan (2007) report that Calgary surveys revealed that approximately 45% of all reported business stops were made to provide a service and not to deliver or pickup goods.

Recently, a number of commercial vehicle travel demand models have been proposed. A brief overview of these models is provided in the Literature Review section of this paper.

A lack of data availability is a major impediment to the development of high-quality agent-based commercial vehicle travel models. According to Giuliano et al (2010), analysts would ideally have accurate data on commodity flows by different industry sectors, including origins and destinations and selected modes and routes. This information is required for different business enterprises that vary greatly in size, product mix and their mode of operation.

Such information is often obtained by asking commercial establishments to complete shipping surveys. Survey-based data collection for urban commercial vehicle travel is difficult, time consuming, and expensive (McCabe et al., 2006). Low response rates (between 5% and 25%) are also common, largely because of response burden and privacy concerns (Roorda et al., 2008). Due to the burden placed upon respondents, the duration of urban commercial vehicle surveys is usually limited to a single day.

Data collected from in-vehicle global positioning system (GPS) units provide another means of recording vehicle movements over an extended time period. Many firms in North America have already installed GPS units to monitor driver hours of service, monitor the distance travelled in each state or province for fuel tax records, and allow fleet managers to track their vehicles. For example, XRS (one company that provides fleet management services) monitored approximately 114,000 trucks across North America (XRS, 2012).

Compared with multiple-day surveys, GPS data are better able to: 1) capture short and infrequent trips; 2) provide accurate temporal information; 3) provide travel information over multiple days, and; 4) offer detailed route choice, travel itinerary and spatial location, while not placing additional burden upon the respondent (Pendyala, 2003). However, deficiencies of GPS data include:

- GPS data do not contain shipment information such as the weight, volume, commodity type or whether the shipment is direct or is one leg in a consolidated shipment.
- No information is available about visits to a destination made by unmonitored vehicles.
- Due to privacy concerns, information may not be available about the carrier, visited customers or the vehicle type.

Passively-collected GPS data are a promising data source for estimating an urban commercial logistics decisions travel forecasting model for two reasons, which are described below.

The first reason is that there is a lack of suitable data available to estimate *urban* commercial travel forecasting models. Many of the data sources that do exist (for example the Commodity flow survey in the United States and Ontario road-intercept commercial vehicle survey (CVS) are primarily targeted towards long-distance trips that occur between urban centres. While surveys in individual cities have been conducted, a lack of consistency in survey data between cities makes it difficult to transfer models. Since GPS data are much more widespread, however, similar GPS data can be obtained in many locations allowing much easier model estimation and also the ability to transfer models between locations.

The second reason is that the lack of shipment information is less of an issue for urban commercial travel than for long-distance commercial travel. Due to transportation costs, firms pay particular attention to the optimization of the long-distance components of their supply chain. For local deliveries, however, firms must be responsive to their clients meaning that they cannot wait for a full vehicle before making a shipment. This is called pull-logistics and is becoming more common (Simchi-Levi et al, 2003). Also, the penalties are lower for non-optimal shipments.

The purpose of this paper is to present the *FREight LOgistics DEcisions* (FRELODE) modelling framework that will be estimated for an urban area using passively-collected GPS data. This framework is designed to fit within a larger agent-based commercial vehicle framework that is currently under development at the University of Toronto.

This paper is organized as follows. The Literature Review section provides an overview of recently proposed agent-based commercial vehicle travel models. Following this overview, the "Conceptual Framework" section outlines an agent-based conceptual framework, including an overview of the FRELODE urban logistics decisions framework that is the focus of this paper. Following that, the "GPS Data and Data Processing" section describes the passively-collected GPS data that are used to estimate the component models to the framework, including GPS data processing techniques that were designed for this analysis. The "Framework Implementation" section then provides details on component models within the FRELODE framework that have been estimated from the passively-collected GPS dataset. The final section is a discussion on "Policy Applications", which examines the ability of this modelling framework to forecast the effect of policy and infrastructure changes on freight travel patterns.

LITERATURE REVIEW

This section provides a brief overview of recently proposed commercial vehicle travel models that address some of the deficiencies of the "four-step" modelling process for commercial vehicle travel modelling. Models are separated into categories to reflect the different objectives of different commercial vehicle travel models.

Supply-Chain (Logistics) models focus on accurate representation of the supply chains of different firms, paying particular attention to accurately model behaviour such as shipment size and frequency, mode choice and shipment bundling. An example model in this category is the Norway and Sweden Freight Transportation Models of De Jong & Ben Akiva (2007). This model estimates shipment frequencies (and hence sizes) in a manner that minimizes combined transportation and inventory costs, and selects the transportation chain including the modes for each shipment. This model consolidates multiple shipments into larger vehicles to incorporate economies of scale in freight travel.

Urban logistics models incorporate logistics behaviour, such as commodity-based truck tours, with a focus on urban settings. The Tokyo model of Wisetjindawat et al (2007) is one example of this model category. This model uses similar steps to the "four-step" modelling system, but considers (for example) the availability of distribution channels in vendor selection, shipment frequencies and deliveries made directly by a shipper or by a carrier.

The Calgary model (Hunt & Stefan, 2007) and the Ohio Statewide Model (Gliebe et al, 2007) are both examples of *tour-based models*. Tour-based models explicitly generate tours in urban areas. After tours are generated, the stops undertaken in a tour are predicted. These models also explicitly consider service trips as well as pickup and delivery trips. The model of Wang & Holguin-Veras (2008) is another example of a tour-based model. This model organizes shipments into tours that satisfy the total goods delivered between each origin-destination pair. This model could generate tours from a commodity-based demand matrix, perhaps as estimated using Input-Output economic models.

Hybrid models, as defined in this work, combine elements of longer distance supply-chain models with local tour-based models. Examples include a hybrid model of the Los Angeles region, by Fischer et al (2005) and the FHWA Freight Forecasting Framework regional model that is currently under development by Outwater et al (2012).

CONCEPTUAL FRAMEWORK

Roorda et al (2010) present an agent-based microsimulation framework that explicitly represents the diversity of business establishments, and the impact of interactions between business establishments on commercial travel behaviour in study region. It includes three components, as follows:

1. The *Commodity Contract Formation* component predicts the supply and demand of commodities for establishments in the study area, and uses a market-interaction approach to match commodity orders from shippers to receivers in order to obtain a list of shipments between firms.

2. The *Logistics Contract Formation* component represents how shippers select carriers to undertake the physical delivery of the shipment to the receiver. An operational set of models have been developed for this component (Cavalcante & Roorda 2013a/2013b).

3. The *Logistics Decisions* component focuses on estimating how carriers execute delivery of their contracted shipments, including mode selection, load consolidation, vehicle type selection and vehicle scheduling (including stop dwell times).

This paper further details the framework for the logistics decisions component of the framework. The model inputs for this component include a list of shipments that require delivery by each carrier. Shipment attributes include:

- annual shipment weight to be delivered between the shipper and receiver
- shipper and receiver locations
- shipment commodity type
- the shipping pattern

The shipping pattern for each shipper/receiver pair is classified into one of three market segments: frequent shipments, regularly scheduled shipments and stochastically scheduled shipments.

Carriers have a list of shipments for all of their clients. Carriers plan their deliveries considering all contracted shipments simultaneously, allowing them to develop trip chains, in which a vehicle visits multiple destinations in a single tour.

This framework has been designed to use passively-collected GPS data as the primary data source for model estimation. Passively-collected GPS data offer many advantages, chiefly that data can be collected for long time periods without burdening respondents. Disadvantages of this data source are the lack of information about the shipment, the shipper and receiver and the carrier. This logistics decisions modelling framework has been designed around these limitations. One of the early decisions was to limit the modelling framework to urban commercial vehicle movements, for which very little data are currently available from existing data sources and for which the lack of shipment information is felt to be less crucial than for inter-city travel. More detail of the GPS data source and selected processing steps are described later in this paper.

Figure 1 shows the structure of the FREight LOGistics DEcisions (FRELODE) framework, which draws from Roorda et al (2010) and Outwater et al (2012). A description of each component is presented below. The Framework Implementation section presents more detail for two components that have been estimated.

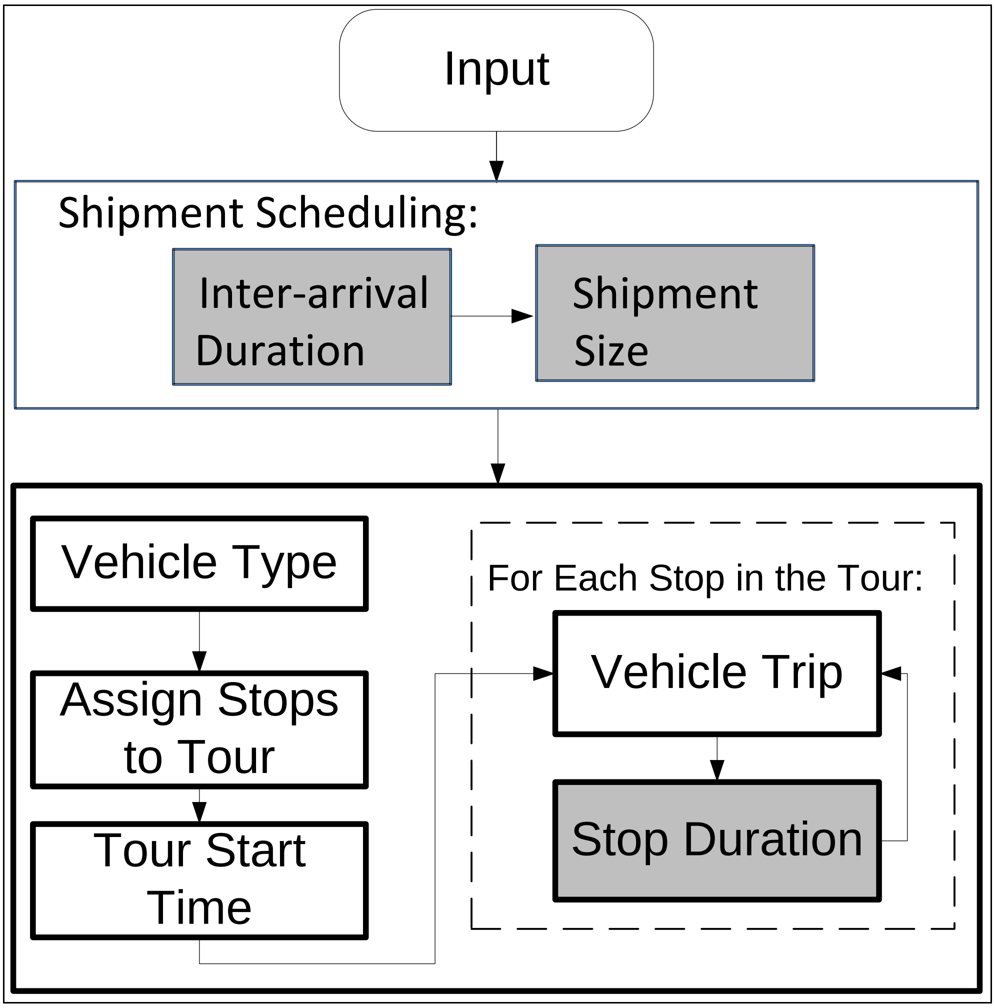

Figure 1: FRELODE framework

This framework recognizes that shipments may be scheduled for frequent delivery, scheduled for infrequent delivery or unscheduled (shipments or services are made on request and not on a predetermined timeframe). The *Inter-Arrival Duration* model is used to assign shipments to specific days in the study period.

The subsequent model components of the framework predict the tour formation behaviour given a list of shipments to be delivered on a given day. The shaded boxes in Figure 1 indicate the model components that have been estimated for this paper. A summary of model estimation is shown in the following sections.

Shipment Scheduling

The *inter-arrival duration model* identifies the day of each shipment and is estimated based on data from observations of the number of days between visits to the same destination by the same vehicle fleet operator. The inter-arrival duration model (Sharman & Roorda, 2013) is summarized in the *Framework Implementation* section of this paper.

Shipment size is calculated assuming a constant shipment rate. Hence the shipment size can be calculated using the annual volume of goods shipped between the shipper and receiver and the number of days since the previous visit.

Vehicle Type Selection

After the day of each shipment has been scheduled, the following steps model the commercial trips made in a single day. The first step is to select a vehicle class (light, medium or heavy) used to deliver shipments to the vehicle. We proposed to estimate this model using a multinomial logit model with three categories of truck size (light, medium and heavy). This component has not yet been estimated as no vehicle information was suppressed in the current GPS data source.

Assign Stops to Tour

The following step groups the stops visited on the same day by the same vehicle type into tours. The vehicle type (and hence the capacity of the vehicle) is input into this model component, since this affects the number of stops that can be made within a single tour. While a standard vehicle routing problem algorithm could be used to develop the optimal tour given constraints such as vehicle capacity and driver shift limitations, this approach requires significant computational resources.

A similar approach to that presented in Outwater et al (2012) could be used in this framework. They used hierarchical clustering to group the stops into tours and then used a greedy-algorithm to sequence stops in the tour. This combination of methods is simpler than using a Vehicle Routing Problem approach, but may be less sensitive to policy changes and congestion effects.

Tour Start Time

Once the stops have been assigned to tours, the Tour Start Time components selects a time of day when the vehicle leaves the depot to commence the tour. This occurs after assigning stops to tours because the number of stops visited on a tour impacts the time that a vehicle leaves to start a tour.

Vehicle Trip

For every trip in the tour, the travel route for each leg of the tour can be found using user equilibrium traffic assignment considering both commercial vehicle and passenger flows and time of day. Trip travel time is an outcome of the traffic assignment procedure, which is fed back into the stop assignment. Iterations are required to ensure that assumptions about travel time, made in the assignment of stops to tours, are consistent with model travel times. Given the trip start time and the trip duration, the arrival time at the next destination on the tour can be calculated.

Stop Duration

Stop duration reflects the amount of time that a vehicle remains at a stop, including vehicle loading and unloading, driver breaks or time spent at a service call. Estimating stop duration determines when a vehicle will leave for the next stop in the tour, and must be taken into account in the formation of tours. Stop duration is also useful for estimating demand for parking and idling emissions prediction. Hazard stop duration models have been estimated and are summarized in the *Framework Implementation* section of this paper and a complete description is provided in Sharman et al (2012).

GPS DATA AND DATA PROCESSING

GPS data used to estimate components of this modelling system were provided by Turnpike Global Technologies Inc., now called XRS. XRS installs and manages RouteTracker GPS units that monitor vehicle movements and driver hours of service compliance for their clients. The dataset includes GPS records for vehicles that operated in the Greater Toronto and Hamilton Area in southern Ontario, Canada between the days of April 1st and June 30th, 2007. It includes the tracked locations of 1618 vehicles operated by 77 firms, including over 7 million GPS points. Figure 2 shows the study region.

Figure 2: Boundaries for the GPS Study Area

Due to the size of the dataset, completely automated data processing was required to convert the raw GPS data into a list of trips, trip-ends, and tours (complete with attributes) suitable for estimation of commercial vehicle travel demand models. While the focus of this paper is not on the GPS data processing, certain processing steps are highlighted due to their direct impact on model implementation, discussed shortly. More details of the data processing are described in Sharman and Roorda (2010) and in Sharman et al. (2012).

One of the issues with using GPS data to estimate activity-based models is the need to relate individual trips ends to each other and to other data sources in order to provide context and land-use attributes suitable for model estimation. In the *destination identification* data processing step, GPS-recorded trip ends were grouped into *destinations*, which reflect a best estimate of activities accurate to the property parcel (Sharman & Roorda, 2011). This clustering is important as it allows an analysis to focus on the destination location rather than on an individual trip end. Grouping trip ends into destinations allowed estimation of longitudinal models, such as the *inter-arrival duration model* described in the Framework Implementation section of this paper.

Another issue with using passively-collected GPS data to estimate travel demand models is that the GPS records do not provide information about shipped goods or the visited locations. All land-use model attributes must be inferred from other data sources. Aggregate land-use attributes such as census data and travel analysis zone level household travel survey data were used in model estimation. It was also desired to obtain land-use information at a more refined level, ideally down to the property parcel. It was difficult to directly obtain property-parcel information, such as zoning information, since the study area spanned multiple municipalities. The following procedure was devised to obtain information about businesses located in a property-parcel for more accurate model estimation.

All destinations were assigned to a property parcel, obtained from Teranet (2009), using a spatial join conducted between the centroid of the GPS stops assigned to a single destination and the property parcels. Many (but not all) of the property parcels included the address as an attribute. A computer program was written using VBA that matched the address of parcels with addresses of firms given in the InfoCanada database of companies, which provides information about companies, including Standard Industrial Classification (SIC) categories (United States Department of Labor, n.d.), the number of employees and the sales volume.

Many firms may be located on the same property parcel. No attempt was made to infer the actual visited firm. Instead the computer program output aggregated property parcel information, such as the total sales volume of firms, the total number of employees and dummy variables that describe the establishment industry types were extracted from the InfoCanada database. For example, a SIC explanatory variable, $\delta_{\text{parcel has manufacturing}}$, was set to “1” if any establishment located on the property parcel undertook manufacturing activities and was set to “0” otherwise.

FRAMEWORK IMPLEMENTATION

This section provides more details of the *Inter-Arrival Duration* the *Stop Duration* models that are already estimated.

Inter-Arrival Duration

Other freight models, such as de Jong and Ben-Akiva (2007) and Liedtke (2009), calculate shipment frequencies that minimize combined inventory and transportation costs. In the current work, however, shipment details (e.g. size and commodity type), inventory costs and ordering costs could not be observed. Hence a different scheduling approach is proposed, using the observed longitudinal GPS records to model the *inter-arrival duration*, defined here as the number of days between visits to the same disaggregate destination by the same vehicle fleet operator. This approach uses these data to estimate disaggregate statistical models of inter-arrival duration that assess the effect of time, location and land-use attributes. This model is presented in more detail in Sharman and Roorda (2013), but is summarized here to better present the modelling framework.

Input variables to this model are obtainable from the GPS data given the previously described processing steps. A summary of the input variables is shown below:

- Weekday of the stop preceding the inter-arrival duration of interest. These were treated as dummy variables for different days of the week.

- Distance between the destination and the nearest carrier depot. This distance variable was considered more important than the distance of inbound and outbound effects due to trip chaining.

- Distance from the destination to the nearest freeway.

- Dummy variables reflecting industry classifications of firms operating on the property parcel (e.g. δ parcel has food retail = 1 if the property parcel contains at least one food retail establishment)

Market Segmentation

Before modelling the inter-arrival durations, clustered destinations were split into three different segments:

1. **Frequently-visited destinations**: average of at least 2 visits per week.

2. **Regularly-scheduled destinations**: average rate of less than two visits per week and a coefficient of variance of 0.7 or below. These destinations operate using fixed shipment schedules (e.g. weekly deliveries

3. **Unscheduled destinations**: average rate of less than two visits per week and a coefficient of variance above 0.7. These are destinations where the shipments are not made on regular schedules.

Categorizing firms clarified firm shipping behaviour and also improved the fit of the estimated models. It is anticipated that this segmentation would be better performed using survey data as more information is available than from the GPS data. A market segmentation multinomial logit model was also estimated from the GPS data in case such information cannot be obtained from surveys.

Inter-arrival duration model

Different visits to the same destination are not independent events. A multilevel random-intercept multinomial logit model was estimated for each market segment through Markov Chain Monte Carlo (MCMC) estimation (Browne, 2009) using the software package MLwiN (Rasbash et al., 2009).

Model evaluation showed that the multilevel models outperformed single level (traditional) multinomial logit models and that the segmented models outperformed a non-segmented model. Modelled coefficients (not shown here) are intuitive revealing expected day of week effects (e.g. fewer deliveries on weekends), longer inter-arrival durations as the distances between the carrier depot and the destination, and the distance of the destination to the nearest freeway, are increased. These two measures are proxy variables for the transportation costs, and they confirm the expected result that shipment frequency is reduced as transportation costs increase.

Few destination parcel-level SIC attributes were found to be significant and to improve the model fit. This is not unexpected as a property parcel can accommodate many different establishments and because firms sharing the same SIC attributes are heterogeneous. Manufacturing, retail and wholesalers of non-durable goods exhibit longer inter-arrival durations, while freight service providers had more frequent trips.

Stop Duration

Input variables to this model are obtainable from the GPS data given the previously described processing steps. A summary of the input variables is shown below:

- Arrival time at the stop.
- A *dense area* dummy variable, which is 1 if a region with a gross combined population and employment density of over 3500 per square kilometer. This definition is consistent with Newman & Kenworthy (2006) while the density information was obtained from the 2006 Transportation Tomorrow Survey.
- Distances of inbound and outbound trips.
- Number of stops on the tour
- Total sales value (in $) of all firms operating on the property parcel.
- Dummy variables reflecting industry classifications of firms operating on the property parcel (e.g. δ parcel has durable wholesale = 1 if the property parcel contains at least one wholesaler of durable goods).

Different hazard model specifications were tested in Sharman et al (2012). A continuous parametric hazard model was found to outperform non-parametric hazard models for this analysis. Calculated parameters were as expected, with longer stops undertaken in the morning, a positive correlation between the distance of inbound and outbound trips and stop duration and a negative correlation between the number of stops on the tour and the stop duration. Interested readers are referred to Sharman et al (2012) for the detailed model specification.

POLICY APPLICATIONS

Primary policy questions include the effect of available infrastructure, transportation costs and land-use patterns on commercial vehicle travel. Different types of policy response include: response to land-use changes, response to local design, response to changing transportation costs and response to infrastructure changes. The ability of this model to respond to these different changes are summarized below:

Response to land-use changes

The sensitivity to land-use changes is primarily in the *Shipment Scheduling* and the *Assign Stops to Tours* model components. The *Shipment Secheduling* component can use land-use attributes of destinations to predict shipment inter-arrival durations. Land-use is also important to determine the location of carriers and of shippers and receivers. Effects on shipment frequencies of changing the distances between carriers, shippers and receivers can also be incorporated in the *inter-arrival durations* model component.

Effects of land-use changes can also be incorporated into the *Assign Stops to Tours* model component, as distances between the different customers will determine shipment bundling characteristics.

Response to local design concerns

The stop duration model has an important policy application in that this model can be used to analyze parking and loading requirements in an area. If more vehicles can attempt to access a particular property or area than can be handled, then congestion may form as vehicles must either park illegally or wait until a space clears for them to load.

Response to changing transportation costs

Changing transportation costs is expected to influence both shipment frequency and tour formation travel behaviour. Although the *Inter-Arrival Duration* component does not have a cost component, the effect of changing transportation costs can be modelled by adjusting the distances between the carrier depot and the destination. Transportation costs are also expected to have a noticeable impact on tour formation, and can be included in the *Assign Stops to Tours* component.

Response to infrastructure changes

Infrastructure improvements are expected to decrease travel costs and time, thereby increasing shipment frequency and possibly decreasing tour lengths by reducing the penalty for non-optimal shipment routing. The *Shipment Days* component can accommodate infrastructure improvements. For example the distance to freeway variable can be used to forecast the effects of additional freeway construction. In the *Assign Stops to Tours* component, travel times can be included in the tour construction heuristics. These would include the effects of infrastructure on travel time improvements.

CONCLUSIONS

A lack of available data has hindered development of high-quality commercial vehicle forecasting models. Few establishment-based commercial vehicle travel surveys have been conducted that can provide insights into urban commercial travel behaviour.

Vehicle location data collected from on-board vehicle GPS recorders provide another promising data source that can complement existing travel surveys. While GPS data do not include important information such as the shipment information and information about shippers, receivers and carriers, advantages of GPS data include that they are widely available and hence models can be estimated in many cities without the need for time-consuming, expensive and burdensome establishment travel surveys.

This paper presents a framework of the FRELODE urban logistics model that is designed to be estimated using passively-collected GPS data. This model will form one component in a larger agent-based commercial vehicle model currently under development by University of Toronto researchers.

Component steps in the FRELODE model include shipment frequency, vehicle choice, tour formation, tour start time and stop duration models. The shipment frequency and stop duration models have been estimated and are summarized in this work. The model is designed to respond to changes in land-use, to reflect issues of lack of parking or loading spaces at a local level, changes in transportation costs and also infrastructure changes.

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REFERENCES

Boerkamps, J. H. K, A. J. van Binsbergen, and P. H. L. Bovy (2000). Modeling behavioural aspects of urban freight movement in supply chains. *Transportation Research Record,* 1725, 17-25.

Browne, W.J. (2009). *MCMC Estimation in MLwiN v2.1*, Centre for Multilevel Modelling, University of Bristol.

Cavalcante, R. and M. J. Roorda (2013a) Freight Market Interactions Simulation (FREMIS): An Urban Application. *In: 13th World Conference on Transport Research – WCTR 2013*, July 15-18, Rio de Janeiro, Brazil

Cavalcante, R. and M. J. Roorda (2013b). Freight Market Interactions Simulation (FREMIS): An Agent-Based Modeling Framework. *Procedia Computer Science*. In press.

de Jong, G. and M. Ben-Akiva (2007). A micro-simulation model of shipment size and transport chain choice, *Transportation Research Part B: Methodological*, 41(9), 950-965.

de Jong, G., I. Vierth, L. Tavasszy and M. Ben-Akiva (2012). Recent developments in national and international freight transport models within Europe, *Transportation*, 40(2), 347-371.

Fischer, M., M. Outwater, L. Cheng, D. Ahanotu and R. Calix (2005). An innovative framework for modeling freight transportation in Los Angeles county. *Transportation Research Record*, 1906, 105-112.

Giuliano, G., P. Gordon, Q. Pan, J. Y. Park and L. L. Wang (2010). Estimating freight flows for metropolitan area highway networks using secondary data sources, *Networks and Spatial Economics*, 10(1), 73-91.

Gliebe, J., O. Cohen and J. Hunt (2007). A dynamic choice model of urban commercial vehicle and person activity patterns, In: *Proceedings, 86th Annual Meeting of the Transportation Research Board*.

Hensher, D. and S. M. Puckett (2005). Refocusing the modelling of freight distribution: Development of an economic-based framework to evaluate supply chain behaviour in response to congestion charging, *Transportation*. 32(6), 573-602.

Hensher, D. and M. Figliozzi (2007). Behavioural insights into the modelling of freight transportation and distribution systems*, Transportation Research Part B,* 41(9), 921-923.

Holguin-Veras, J. and E. Thorson (2000). Trip length distributions in commodity-based and trip-based freight demand modeling: investigation of relationships, *Transportation Research Record*, 1707, 37-48.

Holguin-Veras, J. and G. Patil (2005). Observed trip chain behaviour of commercial vehicles, Transportation Research Record, 1906, 74-80.

Hunt, J. and K. Stefan (2007). 'Tour-based microsimulation of urban commercial movements', *Transportation Research Part B*,41(9), 981-1013.

InfoGroup (n.d.). *InfoCanada*.

Liedtke, G. (2009). Principles of micro-behavior commodity transport modeling, *Transportation Research Part E*, 45 (5), 795-809.

McCabe, S., H. Kwan and M. J. Roorda (2006). Freight transportation: who is the decision maker?, In: *53rd Annual North American Meetings of the Regional Science Association International*, Toronto, 15-18 November 2006.

Newman P. and J. Kenworthy (2006) Urban Design to Reduce Automobile Dependence, Opolis: *An International Journal of Suburban and Metropolitan Studies*, 2 (1).

Outwater, M., C. Smith, K. Wies, S. Yoder, B. Sana, J. Chen (2012). Tour-based and supply chain modelling for freight: an integrated model demonstration in Chicago. *Transportation Letters*, in press.

Pendyala, R. (2003). *Measuring day-to-day variability in travel behavior using GPS data*, Technical report, FHWA, U.S. Department of Transportation.

Rasbash, J., C. Charlton, W. J. Browne, M. Healy and B. Cameron (2009). *MLwiN Version 2.1*, Centre for Multilevel Modelling, University of Bristol.

Roorda, M. J, H. Kwan and S. McCabe (2008). Comparison of GPS and driver-reported urban commercial vehicle tours and stops, In: *Proceedings, 87th Annual Meeting of the Transportation Research Board*, Washington DC, 13–17 January 2008

Roorda, M. J., R. Cavalcante, S. McCabe, H. Kwan (2010). A conceptual framework for agent-based modelling of logistics services. *Transportation Research Part E*, 46, 18-31.

Samimi, A., K. Mohammadian and K. Kawamurai (2010). A behavioral freight movement microsimulation model: method and data, Transportation Letters. 2010(2), 53-62.

Sharman, B. and M. J. Roorda (2010). Analysis tool to process passively-collected GPS data for commercial vehicle demand modelling applications, In: *TRB - SHRP2 Symposium: Innovations in Freight Demand*, September 15, 2010, Washington DC.

Sharman, B. and M. J. Roorda (2011). Analysis of freight GPS data: A clustering approach for identifying trip destinations, *Transportation Research Record.* 2246, 83-91.

Sharman, B., M. J. Roorda and K. Nurul Habib (2012). Comparison of parametric and non-parametric hazard models of stop durations on urban commercial vehicle tours, *Transportation Research Record.* 2269, 117-126.

Sharman, B. and M. J. Roorda (2013). Multilevel modeling of commercial vehicle inter-arrival duration using GPS data, *In: Procedings of the 92nd Annual Meeting of the Transportion Research Board.*

Simchi-Levi, D., P. Kaminsky, and E. Simchi-Levi (2003). *Designing & Managing the Supply Chain: Concepts, Strategies & Case Studies*, Second Edition, McGraw Hill, Boston.

Smith, C. (2012). Tour-based and Supply Chain Modeling for Freight in Chicago, *Presented at IATBR 2012*, Toronto.

Teranet. *Ownership Parcel Database. 2009.*

United States Department of Labor, (n.d.), [online] http://www.osha.gov/pls/imis/sic_manual.html.

Wang, Q., and J. Holguin-Veras (2008). Investigation on the attributes determining trip chaining behavior in hybrid micro-simulation urban freight models, *Transportation Research Record: Journal of the Transportation Research Board*, 2066, 1-8.

Wisetjindawat, W., K. Sano, S. Matsumoto and P, Raothanachonkun (2007). Micro-simulation model for modeling freight agents interactions in urban freight movement, In: *Proceedings, 86th Annual Meeting of Transportation Research Board*.

XRS (2012). *'Xata Reports Fiscal 2012 Third Quarter Reports'*.