Collecting Commercial Vehicle Tour Data with Passive Global Positioning System Technology

Issues and Potential Applications

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The assessment of strategies designed to manage the continued growth in road-based freight and associated externalities has been hampered by a paucity of disaggregate data on commercial vehicle movements. When disaggregated data are 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. Over the past 15 years, the ability to collect detailed travel information has been expanded by developments in global positioning system (GPS) technology. In mid-2006, a GPS survey of commercial vehicles was piloted in Melbourne, Australia, to support a major update of freight data and modeling capabilities in the metropolitan region. The survey used passive GPS methods in which the truck driver's involvement in the data collection effort was minimal. The contributions of this research to the field of urban freight data collection were fourfold: (*a*) describing implementation issues with the data collection, (*b*) detailing the algorithms used to process the raw GPS data into meaningful travel and trip information, (*c*) presenting a discussion of pilot survey data tour results, and (*d*) discussing potential uses and limitations of GPS technology in urban freight modeling and planning. Despite processing challenges, GPS provides an appealing method to enrich commercial vehicle data collection and enhance our understanding of on-road behavior. Because increasing numbers of commercial vehicles become equipped with GPS receivers, only privacy concerns remain as a major barrier to gathering and using such data on a widespread basis in the future.

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 kilometers traveled (VKT) in urban areas (*1*). For instance, a recent U.S.-based study showed that commercial vehicles account for, on average, almost 10% of total VKT (*2*). In developed countries, freight road transport continues to grow at a faster rate than the gross domestic product (*3*). This growth in commercial vehicle activity is increasing preexisting 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 kilometer than the corresponding costs of a private car (*4*).

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 modeling remains a relatively immature field in which most models and applications are of a highly aggregate nature. Models of this type are ill suited to explain and predict the implications of behavioral policy changes such as a change in allowable operating hours, the introduction of congestion toll charges, or the introduction of time restrictions on deliveries. Commercial vehicle tours also have been largely ignored in most urban freight models around the world (*5*), with notable exceptions (*6*). 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 (*7, 8*).

A primary reason for this limited understanding of freight movements is the paucity of disaggregate data on commercial vehicle movements (*9*). 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 because they contain sensitive customer information. When disaggregated data are 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 example, a study based in Sydney, Australia, analyzed several months of detailed truck activity records (*10*). Route patterns were identified, and their relationship to trip and tour length distribution was analyzed. The analysis also highlighted how travel between different industrial suburbs explained the shape of multimodal trip length distributions and how congestion affects the duration of tours.

Over the last 15 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 with-

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out relying on participant recall (*11*). Although there are now several example applications where GPS technology has been used to collect personal travel information (*11, 12*), in the context of commercial vehicles, GPS-based data collection efforts have mostly focused on the monitoring of intercity truck movements (*9*). For instance, in the United States starting in 2005, approximately 250,000 trucks per year have been monitored with GPS to assess speed and travel time reliability on five major interstate freight routes (*13*). The city of Ontario, Canada, has conducted GPS studies to complement its commercial vehicle survey (*14*). Similarly, in the United Kingdom, GPS data have been used to calculate travel times, travel time variability, and average speeds on the trunk network (*15*). 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 behavior, such as speeding or exceeding legislated driving hours. The problem appears to be that although the profession has largely allayed confidentiality fears in personal travel surveys, private businesses are still 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 worldwide. 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 paper 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 and GIS technologies in urban freight modeling and planning.

STUDY DESCRIPTION

The GPS data collection effort was undertaken as a pilot study for an update of freight data and modeling capabilities in the Greater Melbourne region. The Greater Melbourne region covers a spatial area of 7,700 km^2 and is home to 3.6 million inhabitants (Figure 1). The main commercial center 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 southeast and north of the city. Within the region, there are a number of definable major freight activity centers, 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 centers, which has put the road system under increasing strain.

FIGURE 1 Map of study area showing major freight centers and freight corridors.

In addition, there are numerous local freight trips generated by small retail business deliveries and services that cater to a broad range of personal, commercial, and community needs.

The rationale for the GPS data collection effort was multifaceted. 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, it was important 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 that are currently barely reported and partially understood (e.g., trip tours, interday 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 a useful tool for companies looking for ways to improve and benchmark their operations. Again, this played an important role in encouraging companies to participate.

DATA COLLECTION, PROCESSING, AND ACCURACY

For the pilot study, 1 week's worth of GPS data were collected for 30 trucks (i.e., 210 truck-days). 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 and competitiveness would not be compromised and that noteworthy results would be reported back to them. After the agreement to participate, a representative of the study team visited the truck driver and installed a GEOSTATS® in-vehicle GPS device, which is reliable for monitoring private car travel (12). 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, 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. Although it was a simple installation procedure, the ultimate quality of the data collected hinged on correct installation and driver goodwill. After 1 week, our representative went back to the truck company and retrieved 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 on the order of tens of megabytes for 1 week's worth of vehicle data, necessitates that intelligent and 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), two major problems affect the completeness and accuracy of GPS data. First is the loss of data that occurs at the beginning of a trip 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 1 h, the firm ware 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 1 h, the device has to recompute the position, which can take anywhere from 20 s to 2 min if the device is stationary and up to 15 min if the device is moving—known as a "cold start." Unfortunately, this can lead to the loss of short trips (typically 1–2 km) or incorrect information on the duration and distance of trips that do eventually pick up a signal.

The second problem is the loss of or degradation of GPS data during a trip. This occurs when there is not a clear line of sight to the sky or the antenna or 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 traveling between tall buildings, such as in downtown Melbourne.

To deal with these problems, computer software applications were tailored and applied using the PYTHON™ programming language and the scripting language of the TransCAD™ GIS package, for managing, manipulating, and processing GPS data. The processing routines, although developed for car-based travel, required minor modifications for trucks. Full details of the car-based processing routines are detailed in Fitzgerald et al. (16). However, an overview of the main steps required to convert the raw GPS to the final product of trip tables is provided here.

Data Preprocessing

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. After this are routines for identifying and dealing with problematic records. Specifically, all data points with too few (less than four) satellites in view or a value of horizontal dilution of precision 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-m (0.00005°) change in either latitude or longitude, and heading also being zero or unchanged. Finally, all records that occur outside a predefined 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 because of congestion, signals,

waiting to turn, and so forth. 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 (6 m 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 minimizing the number of spurious trip ends. In the case of car trips, experimentation has shown that 120 s is a reasonable threshold, with only 3% of the trip ends turning out to be invalid (*16*). In the case of truck trips, however, this was too short of a time and resulted in too many spurious trip ends being created. A range of times between 120 and 300 s was experimented with before concluding that 240 s 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. Truck acceleration rates, especially when heavily laden, 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 (e.g., year, model, engine), the payload distribution (e.g., commodity densities, shipment sizes), 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 s 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 nondetectable 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 that any genuine stops have not been inadvertently missed 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. Although some of these problems can be mitigated by defining a speed cutoff 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 m (distance based on experimentation) of each other for the full 240 s, 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. As points of clarification, the numbers represent the total seconds of GPS data. Missing data are identified by determining

TABLE 1   Data Quality Assessment (before processing)

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

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

whether the elapsed time between each data record is more than 1 s and less than 4 min (the cutoff for defining stops). Bad records are identified as having less than four satellites in view or a horizontal dilution of precision of five or more. Overall, approximately 5% of data were classified as bad or missing, which represented approximately 70 h of data, a significant problem.

Bad or 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 was 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 or 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 (*16*).

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, a database of geocoded businesses was not available but clearly if this information were available, it 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. Examples 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 min. After a 4-min stop, the truck proceeded on a trip to the Docklands, covering the 9.9 km in a time of 39:53 min, where it stopped for 4:21 min. The truck made seven further stops before arriving back in Heidelberg
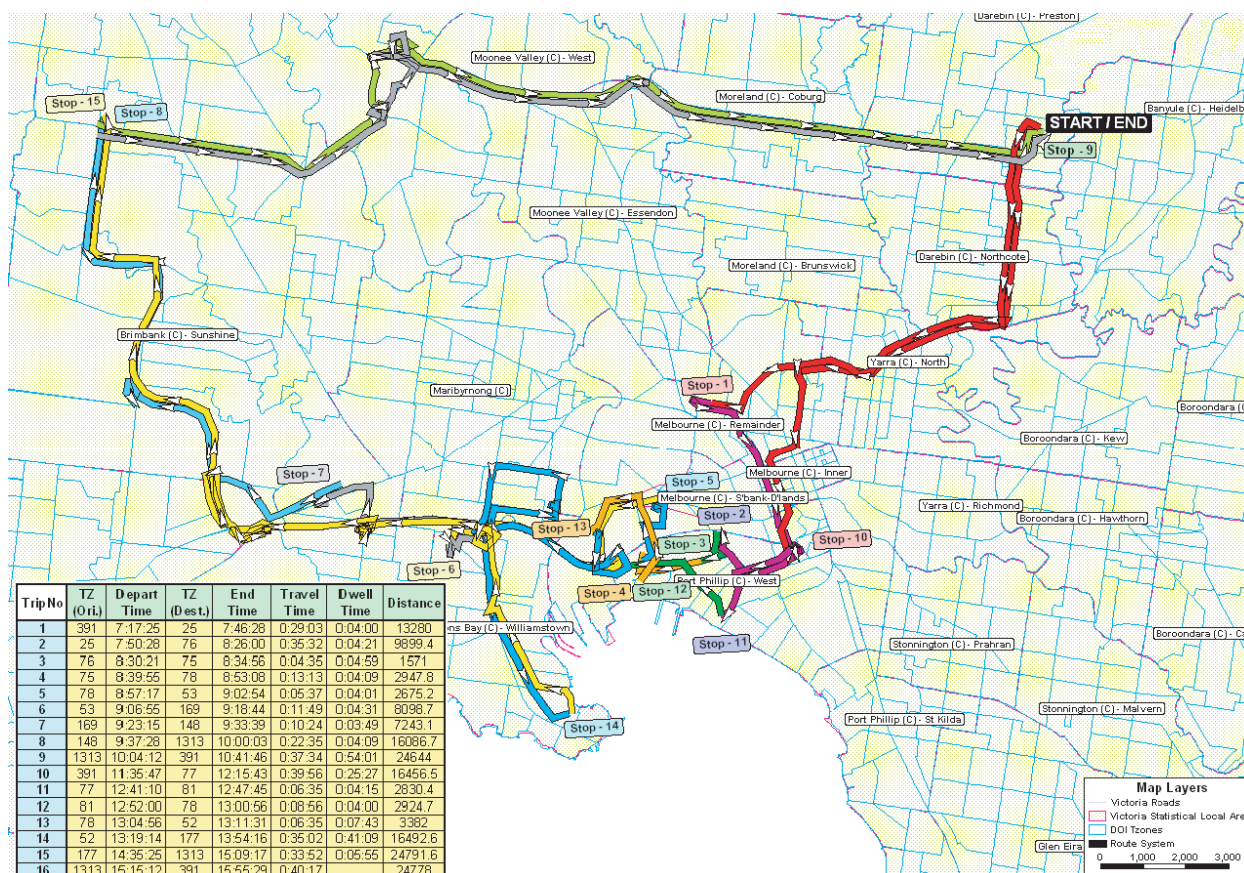
FIGURE 2   Example GPS plot of truck trips.

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.

Processing Time

The time required to run the automated processing routines for the 30 trucks averaged 1 h per truck (4 min 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 approximately 60 h, of which half the time is computer processing time.

TOUR RESULTS

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 km long and lasts approximately 8½ h. Of this time, approximately two-thirds of the time is spent on the road at an average speed of 33 km/h, with the remaining third stopped (e.g., loading or unloading, paperwork, refueling). The use of averages hides the fact there is a great range across the various statistics with the longest tour in terms of time lasting almost 13 h, and the longest in terms of distance

TABLE 2   Summary Data

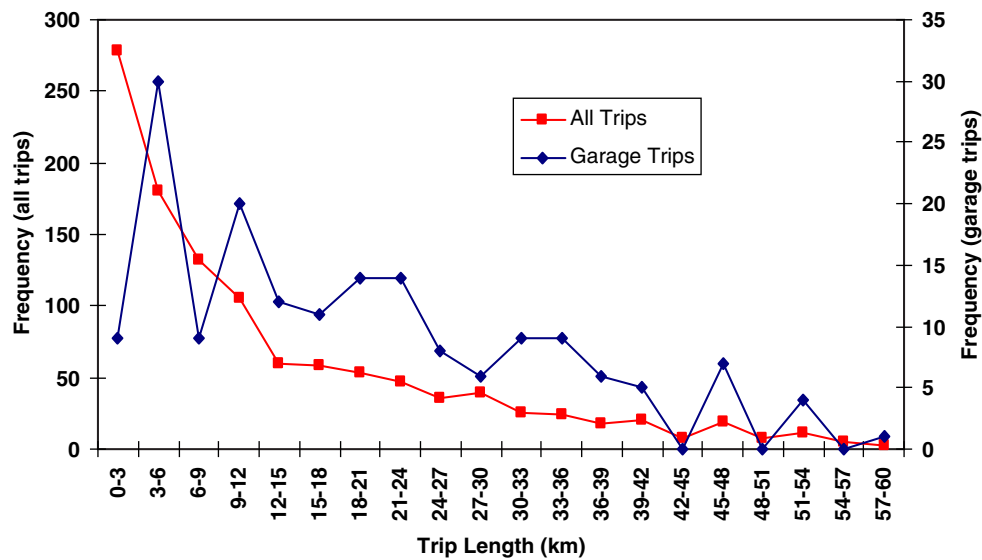| | Trip Distance (km) | Stops per Tour | Tour Distance (km) | Total Tour Length (h) | Average Tour Speed (km/h) | Garage Trips | |
						Distance (km)	Average Speed (km/h)
Average	15.9	12.2	184.4	8.5	33.1	23.39	33.94
Median	18.9	4.7	71.1	2.0	9.4	19.18	30.90
St. dev.	9.0	11.0	177.2	9.0	32.1	18.48	13.79
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

FIGURE 3   All trips versus garage-based trips: trip length distribution.

lasting 357 km. As expected for the distribution of most nonnegative 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 use and number of trips per day.

To provide some points of comparison, the city of Calgary reports approximately 6 stops per tour (6), Denver reports 5.6 (1), and data from Amsterdam indicate 6.2 stops per tour (17). 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 approximately 25 (18).

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 and 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 for all trips follows a continuously decreasing curve, whereas for garage trips it is significantly different and shows a multimodal distribution. Garage-based trips trip length distribution exhibits clear peaks between

3 to 6 km, 9 to 12 km, and 18 to 24 km. 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 (10).

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, that is, between 18:00 and 5:30. The lowest average and median speeds are observed during the morning and evening peaks (7:30 to 9:30 and 15:30 to 18:00). A travel speed reduction of almost 40% can be observed between evening and night and peak times. The highest proportion of trip starts occur in the morning peak. Almost 80% of the trips take place during 8 h, between 7:30 and 15:30. These figures indicate the customer preference for deliveries during normal business hours and early morning hours.

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

TABLE 3   Travel Speed by Time of Day

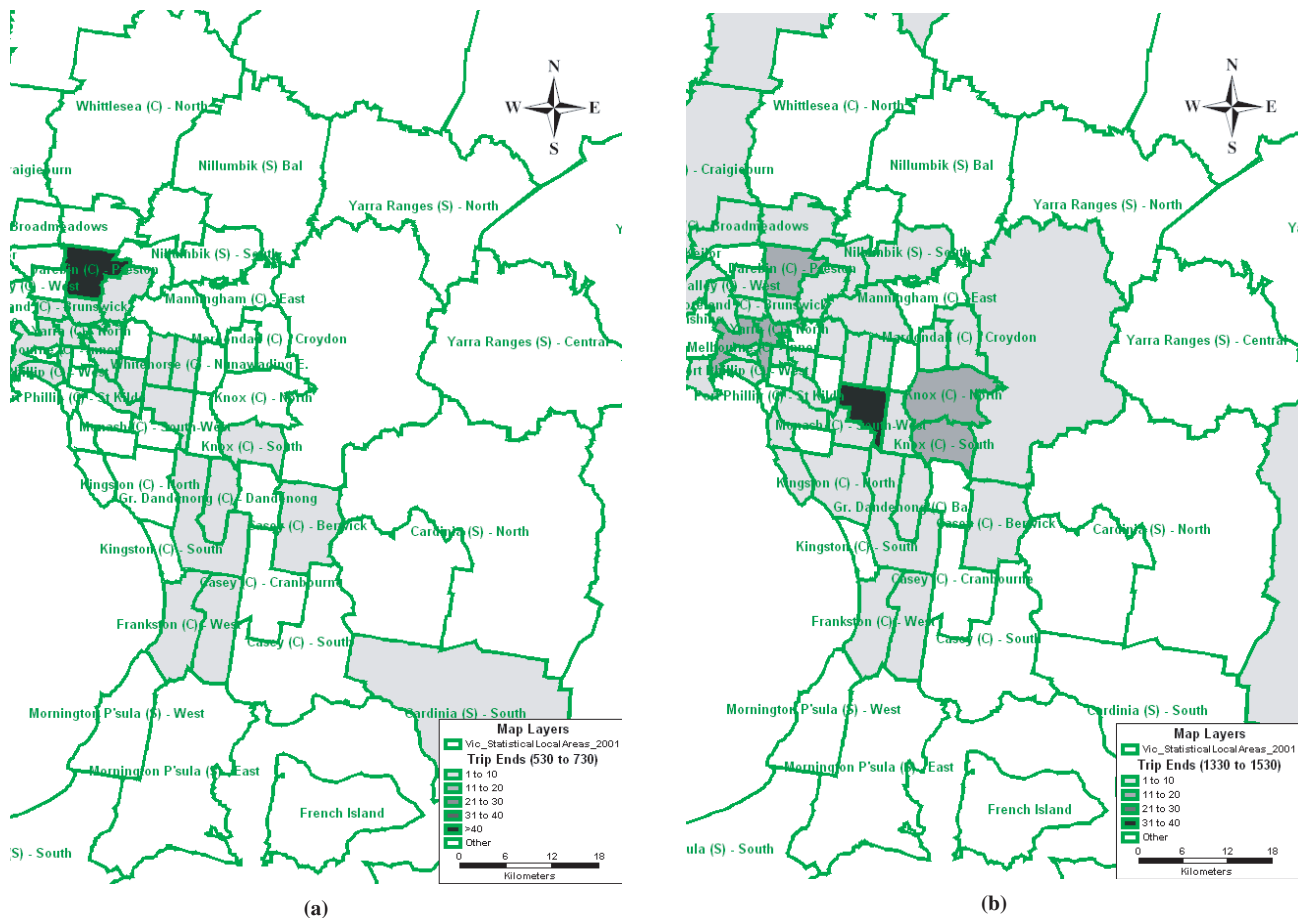| Departure Time	18:00 to 5:30	5:30 to 7:30	7:30 to 9:30	9:30 to 11:30	11:30 to 13:30	13:30 to 15:30	15:30 to 18:00
Average speed (km/h)	44.0	32.9	26.1	32.3	28.8	29.7	24.5
Median speed (km/h)	39.5	31.0	23.2	30.4	28.3	28.0	25.3
St. dev. speed (km/h)	22.4	14.3	15.0	17.7	14.1	13.8	11.9
% total trips	2.5%	8.2%	22.6%	20.2%	18.4%	19.7%	8.5%

FIGURE 4 Comparison of trip ends (*a*) 5:30 to 7:30 to (*b*) 13:30 to 15:30.

ends by Statistical Local Area (SLA) for the time periods of 5:30 to 7:30 and 13:30 to 15:30.

The combination of GIS sociodemographic 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 (*19*). 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 intercustomer trips is also useful to understand the distribution of trips, travel patterns between zones, and percentage of empty or 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 (*8*).

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 (*20*). This is significant because payload is a key measure to determine the efficiency of urban freight systems (*8*). 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 depends 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. Although this has been done for passenger vehicles (*21*), to our knowledge this has not yet been done for commercial vehicles. In Australia, the recently completed National In-Service Emissions Study 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.

A significant limitation of nonintrusive GPS collected data is the lack of behavioral 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 behavior of the driver and vehicle can be quite different depending on whether the vehicle is loaded or empty or given the value of the activity or commodity that must be delivered at the end of the trip. Further, if drivers and vehicles regularly replace each other, operating within a coordinated fleet, the response or behavior of one driver will be dependant on the location and status of other vehicles (e.g., a repair utility crew and vehicle). As with passenger data collection, GPS data collection methods can be a great comple-
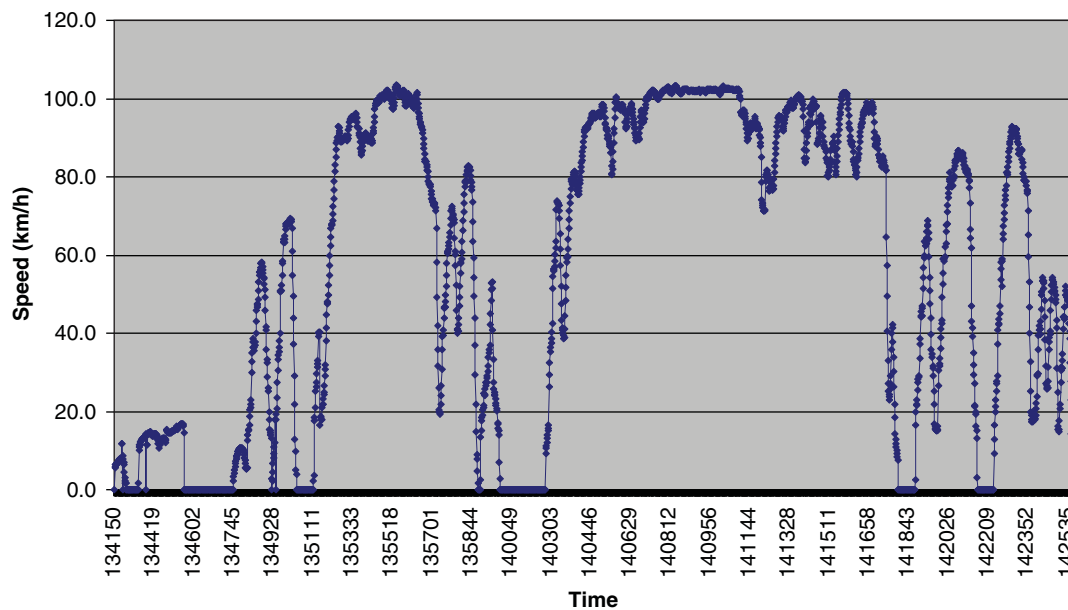
FIGURE 5   Example GPS speed-time profile for truck B1V1.

DISCUSSION OF RESULTS AND CONCLUSIONS

This paper presents the issues of 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, companies are reluctant to divulge what they see as confidential information on their business practices to competitors. Changing this perception relies on convincing freight operators there is value to them in providing such data to researchers and policy makers to improve 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 data set 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 described 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 analyze second-by-second truck travel information such as tour duration, speed, number of stops, and distance traveled. 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 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 because of 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 is, 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, because of sampling issues, traditional freight data collection methods are likely to remain indispensable for validation purposes.

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