COMMERCIAL VEHICLE TOUR DATA COLLECTION USING PASSIVE GPS TECHNOLOGY: ISSUES AND POTENTIAL APPLICATIONS

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ABSTRACT

In mid-2006 a GPS survey of commercial vehicles was piloted in Melbourne, Australia to support a major update of freight data and modelling capabilities in the metropolitan region. This survey marked the first of its kind in Australia, and to the best of the authors' knowledge, one of the first world-wide. This paper presents the issues surrounding the collection and use of GPS data as a method to provide information on commercial vehicle tours within an urban setting. The paper focuses on *passive* GPS methods where the truck driver's involvement in the data collection effort is minimal. We address (a) implementation issues with the data collection, (b) the algorithms used to process the raw GPS data into meaningful trip tour information, (c) pilot survey data tour results, and (d) potential uses and limitations of passive GPS technology in urban freight modelling and planning. Despite processing challenges, GPS provides an appealing method to enrich commercial vehicle data collection and enhance our understanding of on-road behaviour. As increasing numbers of commercial vehicles become equipped with GPS receivers, we argue only privacy concerns remain as a major barrier to gathering and using such data on a wide-spread basis in the future.

(198 words)

KEYWORDS: Freight Data Collection, Commercial Vehicle Tours, GPS, Freight Data Collection

INTRODUCTION

The efficient movement of groceries, consumer products, industrial supplies and other staples of modern life is critical to the competitiveness and development of urban economies. Urban freight transport plays a critical role in meeting these demands. Recent trends in consumer purchasing patterns, such as home-deliveries, and industry logistics, such as just-in-time deliveries, are contributing to an ever-increasing proportion of freight vehicle-kilometres travelled (VKT) in urban areas (Holguin-Veras and Patil, 2005). For instance, a recent USA based study shows that commercial vehicles moving goods or providing services account for, on average, almost 10 percent of total VKT (Outwater et al., 2005). In developed countries, freight road transport continues to grow at a faster rate than the gross domestic product (OECD, 2006). This growth in commercial vehicle activity is increasing pre-existing concerns over the associated negative externalities of urban freight movements. These externalities include greenhouse gases, air pollution, safety and congestion and have been estimated to be as much as four times greater in terms of costs per kilometre than the corresponding costs of a private car (Bjorner, 1999).

Despite the critical role played by freight transportation, urban freight movements have not received the same level of attention as that given to the movements of people. Urban freight transportation modelling remains a relatively immature field where most models and applications are of a highly aggregate nature. Models of this type are ill-suited to explain and predict the implications of behavioural policy changes such as a change in allowable operating hours, the introduction of congestion toll charges, or time restrictions on deliveries. Commercial vehicle tours have also been largely ignored in most urban freight models around the world (Ambrosini and Routhier, 2004) with notable exceptions (Hunt and Stefan, 2007). Tours can be classified according to their routing constraints and supply chain characteristics such as cargo time sensitivity; these tour characteristics have a significant impact on the efficiency and VKT generated by freight movements in urban areas (Figliozzi, 2006; Figliozzi, 2007).

A primary reason for this limited understanding of freight movements is the paucity of disaggregate data on commercial vehicle movements (McCormack and Hallenbeck, 2006). Although most trucking companies keep run sheets of their truck activities for their own business and benchmarking purposes, these detailed records are rarely made available to others since they contain sensitive customer information. When disaggregated data is available, the analysis of commercial vehicle route and trip chain structure can provide insightful information about urban commercial vehicle tours, travel patterns and congestion levels. For instance, a study based in Sydney, Australia, analysed several months of detailed truck activity records (Figliozzi et al., 2007). Route patterns were identified and their relationship to trip and tour length distribution was analysed. The analysis also highlighted how travel between different industrial suburbs explained the shape of multimodal trip length distributions and how congestion impacts the duration of tours.

Over the last fifteen years, the ability to collect detailed travel information has been expanded by developments in Global Positioning System (GPS) technology. With GPS, it is now possible through integration with Geographic Information Systems (GIS) to determine origins, destinations, travel times, distances, routes and vehicle speeds at highly disaggregate levels of spatial and temporal resolution without relying on participant recall (Wolf et al., 2003). While there are now several example applications where GPS technology has been used to collect personal travel information (e.g., Wolf et al., 2003, Stopher et al., 2005), in the context of commercial vehicles, GPS-based data collection efforts have mostly focused on the monitoring of intercity truck movements (McCormack and Hallenbeck, 2006). For instance, in the United States starting in 2005, around 250,000 trucks per year have been monitored with GPS to assess speed and travel time reliability on five major interstate freight routes (Federal Highways Administration, 2006). The city of Ontario has conducted GPS studies to complement its commercial vehicle survey, however, to the best of the authors' knowledge the results and methodology has not been yet published (Sureshan, 2006). Similarly, in the UK, GPS data have been used to calculate travel times, travel time variability, and average speeds on the trunk network (Hudson and Rhys-Tyler, 2004). The scarce usage of truck GPS data cannot be attributed to the fact that these data cannot be readily collected. It is increasingly common (certainly in Australia and most developed economies) for commercial vehicles to be fitted with GPS receivers as part of the monitoring of operations and driver behaviour, such as speeding or exceeding legislated driving hours. The problem appears to be that while the profession has largely allayed confidentiality fears in personal travel surveys, private businesses are still in the main unwilling to disclose information that may be used by competitors or that may infringe customers' rights regarding privacy, proprietary data or security.

In June, 2006, a GPS survey of commercial vehicles was piloted in Melbourne, Australia. This survey marked the first of its kind in Australia, and to the best of the authors' knowledge, one of the first world-wide. This paper reports on the survey effort and the insights and potential uses of such data in studying tour information of commercial vehicles. The contributions of this research to the field of urban freight data collection are fourfold: this article will (a) describe implementation issues with the data collection, (b) detail the algorithms used to process the raw GPS data into meaningful travel and trip information, (c) present a discussion of pilot survey data tour results, and (d) discuss potential uses and limitations of GPS/GIS technologies in urban freight modelling and planning.

STUDY DESCRIPTION

The GPS data collection effort on which this paper is based was undertaken as a pilot study for a major update of freight data and modelling capabilities in the Greater Melbourne region. The Greater Melbourne region covers a spatial area of 7,700 square kilometres and is home to 3.6 million inhabitants (FIGURE 1). The main commercial centre lies on the northern bank of the Yarra River, which enters Port Philip Bay to the north with major housing growth now focused on corridors to the south-east and north of the city. Within the region, there are a number of definable major freight activity centres, most notably the Port of Melbourne, the Western Ring Road Corridor and the Dandenong industrial precinct. Heavy and rapidly growing road-based freight movements occur between these centres, which has put the road system under increasing strain. In addition, there are numerous local freight trips generated by small retail business deliveries/services that cater to a broad range of personal, commercial and community needs.

<<Figure 1 here>>

The rationale for the GPS data collection effort was multi-faceted. First, and perhaps fundamentally, it had to be established whether it was feasible and practical to get companies and truck drivers to agree to participate. Second, we wanted to determine to what extent GPS might supplement or cross-check the information coming from the driver run sheet, the traditional source of origin/destination and timing information - this was a major 'selling' point to encourage companies to participate. Third, there was interest in determining what the GPS information could provide about characteristics of freight trips which are currently barely reported and partially understood (e.g., trip tours, inter-day variability) or simply unavailable (e.g., route choice). Finally, there was interest in establishing what types of performance measures or useful information could be obtained from GPS data. These performance measures can be useful tool for companies looking for ways to improve/benchmark their operations – again, this played an important role in encouraging companies to participate.

Data Collection, Processing, and Accuracy

For the pilot study, one-weeks worth of GPS data were collected for 30 trucks, i.e., 210 truck-days of data. The companies recruited into the study were responsible for the delivery of a range of products including office supplies, paper, restaurant foods, quarry materials, and general freight. All trucks in the study were Australian Class 3 (two axle truck with dual wheels) or Class 4 (two axle truck with dual wheels plus a trailer or three or more axles). Getting companies to participate in the study required assurances that confidentiality/competitiveness would not be compromised and that noteworthy results would be reported back to them. Following the agreement to participate, a representative from our office would visit the truck driver and install a GEOSTATS® in-vehicle GPS device, which we have found to be very reliable for collecting private car travel as part of personal travel surveys (Stopher et al., 2005). The device draws power from the cigarette lighter and is capable of storing second-by-second information for several weeks. The antenna can be placed on the dash or preferably on the roof to maximize the likelihood of maintaining a good line of sight to the satellites. Importantly, in our opinion, the data collection is passive in that once the GPS device is installed no human intervention is required. Truck drivers endure hectic working conditions and expecting them to interact with the GPS device is not only unrealistic but also affects the willingness of drivers and companies to participate in the data collection effort. The importance of having a qualified employee to assist with the initial installation of the device and address driver's questions and concerns cannot be overlooked. While it was a simple installation procedure, the ultimate quality of the data collected hinged on correct installation and driver goodwill. After one week, our representative would go back to the truck company and retrieve the device. Data were then downloaded using the software that comes with the GPS device ready for processing.

Processing 'raw' GPS data into discrete trips for meaningful analysis presents many challenges. First, the volume of data, usually in the order of tens of megabytes for a week worth of vehicle-data, necessitates that intelligent/automated processing algorithms are developed and that efficient data management strategies are in place. Second, given that GPS data are provided as a continuous stream, there is the issue of how to correctly identify trip-ends. Third, despite improvements in hardware and the removal of selective availability in 2000 (intentional degradation of signal by the U.S. military), there are two major problems affecting the completeness and accuracy of GPS data. First is the loss of data that occurs at the beginning of a trip due because of the time required to lock onto sufficient satellites (four or more) to infer the correct position. This in turn varies dependent on how much time has elapsed since the GPS last had satellites in view, the quality of satellite coverage and whether the vehicle is in motion. If the elapsed time since the GPS last had satellites in view is less than one hour, the firmware in the GPS device assumes the current position is the same as the last recorded position and recording is rapid – known as a “warm start”. If, however the elapsed time since the GPS last had satellites in view is greater than one hour, the device has to re-compute the position, which can take anywhere from 20 seconds to two minutes (if the device is stationary) and up to 15 minutes (if the device is moving) - known as a “cold start”. Unfortunately, this can lead to the loss of short trips (typically 1-2 kilometres in our experience) or incorrect information on the duration and distance of trips that do eventually pick up a signal.

The second problem is the loss or degradation of GPS data during a trip. This occurs when there is not a clear line of sight to the sky and/or the antenna/receiver is not able to pick up the satellite information. Signal loss typically occurs because of overhead obstructions such as tunnels, bridges, and trees acting as barriers. Signal degradation generally occurs because of either atmospheric conditions or travelling between tall buildings, such as in downtown Melbourne.

To deal with these problems, we tailored and applied a number of computer software applications using the PYTHON™ programming language and the scripting language of the TransCAD™ GIS package, for managing, manipulating, and processing GPS data. The processing routines, while developed for car-based travel, required minor modifications for trucks. While full details of the car-based processing routines are detailed by (Fitzgerald et al., 2006), we provide an overview of the major steps here.

Four major steps were required to convert the raw GPS to the final product of trip tables:

Data Pre-processing

The first step proceeds through some simple reformatting steps, including the calculation of local date and time, correction of the latitude and longitude record, conversion of time to MS Excel time format, and computation of distance and elapsed time. Following this are routines for identifying and dealing with problematic records. Specifically, all data points with too few (less than four) satellites in view and/or a value of Horizontal Dilution of Precision (HDOP) of five or greater are removed, except for each of the first occurrence of such data points in any group of data points of this type. Then, any data points where no movement is recorded are dropped, where no movement is detected based on the following conditions: speed being zero, less than a 15 metre (0.00005º) change in either latitude or longitude, and heading also being zero or unchanged. Finally, all records that occur outside a pre-defined geographical area are scrutinized for validity and flagged as invalid if the inferred speed between them and the previous GPS point within the region is greater than 150 km/h.

Trip Identification Algorithm

The detection of trip ends from GPS data entails the need for a rule-based algorithm that is able to differentiate between genuine stops and those associated with stops in traffic due to congestion, signals, waiting to turn etc. The algorithm works by flagging any points where the difference in movement from the previous point is less than the accuracy rating of the device (six metres in this case), the heading is unchanged, the speed is zero and the elapsed time during which these conditions hold is below a specific time threshold. The critical issue is establishing an appropriate time threshold, which captures as many genuine trip-ends as possible, while minimising the number of spurious trip-ends. In the case of car trips, experimentation has shown that 120 seconds is a reasonable threshold, with only three percent of the trip ends turning out to be invalid (Fitzgerald et al., 2006). In the case of truck trips, however, we found this was too short a time and resulted in too many spurious trip ends being created. We experimented with a range of times between 120 and 300 seconds before concluding that 240 seconds provided the best compromise between incorrect identification of stops and missing of genuine stops.

Certain commercial vehicles move at a slower speed than passenger cars, which can affect the threshold to differentiate between genuine and spurious stops. Trucks acceleration rates, especially when heavy loaded, are substantially lower than car acceleration rates. In addition, large commercial vehicles move at low speed in narrow or congested urban areas. Therefore, the threshold must be application specific and may depend on the distribution of the truck types (year, model, engine, etc.), the payload distribution (commodity densities, shipment sizes, etc.), and network characteristics.

The trip detection algorithms also address a number of other issues, which do the following:

- Flag records where the engine was turned off for between 30 and 120 seconds as a potential trip end for manual inspection.

- Detect a trip end that occurs when direction is reversed, but there is a very short or non-detectable stop such as when a driver makes a U-turn.
- Determine whether a trip ended and a new one started during a period of signal loss in the middle of what appears to be one trip. This involves looking at the speeds, times and distances of the known points.
- Determine whether there is a loss of signal at the beginning of a trip. If there is a loss of signal the record is repaired.
- Check we have not inadvertently missed any genuine stops because of the signal waiver problem. The issue here is that when a vehicle is stationary, the GPS measurements fluctuate around the point, implying (to the trip identification algorithm) the vehicle is moving. While some of these problems can be mitigated by defining a speed cut-off below which measurements are not recorded, this does not entirely remove the problem. Therefore, we have defined a rule that if points are within 30 metres (distance based on experimentation) of each other for the full 240 seconds, a trip-end is identified.
- Check trips made over a very short distance are genuine. One of the frequent problems found with the truck information was that there were many short 'trips', which were sometimes genuine and sometimes clearly the truck moving in the holding yard. These trips were flagged through the automated process and then manually checked.

Signal Loss and Data Repair

TABLE 1 provides a summary of the data quality problems from the raw GPS data, resulting from the signal acquisition and drop-out problems described previously. As points of clarification, the numbers represent the total seconds of GPS data. Missing data are identified by looking to see whether the elapsed time between each data record is more than one second and less than four minutes (the cut-off for defining stops). Bad records are identified as having less than four satellites in view and/or a HDOP of five or more. Overall, around five percent of data were classified as bad/missing, which represented around 70 hours of data, clearly a significant problem.

<<Table 1 here>>

Bad/missing records were dealt with by deleting those points and then using logic to impute the points to (in effect) recreate the entire second-by-second trip records. In terms of start-up loss, information on the known end point of the previous trip and the GIS-based network distance to the current (known) trip point is used to impute the trip records. In the case of the truck trips, incidences of signal start-up loss problem were much less in comparison to cars, presumably because trucks generally have a long engine idle/start-up time, providing enough time to acquire a positional fix from the GPS. In terms of correcting for signal loss en-route, two major issues needed to be resolved. First, it had to be established whether a stop could have occurred during the period of signal loss, which involves estimating the speed of the gap if it were possible for a minimum stop to have occurred. Second the route had to be established, something currently done by using the GIS-based shortest network path (see (Fitzgerald et al., 2006)).

Location Information

The final step of the automated component of the processing uses simple GIS geocoding techniques to attach the Traffic Zone, Local Government Area, Suburb, town, and street address for each trip-end. Note, we did not have a database of geocoded businesses available but clearly if this were available, this could also be included.

Final Output

The final output of the processing was a summary trip-level file for further analysis, a second-by-second file of all the trips and a daily map showing the trip information. An example of the summary trip-level information and a daily map are presented for one truck in FIGURE 2. In this example, the truck began the day at the depot in the town of Heidelberg West at 7:17 a.m. and proceeded on a 13.28 km trip to a destination in North Melbourne, which took 33 minutes. Following a four minute stop, the truck proceeded on a trip to the Docklands, covering the 9.9 km in a time of 39:53 minutes, where it stopped for 4:21 minutes. The truck made a further seven stops before arriving back in Heidelberg West at 12:15:43. In the afternoon, the truck made a six stop tour, before finishing the day back in Heidelberg West at 15:55:29.

<<Figure 2 here>>

Processing Time

The time required to run the automated processing routines for the 30 trucks averaged one hour per truck (four minutes per truck day). In addition, a further hour (on average) was required to manually check the output for each truck, meaning that the entire data set was processed and checked in around 60 hours of which half the time is computer processing time.

TOUR RESULTS

This section describes characteristics and statistics of the tours obtained from the pilot survey. It must be emphasized that the pilot survey was not based on a random sample and therefore it is not an unbiased representation of truck travel and trip characteristics in Melbourne. A summary of the data (TABLE 2) suggests the average pilot survey tour is approximately 184 kilometers long and lasts around 8 ½ hours. Of this time, approximately two-thirds of the time is spend on the road at an average speed of 33 km/h, with the remaining third stopped (loading/unloading, paperwork, refuelling, etc.). The use of averages hide the fact there is a great range across the various statistics with the longest tour in terms of time lasting almost 13 hours, and the longest in terms of distance lasting 138 km. As expected for the distribution of most non-negative random variables, the shape of the tour distances and length distributions is skewed. In all cases the average is higher than the median which is expected because it is impossible to record negative distances or travel times. The statistics also appear to corroborate the fact that commercial vehicles have quite different usage patterns than private trips, with (in general) a greater utilization and number of trips per day.

<<Table 2 here>>

To provide some points of comparison, the city of Calgary reports approximately 6 stops per tour (Hunt and Stefan, 2005), Denver reports 5.6 (Holguin-Veras and Patil, 2005) and data from Amsterdam indicate 6.2 stops per tour (Vleugel and Janic, 2004). The data from Melbourne indicates an even higher number of stops per tour: the average number of stops per tour is 12.2 in the collected Melbourne data. Although the average number of stops in Melbourne is higher it is not unusual, for example, the average number of stops in the soft drink industry distribution routes is around 25 (Golden and Wasil, 1987).

TABLE 2 also provides results for garage trips, defined as the first and last trips in the tour. Although the median trip distance for garage trips changes slightly, the median travel speed increases significantly. This strongly suggests the usage of primary links of the network system to travel to/from the depot, which can be verified by plots of individual truck route maps such as the one shown in FIGURE 2. Customer door-to-door trips in secondary or local roads have lower travel speeds. FIGURE 3 shows the trip length distribution (TLD) for all trips follows a continuously decreasing curve, while for garage trips it is significantly different and shows a multimodal distribution. Garage-based trips TLD exhibit clear peaks between 3 to 6 kilometres, 9 to 12 kilometres, and 18 to 24 kilometres. Empirical observations confirm that multimodal trip length distributions are found in practice; these peaks indicate the location of a customer service area, industrial suburb, or a trip attracting area (Figliozzi et al., 2007).

<<Figure 3 here>>

The impact of time of the day on travel time is shown in TABLE 3. Not surprisingly, the highest average and median speed is observed in the evening and night hours, i.e., between 18:00-5:30. The lowest average and median speed is observed during the morning and evening peaks (7:30-9:30 and 15:30-18:00). A travel speed reduction of almost 40% can be observed between evening/night and peak times. The highest proportion of trips starts, occur in the morning peak. Almost 80% of the trips take place during 8 hours, between 7:30 and 15:30. These figures indicate the customer preference for deliveries during normal business hours and early morning hours.

<<Table 3 here>>

POTENTIAL APPLICATIONS OF PASSIVE GPS DATA

The capacity of GPS technology to provide reliable and detailed time-space data in an efficient and economical manner has many potential applications in transportation engineering. For instance, GPS data collection can be successfully used to build precise origin-destination matrices broken down by time of day. One example is provided in FIGURE 4, which shows the spatial distribution of trip ends by Statistical Local Area (SLA) for the time periods of 5:30 – 7:30 and 13:30 – 15:30.

<<Figure 4 here>>

The combination of GIS socio-demographic data and GIS truck trip data can be invaluable for trip generation models. Most truck trip generation tables are commonly based on linear regressions by land-use category and as a function of employment by industry sector (Fisher and Han, 2001). A particularly useful application of GPS data is to construct trip length distributions. The gravity model is a popular technique to model trip distribution and this model is usually calibrated by comparing the trip length distribution and trip length averages in the model against the observed trip length distribution and average trip length. The distinction between garage-based trips and inter-customer trips is also useful to understand the distribution of trips, travel patterns between zones, and percentage of empty/loaded trips. The percentage of empty trips is linked to the average number of stops per tour and the location of the garage or depot (Figliozzi, 2007).

GPS freight data can be effectively combined with Weight in Motion (WIM) data collection methods. Most of the truck weight and payload information is generated for pavement management purposes although it can be used to estimate the distribution of payloads (Figliozzi et al., 2000). This is significant because payload is a key measure to determine the efficiency of urban freight systems (Figliozzi, 2007). The combination of GPS and WIM data can be used to track payload and percentage fill truck time-trends by transportation planning agencies. The temporal dimensions of urban freight trips have largely been neglected; however, average travel speed is time dependent and the impact of commercial vehicles on urban environments depend on the departure and return time to the depot.

Another potentially useful application of the GPS-based data is to develop speed-time profiles (such as the example shown in FIGURE 5) as inputs to fuel consumption and emissions models. While this has been done for passenger vehicles (e.g., Jackson et al., 2005), to our knowledge this has not yet been done for commercial vehicles. In Australia, the recently-completed National In-Service Emissions Study (NISE) database provides emission factors for commercial vehicles, which could be combined with GPS data to provide an estimate of 'real-world' emissions as the vehicle proceeds through the network.

<<Figure 5 here>>

A significant limitation of non-intrusive GPS collected data is the lack of behavioural data. For example, GPS data can be used to monitor how commercial vehicles respond to congestion pricing or bottlenecks. However, disaggregation of the data may be necessary for policy or planning purposes. Commercial vehicles include a broad range of vehicle types and activities such as package and mail delivery, urban freight distribution, utilities, trades and services, and construction activities. The behaviour of the driver/vehicle can be quite different depending on whether the vehicle is loaded or empty or given the value of the activity/commodity that must be delivered at the end of the trip. Further, if vehicles/drivers regularly replace each other, operating within a coordinated fleet, the response or behaviour of one driver will be dependant on the location and status of other vehicles (for example a repair utility crew/vehicle). As with passenger data collection, GPS data collection methods can be a great complement to commercial vehicle and business surveys. However, it is unlikely that GPS based data collection will completely replace traditional data collection methods.

DISCUSSION AND CONCLUSIONS

This paper presents the issues surrounding the collection and usage of passive GPS data to provide information on commercial vehicle tours. Perhaps the most pertinent point to make is that (arguably) the potential to gather GPS data from commercial vehicles is much greater than for people given that many trucks are now equipped with GPS receivers. However, the reverse still generally appears to be the case and companies are reluctant to divulge what they see as confidential information on their business practices to competitors. Changing this perception is reliant on convincing freight operators there is value to them of providing such data to researchers and policy-makers to improve their operations – this was the major 'selling' point in the Melbourne pilot reported here. Once the data are obtained, it is also evident that several steps are required to take the raw GPS data and produce a useful dataset for analysis. The sheer volume of data, coupled with issues such as signal drop-out and trip-end identification require the development of intelligent processing algorithms, such as those we describe here.

The paper also explored some of the potential uses of GPS data, particularly through the insights provided on commercial vehicle tour activity. Although the results were specific to the sample recruited for the pilot, it was nevertheless revealing to analyse second-by-second truck travel information such as tour duration, speed, number of stops, and distance travelled. The ability to map vehicle routes at the street level can lead to visual insights on origin-destination patterns. Detailed speed-time profiles can be used to obtain more accurate fuel consumption and emissions estimates. Similarly, the integration of GPS truck data with WIM data can be used to track payload information and percentage of empty trips in urban areas.

Despite the promise of GPS data to enrich urban freight data collection, it is in our opinion unlikely that GPS based data collection will completely replace traffic counts and roadside interviews. One important issue is the percentage of commercial vehicles carrying a data collection GPS device. It is likely that many companies will choose not to volunteer detailed GPS data on their truck operations due to the potential misuse of collected information and the fear of privacy violations. The higher the percentage of intercity passing trucks and local commercial vehicles without GPS devices, the more necessary counting and roadside interviews are. Unless it is mandatory for all commercial vehicles to carry a GPS transmitter, traffic counts are necessary to obtain more comprehensive data. Therefore, due to sampling issues traditional freight data collection methods are likely to remain indispensable for validation purposes.

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List of Tables

TABLE 1 Data Quality Assessment (Before Processing)

	Good Records	Bad/Missing Records*	Total Records
Morning (6 a.m. – 12 p.m.)	1,843,050	96,726	1,939,776
	95%	5%	
Afternoon (12 p.m. – 6 p.m.)	1,643,729	100,800	1,744,529
	94%	6%	
Night (6 p.m. – 6 a.m.)	1,498,446	54,553	1,552,999
	96%	4%	
Total	4,985,225	252,079	5,237,304
	95%	5%	

*Defined as no GPS data recorded or data recorded where HDOP > 5 and/or less than 4 satellites.

TABLE 2 Summary Data

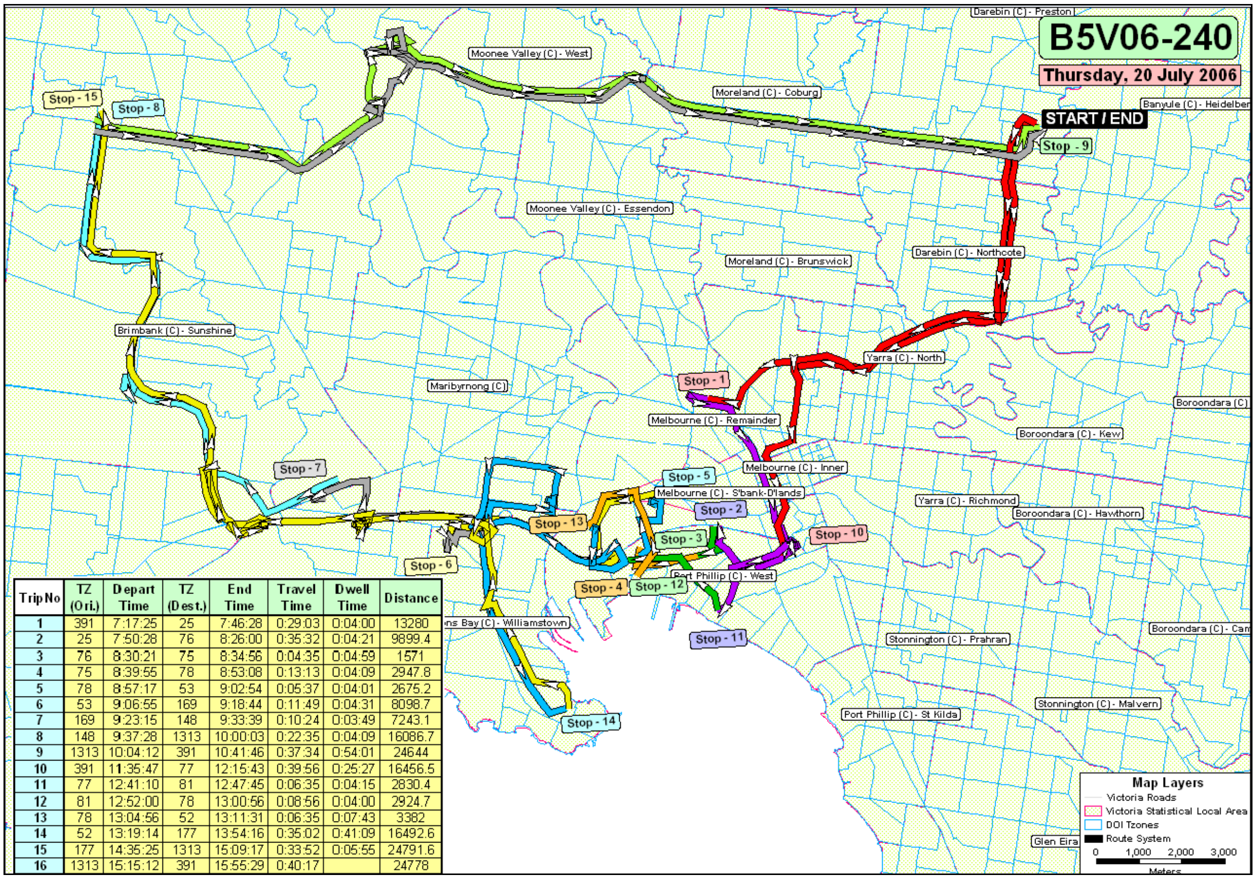
	Trip Distance (km)	Stops per Tour	Tour Distance (km)	Total Tour Length (hours)	Average Tour Speed (Km/hour)	GARAGE-trips - Distance (km)	GARAGE-trips - Average Speed (Km/hour)
Average	15.9	12.2	184.4	8.5	33.1	23.39	33.94
Median	18.9	4.7	71.1	2.0	9.4	19.18	30.90
St. Dev.	9.0	11.0	177.2	9.0	32.1	18.48	13.79
Min.	0.1	4.0	27.6	4.1	9.6	3.51	10.20
Max.	137.6	28.0	357.2	12.8	62.8	121.48	83.80

TABLE 3 Travel Speed by Time of Day

Departure Time	18:00 to 5:30	5:30 to 7:30	7:30 to 9:30	9:30 to 11:30	11:30 to 13:30	13:30 to 15:30	15:30 to 18:00
Average Speed Km/h	44.0	32.9	26.1	32.3	28.8	29.7	24.5
Median Speed Km/h	39.5	31.0	23.2	30.4	28.3	28.0	25.3
St. Dev. Speed Km/h	22.4	14.3	15.0	17.7	14.1	13.8	11.9
% Total Trips	2.5%	8.2%	22.6%	20.2%	18.4%	19.7%	8.5%

List of Figures

FIGURE 1: Map of the Study Area Showing Major Freight Centres and Freight Corridors



Trip No	TZ (Ori.)	Depart Time	TZ (Dest.)	End Time	Travel Time	Dwell Time	Distance
1	391	7:17:25	25	7:46:28	0:29:03	0:04:00	13280
2	25	7:50:28	76	8:26:00	0:35:32	0:04:21	9899.4
3	76	8:30:21	75	8:34:56	0:04:35	0:04:59	1571
4	75	8:39:55	78	8:53:08	0:13:13	0:04:09	2947.8
5	78	8:57:17	53	9:02:54	0:05:37	0:04:01	2675.2
6	53	9:06:55	169	9:18:44	0:11:49	0:04:31	8098.7
7	169	9:23:15	148	9:33:39	0:10:24	0:03:49	7243.1
8	148	9:37:28	1313	10:00:03	0:22:35	0:04:09	16086.7
9	1313	10:04:12	391	10:41:46	0:37:34	0:54:01	24644
10	391	11:35:47	77	12:15:43	0:39:56	0:25:27	16456.5
11	77	12:41:10	81	12:47:45	0:06:35	0:04:15	2830.4
12	81	12:52:00	78	13:00:56	0:08:56	0:04:00	2924.7
13	78	13:04:56	52	13:11:31	0:06:35	0:07:43	3382
14	52	13:19:14	177	13:54:16	0:35:02	0:41:09	16492.6
15	177	14:35:25	1313	15:09:17	0:33:52	0:05:55	24791.6
16	1313	15:15:12	391	15:55:29	0:40:17		24778

FIGURE 2 Example GPS Plot of Truck Trips

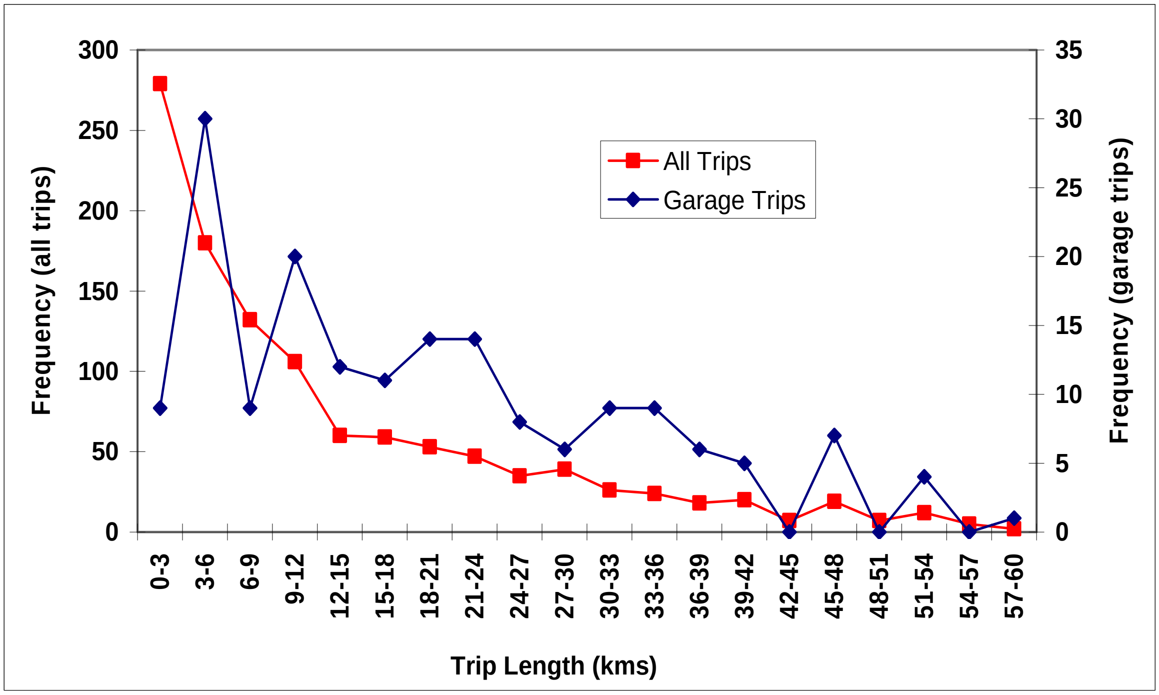


FIGURE 3 All Trips vs. Garage based trips - Trip Length Distribution

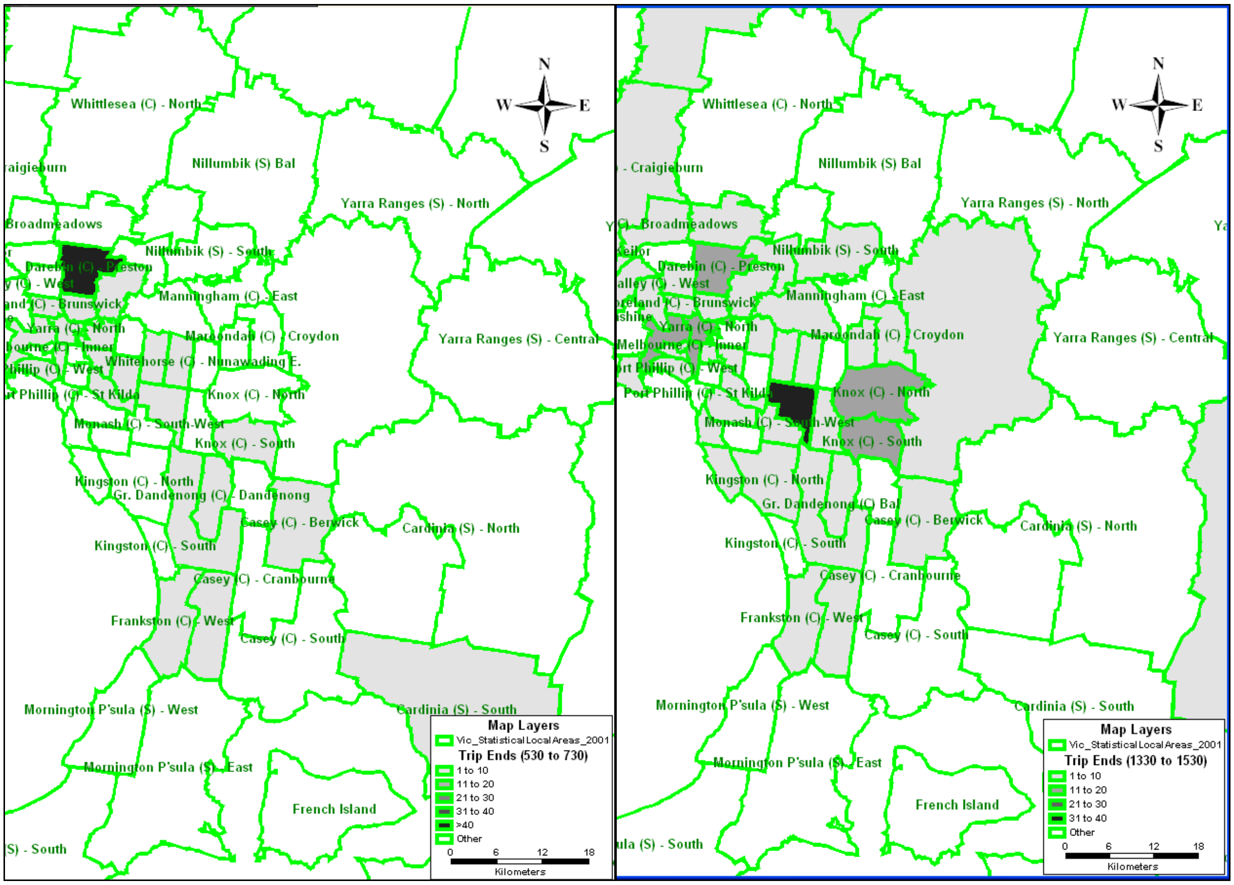


FIGURE 4 Comparison of Trip-Ends (5:30 – 7:30) to (13:30 – 15:30)

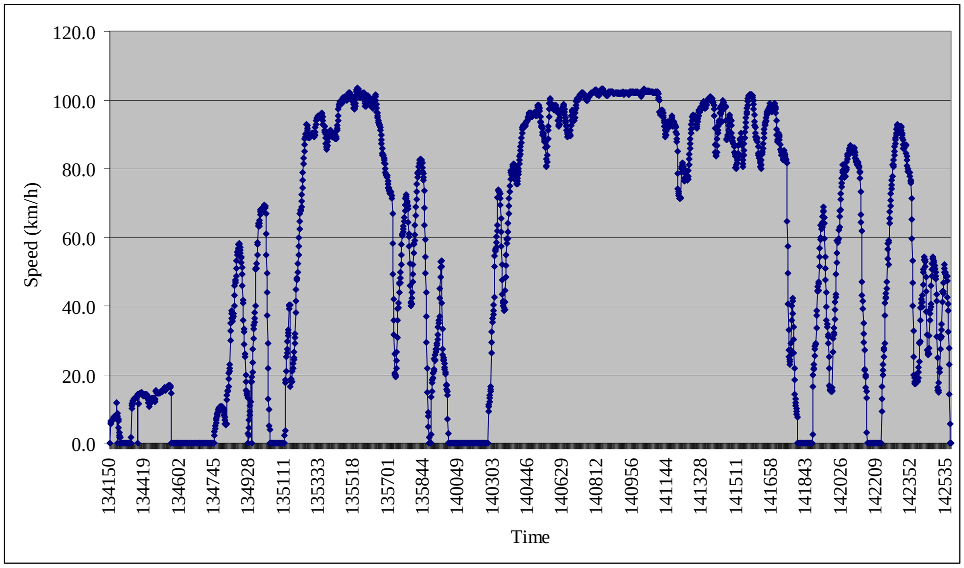


FIGURE 5 Example GPS Speed-Time Profile for Truck B1V1