Freight data collection using GPS and web-based surveys: insights from US truck drivers' survey and perspectives for urban freight

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Published in Case Studies in Transport Policy, 4(1), pp. 38-44, 2016.

Abstract

This paper reports on tools, methods and experimental designs that have been developed to study the routing behavior and movement of trucks. The application of these capabilities is demonstrated with a case study on the route choices of North American intercity truck drivers', with a focus on the choice between tolled and free roads. An extension to the urban freight context, currently ongoing in Singapore, is briefly discussed, highlighting the challenges and main differences compared to the intercity case.

Keywords

GPS tracking, intercity freight route choice, urban freight modeling

1. Introduction

Freight transport accounts for a considerable share of urban and intercity traffic, and the associated externalities. In the US, trucks carry the largest share of freight: in 2002, trucks moved 64% of freight by value, 58% by weight, and 32% by ton-miles (BTS 2011). The movement of freight shipment tonnage is projected to increase by 65-70% by 2020 (FHWA 2007); trucks are expected to haul 75% of the freight tonnage by 2020 (FHWA 2005) and 68% of the value by 2040 (FHWA 2011c). The total annual highway miles driven by trucks increased by 109% between 1980 and 2008, a higher percentage increase than for other vehicle types. Similar trends have also been observed in the EU and other developed economies. The development of models and methods for planning and appraisal of freight transport systems is therefore a key priority. Current freight flow models are based on strong simplifying assumptions and weak behavioral foundations, which limit their explanatory power. A lack of data further limits their applicability. Thus, forecasts based on current models may be biased or imprecise.

There are three main dimensions of freight data collection: freight flows between the points of production and consumption (P-C); the logistics characteristics of shipments (e.g. shipment size, frequency of restocking, structure of the supply chain); and the transport characteristics of shipments (e.g. modes, routes). Freight flows are normally collected using costly and infrequent commodity flow surveys, providing a broad picture of national freight flows. These enable basic forecasting/planning, but do not include detailed information on the underlying logistics and transport choices. Thus, they do not support conversion of P-C flows into origin-destination (O-D) freight flows with the relevant characteristics of each leg of the logistics chain. The complete sequence of O-D flows corresponding to a P-C flows can only be traced by surveying producers and logistics operators, carriers and multimodal transport operators. This information provides useful insights into the supply chain structure (e.g. echelons and intermediate warehouses) and intermediate transport stops (e.g. transit points and intermodal terminals) for the various legs of the transport chain. Unfortunately, such data are not commonly available. When available, they are collected through traditional surveys, which have high costs and low response rates. Traditional surveys also tend to have non-representative samples. These stem from response biases resulting from respondents' short attention spans and limited ability to accurately recall information. In addition, traditional surveys fail in revealing the inter-relations and dependencies among the various entities involved in the freight industry that may influence their choices.

Improving freight data collection is needed to support the development of the next generation of freight transport models. Within the industry, there is already considerable penetration of sensing devices, such as smartphones, GPS loggers and RFID tags. These provide an opportunity to leverage technology to unobtrusively collect a wealth of high-quality data, which could be complemented with information from other sources, such as shippers and carriers.

This paper presents an implementation of a next-generation freight data collection effort. It leverages GPS loggers, advanced sensing and communication technologies and machine learning architecture to deliver previously unobtainable data. These data reflect observed rather than stated information on the decisions of shippers and carriers.

The paper is structured as follows. Section 2 reviews the research on truck intercity route choices. Section 3 describes the data collection approach. Section 4 illustrates the results, showing the potential data quality and detail improvements that can be gained using this approach. Section 5 discusses the adaptation of a similar approach to collection of data on urban freight movements and then concludes.

2. Intercity truck route choices

Toll roads are an increasingly important part of the US road network, with 30-40% of new urban expressway mileage and about 150 new centerline miles expected per year (Perez and Lockwood 2006). Trucks make up a more significant percentage of toll road revenues than their traffic share suggests, because they typically pay higher tolls than cars. Standard & Poor's (2005) report that heavy trucks usually make up around 10% of traffic flow on toll roads, but 25% of the revenues. Accurate predictions of truck flows and the corresponding revenues are therefore crucial for toll road feasibility studies. Unfortunately, there is a record of significant biases and high variance in toll road forecasts (Bain 2009). One source of these errors is in truck drivers' route choice modelling, mainly resulting from the lack of relevant routing behavior observations.

Compared to passenger transportation, only limited work has been done on route choice in the trucking industry. Most truck route choice studies reported in the literature are based on stated preference (SP) data (e.g. Small et al. 1999, Kurri et al. 2000, Bolis and Maggi 2001, Austroads 2003, Hunt and Abraham 2004, Danielis et al. 2005, Fowkes and Whiteing 2006, Zhou et al. 2009, Wood 2011, Toledo et al. 2013). SP studies present respondents with simplified hypothetical choice scenarios. The data collected may suffer from various biases and is generally considered less reliable compared to revealed preference (RP) data. Several studies (Jovicic 1998, de Jong et al. 2004, Hess et al. 2014) use RP data in addition to SP data. These were collected using paper or computerized questionnaires in which respondents recorded their travel. These studies are limited in level of detail and accuracy in which the routes are reported, and in the number of observations that may be obtained from each respondent.

Large-scale data sets on truck route choice behavior have been obtained in varying ways. Hagino et al. (2010) used records of traffic permit applications submitted by drivers. Knorring et al. (2005) collected GPS traces using in-truck systems. However, both studies suffer from substantial limitations: they do not collect any information about the shipments or the drivers. Further, they only include a limited set of route attributes (e.g. travel times, distances and tolls and road characteristics, such as number of lanes) that may be directly derived from a map database. Knorring et al.'s study exemplifies the great potential of the use of GPS data, which is readily available in large quantities from in-truck navigation systems. However, it also shows the need to complement the location data with additional information related to the attributes of the trip and the constraints imposed by the shipment schedule and other factors.

In the first phase of the current study, a traditional driver questionnaire with SP route choice questions was administered. The results of analysis of the collected data are reported in Sun et al. (2013) and Toledo et al. (2013). They show a wide variability in preferences towards toll roads and tolls, with route choices depending on multiple factors that include not only travel times and tolls, but also the probabilities and magnitudes of delays, toll bearing terms, driver compensation methods and shipment characteristics.

The next section describes the second phase of the study, which included a GPS-based RP survey using off-the-shelf GPS loggers to monitor all trips continuously and complemented by web-based prompted recall questionnaires.

3. Data collection system and methods

The architecture of the data collection system developed for this study is based on a combination of GPS loggers that were fitted in the participants' trucks with a web-based survey, as shown in Figure 1. The location data collected by the GPS logger are transmitted in real-time to a backend server. The raw data is than processed to detect stops that the truck has made and to match the location observation to a GIS map database. The processed information is displayed to the participants in a web-interface. The participants are asked to validate the data presented to them and to respond to an additional prompted recall questionnaire.

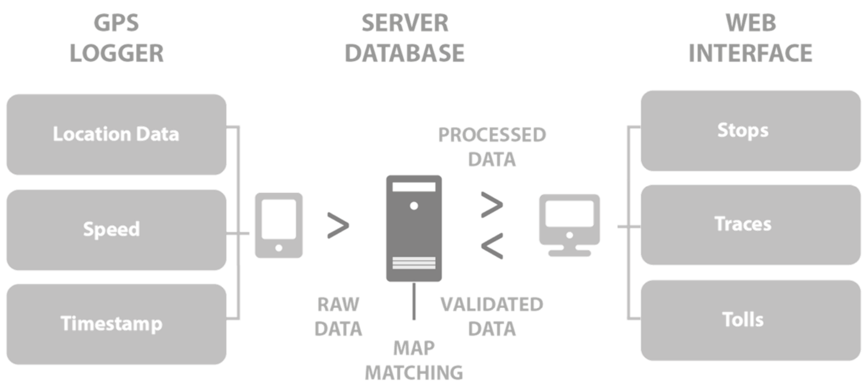


Figure 1 – Architecture for the truck' drivers route choice survey

The GPS loggers continuously collect data on the location and movement of the trucks and transmit this information through wireless networks to an application server. The GPS loggers did not require any professional installation and only need to be connected to the charger (cigarette lighter) in the truck cab. The logger used in the data collection described in Section 4 is a SANAV CT-24-D4F model with a backup battery (Figure 2). The logger can collect location data, instantaneous speed and a timestamp. The reporting intervals can be set up to be either time intervals and/or based on minimum movement distance thresholds. At the end of the GPS data collection, participants were required to return the equipment, so that it could be re-used by subsequent participants.

Figure 2 – GPS logger used in the study

At the backend server, algorithms are applied to match the observations to road segments on a GIS map database and to identify stops made by the drivers. On the matched route, tolling points passed during the trip are also identified. The processed information is shown to participants using dedicated personal webpages. The drivers are asked to log in to these webpages to validate and correct the information on their movement and to provide additional information that could not be inferred from the location information (e.g. pick-up and delivery schedules for loads, tolls and their methods of payment). Specifically, when drivers logged-in they could see a calendar of the days that they have driven, and showing the days that they need to provide information for. After selecting a day, they would see a map showing their route for the day, with the stops they made marked on it, as shown in Figure 3. They then needed to select each of the stops they made, and provide additional information on their activities at these stops.

The location data collection phase typically took between one and four weeks for each participant. The web interface was also used to administer various questionnaires soliciting additional information not directly related to the location data, such as socio-demographic characteristics of the drivers and their employment terms.

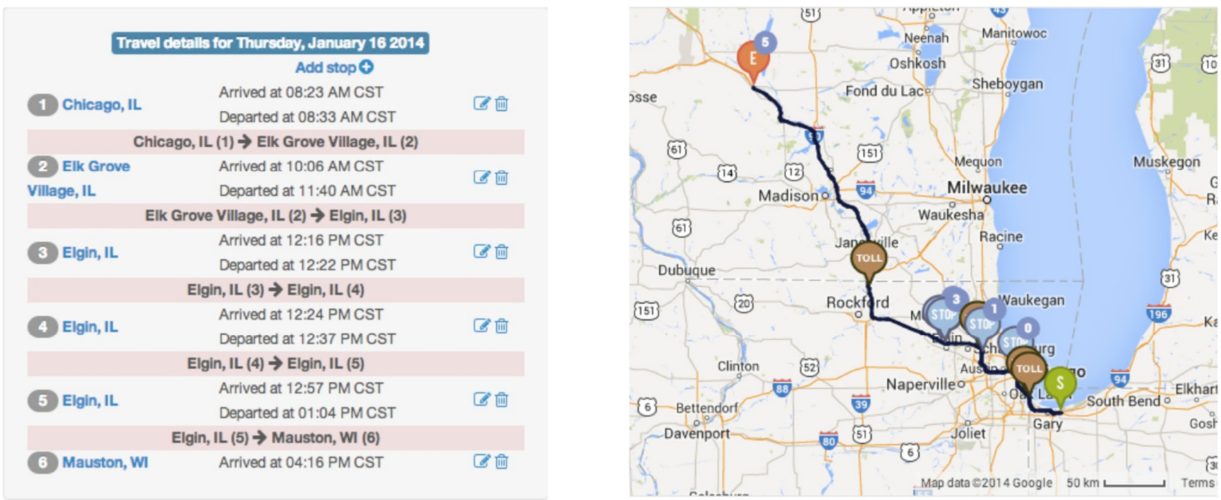
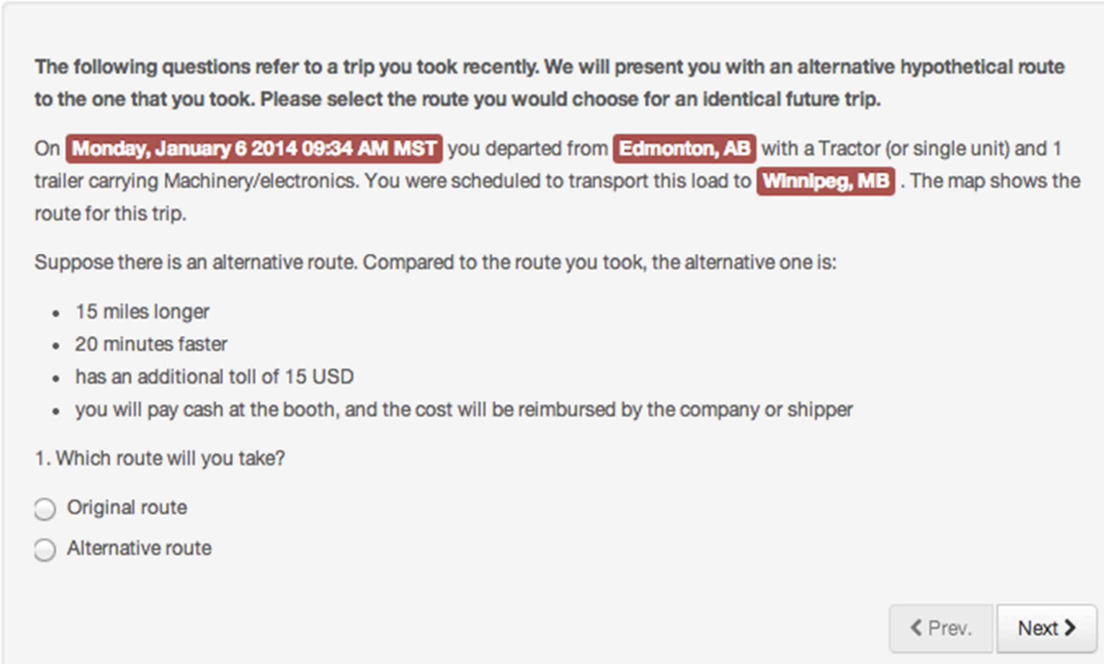


Figure 3 - Screen shots of the daily route (left) and stops screen (right)

The web-based interface gives survey participants a non-monetary benefit of participation in that they can see an analysis of their behavioral patterns as they validate their data. One limitation, however, is that the complexity of the survey meant that many participants had to be guided through the validation process by telephone.

At the end of the GPS data collection period, drivers were asked to complete a final exit survey. This survey collected further socio-demographic information about the driver and included an SP survey. In the SP survey, users were presented with hypothetical route choice scenarios in which alternatives to routes they actually used within the experiment period were presented. An example SP scenario is shown in Figure 4.


The following questions refer to a trip you took recently. We will present you with an alternative hypothetical route to the one that you took. Please select the route you would choose for an identical future trip.

On Monday, January 6 2014 09:34 AM MST you departed from Edmonton, AB with a Tractor (or single unit) and 1 trailer carrying Machinery/electronics. You were scheduled to transport this load to Winnipeg, MB . The map shows the route for this trip.

Suppose there is an alternative route. Compared to the route you took, the alternative one is:

- 15 miles longer
- 20 minutes faster
- has an additional toll of 15 USD
- you will pay cash at the booth, and the cost will be reimbursed by the company or shipper

1. Which route will you take?

○ Original route

○ Alternative route

< Prev. Next >

Figure 4 - Screen shot of the exit survey

Participants to the study were recruited in two ways:

- By telephone, using lists of trucking companies from commercially available databases of *FleetSeek*. Lists of drivers in Texas, Indiana, Ontario, New Jersey and Massachusetts were used.
- In person at truck stops and rest areas. Drivers were approached by a member of the survey team at truck stops in Texas (twice), Indiana (twice), Ontario and Massachusetts.

In-person recruitment at rest stops proved to be much more effective, as GPS loggers could be provided immediately instead of being mailed out. Further, because these drivers spoke to a team member in person instead of over the telephone, contact was more easily maintained. During the recruiting process, drivers received material with information on the project, including its purpose, the data being collected and the incentive plan.

Drivers were compensated for their participation, which was 20 USD for each full working week (5 days) of participation, up to four weeks, and an additional 20 USD for completion of the exit survey. Once participants were recruited, they were invited to register on the experiment webpage. During registration, drivers set up a user account on the system and provided basic socio-demographic and contact information.

4. Results

4.1 Sample statistics

A total of 107 drivers completed at least one week of data collection. The data collected for them covers 2255 validated days. Within this time, 12,617 stops were validated and 1,480 toll point passages were recorded.

The sample makeup in terms of the characteristics of the recruited drivers is presented in Table 1. The sample is generally consistent with the existing literature on truck driver demographics. Global Insight (2005) reports that in 2000, U.S. truck drivers were around 95% male, with 43% over the age of 45. ATRI (2015) reports a significant ageing of the workforce since then: over 55% of drivers were over 45 in 2013. In our sample, drivers are almost exclusively (97%) males. They tend to be older and with long experience: 69% of drivers had been driving for over 10 years, and only 12% had less than 5 years of experience. 50% are over 50 years old, and only 9% are 30 years or younger. 63% of participating drivers were hired drivers. These were almost evenly split among drivers for for-hire carriers and for private fleets. 35% of drivers are owner-operators (OO), who either lease their services to a larger carrier or shipper, or work as self-employed independent contractors and haul free-lance. This share is consistent with figures published by the Census Bureau (USCB 2004). Geographic location of the base location of the drivers reflects the nature of the recruitment process. The largest shares of truckers were located in the Southwest (mostly Texas), Midwest and Canada (mostly Ontario).

The characteristics of the trips and the trucks are presented in Table 2. The largest share of stops is rest stops (28%). Service points (pick-up and delivery) make up 26% of the stops. A large fraction of stops (8%) were reported as other, in many cases without further explanation.

At the vast majority of toll points (86%), payment was made using Electronic Toll Collection (ETC) tags. 8% pay cash, and 6% do not pay on the spot, but get invoiced later. In most cases (68%), the carrier or shipper is responsible for the toll cost. In 26% the driver is responsible for the tolls, and only in 6% the cost is shared between drivers and carriers (e.g. reimbursement of surcharges). A similar result is observed for the penetration rate of ETC tags: 71% of the trucks were equipped with toll tags.

80% of the trips did not involve any special services. The most frequent special service is temperature-controlled shipments (i.e. refrigerated or heated) at 9%. Only small fractions of the shipments involved expedited shipments (4%) and hazardous materials (1%). These numbers compare to the estimates that refrigerated vans are used in 9% of the truck-miles (USCB 2004) and that Hazmats constitute 8% of the ton-miles (FHWA 2010) driven in the US.

Table 1 - Driver characteristics in the sample

Characteristic	Options	% sampled drivers
Driver type	Hired-Company	31%
	Hired-Private	32%
	OO-Leased	19%
	OO-Own	16%
	Other	2%
Years of experience	Less than 1	3%
	1 to 2	5%
	3 to 5	4%
	5 to 10	20%
	Over 10	69%
Age	30 or less	9%
	31-40	7%
	41-50	34%
	51-60	38%
	61 or more	12%
Gender	Males	97%
	Females	3%
Geographic location	New England (MA, CT)	5%
	Atlantic (NY, NJ, PA, MD)	8%
	South (FL, AL, TN)	5%
	Midwest (IL, OH, IN, WI, IA, NE)	22%
	Southwest (TX, OK)	36%
	West (CA, OR)	3%
	Canada (ON, QC, BC, NS, NB)	21%

Table 2 - Freight- and service- related characteristics in the sample

Characteristic	Option	% sample composition
Stops	Load or pick-up	11%
	Unload or drop-off	15%
	Fuel	7%
	Maintenance	4%
	Meals	10%
	Rest	28%
	Home	3%
	Depot	5%
	Other	18%
Toll payments	ETC	86%
	Cash	8%
	Invoice	6%
Toll responsibility	Carrier or shipper	68%
	Shared	6%
	Driver	26%
Electronic tags	Yes	71%
	No	29%
Special services	None	80%
	Temperature controlled	9%
	Expedited or express	4%
	Hazardous materials	1%
	Other	6%

4.3 Analysis illustration

Significant variation in drivers' behavioral patterns is observed, showing several distinct categories of drivers: (i) Drivers who made a series of regular, long tours spanning several days or more; (ii) Drivers who made shorter tours within a smaller region; (iii) Drivers who made a combination of short and long tours; and (iv) Drivers who did not exhibit a distinctive tour pattern, traveling from city to city in search of work. Figure 5 shows examples of time-space diagrams of drivers' travel. The x-axis reports the distance from the drivers' base location (usually home or depot) and the y-axis the time (in days) of observation. Stops are shown as points on the time-space trajectories. The top diagram shows a driver making regular week-long round trips. The middle diagram shows a driver making mostly single day trips (thus returning to the base location every day) with different destinations and the occasional longer trip. The bottom diagram shows a driver with long irregular trips and no clear pattern also with respect to visits to the base location.

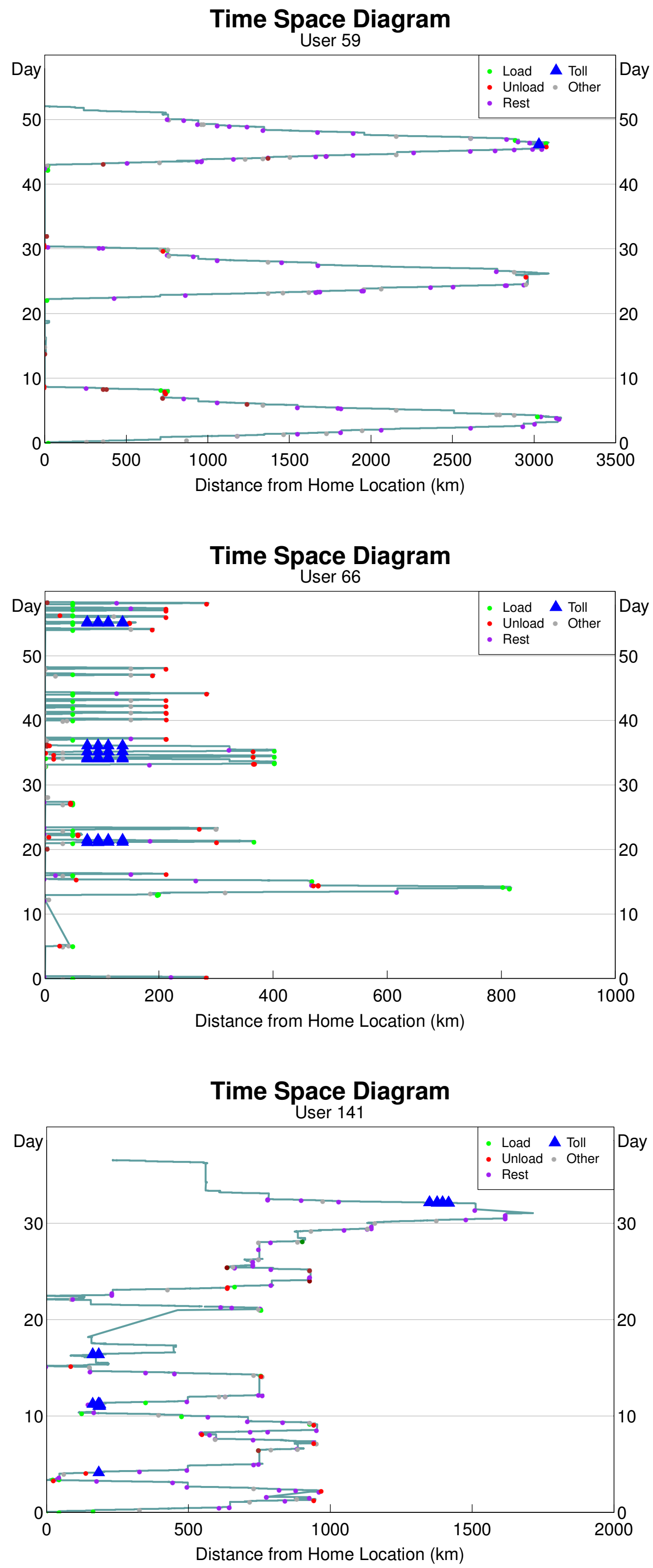


Figure 5 – Examples of observed travel patterns

Monitoring drivers over multiple days also reveals substantial differences in route choices from day to day, and sometimes even within a day. For example, Figure 6 shows two trips from San Antonio TX to Dallas TX made by the same driver. The driver used a toll road to bypass congestion in Austin during a weekday morning peak period (left), and a non-tolled alternative on a similar trip on a Saturday (right). In another example from the Chicago area, shown in Figure 7, the driver used a downtown toll route early in the morning and then a tolled bypass on the return trip in the afternoon peak. These two examples demonstrate the benefits of observing drivers' travel behavior over an extended period of time to capture not only the average behavior, but also its complexity and heterogeneity.

Unfortunately, the stated preference survey did not produce results as significant as in the traditional version in Toledo et al (2013). This might be attributed to the time the survey was conducted, which was after 20 days of validation. Because the SP survey presented trips at the end of the period that may not have been fresh in the minds of the drivers, it may have been difficult for them to recall the context of the hypothetical scenario. Another possibility is that respondents were less engaged at this point, since it was the last part of the survey they had to complete before they received their compensation. This experience provides a valuable lesson in conducting SP surveys based on RP data: presenting scenarios part of the way through the survey, soon after the activity is made, can provide higher-quality data and ensure respondents are still engaged.

Figure 6 – Different observed routes in two trips by the same driver at different times

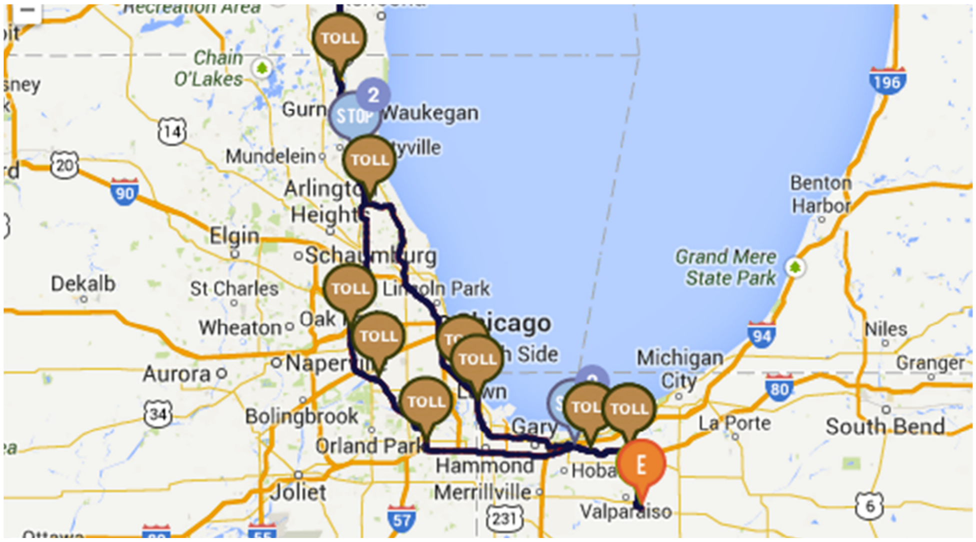


Figure 7 – Different observed routes in a return trip on the same day

5. On-going extension to urban freight and concluding remarks

A natural extension of our freight data collection approach is to urban freight data collection, which presents additional challenges and difficulties. A recent review by Gonzales-Feliu et al. (2013) lists challenges faced in tracking urban freight vehicles:

- Lower GPS data quality, mainly due to interference from the urban environment (e.g. tall buildings and narrower streets);
- Shorter stop durations, also likely to be confounded for instance with stops related to queuing at traffic lights stops and/or to congestion;
- A denser road network, with additional challenges for the map matching of GPS traces;
- Larger number of origins and destinations, resulting in complex and heterogeneous tour patterns; more diverse activities; and
- A considerable variety of commercial vehicles to be tracked (e.g. HGV, LGV, lorries, vans, motorcycles).

Several recent studies tackle some of these issues. Camargo and Tok (2014) deal with the validation of algorithms to generate truck route alternatives using GPS data. Sturm et al. (2014) developed a survey of grocery trucks in Chicago based on GPS data and a driver log. Yang et al. (2014) studied methods to identify stops along a driver’s route.

The freight data collection framework described in Section 3 can be effectively applied in order to overcome the aforementioned issues, thanks to the integration between passive GPS data and respondent-based information, both through the pre-survey and the stops survey. Furthermore, other sensing devices can be applied as well, in conjunction with GPS loggers, as already performed within the Future Mobility Sensing (FMS) framework (Cottrill et al. 2013). FMS is a smartphone-based travel survey system (for both Android and iOS platforms), initially conceived for passengers’ surveys, that collects data with high accuracy and resolution on participants' travel and activity information, thus yielding more detailed and varied data than traditional travel survey approaches. The FMS system was field tested in Singapore (Zhao et al 2015) in conjunction with the 2012 Singapore Land Transport Authority (LTA)'s Household Interview Travel Survey (HITS). More than 1500 participants signed up for the smartphone based survey, and about 800 of them completed the survey (collected data for at least 14 days, and validated at least 5 days). Comparison between FMS and HITS reveals several advantages of FMS over traditional surveys including highly accurate and detailed data, capability to capture heterogeneity of user pattern over multiple days, and low cost.

The FMS concept is currently being adapted to the urban freight context. In this respect, the questionnaires used in the US truck drivers' survey have been enhanced with further information on frequent stops, routes, trips and activity types to capture repetitive behavior. Further stop type options have been added to allow drivers to more accurately describe their activities. In addition, improvements to stop/activity detection algorithms are under development, to extend the period of observation and to enhance machine learning algorithms to include user history and Points of Interest (POI) data. Data collection is already under way in Singapore with new, less expensive GPS loggers (SANAV CT-58). We plan to integrate the GPS traces with smartphone traces to enhance the quality of location data, and also with specially designed on-board diagnostics (OBD) devices to estimate carbon footprint and fuel consumption, both major concerns in city logistics operations.

In summary, the research reported in this paper demonstrates how advanced sensing and communication technologies, combined with machine learning architecture, can be used to collect previously unattainable freight data. Our data collection effort provides a rich, high-quality data set without the participant burden typically faced in traditional surveys. The data reveal in great detail the complexity and heterogeneity of freight travel patterns, providing the building blocks for the next generation of effective and innovative freight models.

Acknowledgments

Support for the urban freight data collection research research has been provided by the Future Urban Mobility project of the Singapore-MIT Alliance for Research and Technology (SMART).

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