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Sample Size Calculation for Studying Transportation Modes from GPS Data

Adel Bolbol[a,*], Tao Cheng[a], Ioannis Tsapakis[a], Andy Chow[a]

[a]*University College London, Gower Street, London WC1E 6BT, UK*

Abstract

The many advantageous features of GPS-based longitudinal surveys associated with prompt recall surveys make such surveys very attractive for travel behaviour studies. However, the sample size calculation procedure for GPS-based surveys is more complicated compared to well-known and widely applied conventional household one/two-day travel surveys. The higher cost of GPS surveys requires scrutiny at the sample size planning stage to ensure cost effectiveness. The essence of sample size calculations problem is of a trade-off between cost/time taking the precision of the survey into account. Different machine learning-based techniques have been developed to infer the transportation mode based upon speed and acceleration calculated from GPS data. However, none of these studies calculate the sample size required for validating these techniques. Calculating the most effective sample size for this inference mainly depends on the variability of these variables which are normally used. To perform this calculation, we develop an understanding of inter-modal (variation between different transportation modes) and intra-modal variability (variation within each transportation mode). The study demonstrates that the motorised modes reflect the highest variability. We use traffic count data to study this variability across different seasonal divisions. The hourly and daily seasonal divisions are proved to be of the highest variability. Extending the survey length also decreases the sample size significantly. This reduction is applied to the calculated sample sizes defining the survey length to be 2 weeks, taking the weekly-seasonality into account.

Keywords: Sampling Size, Mode, Transport, Positional Data, GPS, London

1. Introduction

Travel surveys are one of the most important ways of obtaining critical information needed for transportation planning and decision making. These surveys gather current information about the

* Corresponding author. Tel.: +44 7889831988; fax: +44 20 7679 7920.
E-mail address: a.bolbol@ucl.ac.uk.

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demographic, socioeconomic, and trip-making characteristics of individuals and households. Nevertheless, they are also used to enhance our understanding of travel in relation to the choice, location, and scheduling of daily activities. This enables us to enhance our travel forecasting methods and improve our ability to predict changes in daily travel patterns in response to current social and economic trends and new investments in transportation systems and services. These travel surveys also play a role in evaluating changes in transportation supply and regulation as they occur (Griffiths et al., 2000).

Traditionally, travel surveys used to be conducted using different methods such as telephone and face-to-face interviews and computer-based reporting to maintain a diary (Stopher and Greaves, 2007). These have proven to be a burden for participants to use as well as being expensive and time consuming (Stopher and Metcalf, 1996). Later, a new trend emerged as to use GPS devices in conjunction with traditional surveys (Stopher, 2008). Using GPS devices has proven to minimize trip under-reporting through improved survey methods (Bricka and Bhat, 2006). GPS-based surveys were also found useful for exact time and destination recording and capture of trip underreporting (Wolf, et al., 2003; Schönfelder, et al., 2006).

A further step was to base the diary on GPS devices and subject the respondents to undertake prompted recall surveys. The process of using prompt recall surveys however still proved to be expensive, time consuming and burdensome. Many research groups tackled this problem by attempting to infer travel information from the GPS data automatically (Liao, Fox & Kautz, 2007; Zheng et al., 2008; Bolbol et al., 2012). Among these types of information is the transportation mode (e.g. *cycle*, *walk*, *bus* and so forth) and trip purpose. This inference would eventually replace or complete a lot of the feedback required by participants when labelling and tagging their travel diaries.

Calculating the minimum sample size is an important consideration in this kind of inference models. For conventional one-day or two-day travel surveys, sample size procedures are well known and widely applied; for example, the Travel Survey Manual by Cambridge Systematics (1996). The corresponding sample size procedures for GPS-based panel surveys however, are less well developed. One of the few studies tackling this problem is Xu (2010), where it develops a framework to estimate the effective sample size of GPS-based panel surveys in urban travel behaviour studies for a variety of planning purposes. The study attempts to obtain reliable means for key travel behaviour variables such as demographic characteristics and seasonal factors, using data from only 95 households. Stopher et al. (2008) also attempts to find the best threshold between the minimum sample size and the least sampling period. The study analyses hypothetical and actual multi-day data on person kilometres travelled (PKT), trips, and daily travel time for about 70 persons living in Adelaide, Australia and a second sample of about 500 persons also living in Adelaide. However, there are no studies, to the knowledge of the authors, which calculate the sample size required for validating frameworks attempting to automatically infer the transportation mode from GPS data.

In this study we provide the means to calculate the sample size for transportation mode inference studies by measuring the variability of the relevant variables such as speed and acceleration. The variability is calculated for different modes. For motorised modes, we use data provided by Transport for London (TFL) from their LCAP project obtained from Automatic Number Plate Recognition (ANPR) cameras. The data consists of journey times for each network link, and is by far the best resource for understanding traffic congestion and speeds within London. The dataset consists of 5 minute daily journey times for every link from the beginning and the end of each link. We study the speed variation within an urban environment such as London across daily periods, days and different months taking seasonality into account. On the other hand, for non-motorised modes, outcomes from other studies are used to assign a rough calculation and hence draw comparisons with motorised data variability calculations.

The study proves that motorised modes require a bigger sample size since they comprise of a higher variability. The study also discusses the inter-modal and intra-modal variability of the motorised data within London. The measure of variability calculated and weighted according to each road link's length giving an accurate understanding of the variation in the context of London's network. The daily and monthly variability are also analysed to quantify their effect on the sample size calculation. Speed variability across the day is also quantified and analysed in the light of bus lane users and non-bus lane users. The intra-daily seasonal division is proved to have the highest variability. Therefore, the study proposes extending the sampling period into 2 weeks; and hence decreasing the sample size required (Stopher et al., 2008) as well as taking the weekly seasonality into account. The study also concludes that 100% of the minimum sample size has to contain car and bus modes since they require the highest sample size requirement among other modes.

2. Sample Variability

Sampling for GPS-based survey studies has proved be a pushing problem in the context of transport studies. Therefore, in this section we discuss the process of identifying the sample size and period for such studies. This study takes place in the Greater London area as a case study for what could be considered as an example of a complex urban environment.

2.1. Independent Variable Variability

Estimating the sample size adequate for whichever survey type requires good knowledge of: 1) the *variables* under investigation, 2) their *coefficient of variation* and 3) the *desired accuracy* of measurement together with the level of significance associated with it (Smith, 1979).

The *first* element in the sample size calculation process is identifying the variables to be used in the study. In recent work of ours, we have conducted an ANOVA test on different Independent Variables (IV) derived from GPS data to identify which IV best discriminates between different classes of transportation modes (Bolbol et al., 2012). The outcome of the evaluation identifies the best IVs to be used for the classification as *speed* and *acceleration*.

The *second* element of the calculation process is the Coefficient of variation (*CV*) of the chosen IVs, where the sample size depends largely on how much the variable deviates from its mean. The *CV* is a normalized measure of dispersion of a probability distribution, or a statistical measure of the dispersion of data points in a data series around the mean. It is calculated by dividing the standard deviation (σ) by the mean of the population ($\bar{X}$) as shown in equation 1.

$$CV = {}^{\sigma}/_{\bar{X}} * 100 \qquad (1)$$

The *third* element is the accuracy desired (& significance level) where the accuracy level is the percentage error acceptable to the analyst. Both the accuracy and the significance level are context-dependant elements to be decided by the analyst according to the analyst's experience (Ortúzar and Willumsen, 2011). Once these three factors are defined, the sample size (n) could be computed from equation 2.

$$n = {}^{CV^2\ Z_\alpha^2}/_{E^2} \qquad (2)$$

where E is the level of accuracy and Z_α is the standard normal value for the confidence level (α) required. Since the acceleration is a derivative of speed, the *CV* of speed could also represent the acceleration's variability. The next section analyses a combination of outcomes of different studies aiming at measuring and analysing the variability of speed for non-motorised modes. On the other hand, motorized modes variability is investigated by analysing data from Transport for London's (TFL) London Congestion Analysis Project (LCAP) which is provided to this research.

2.2. Intra-Modal and Inter-Modal Variability

The coefficient of variation of speed (or acceleration) could be computed from speed data available from different resources in this research. However, we need first to consider the different categories/classes (transportation modes) to be used in this calculation, where different modes will have different variability in terms of the speed used. An example could be the difference between walk and car modes, where different car drivers in the population would drive in different manners and speeds, whereas pedestrians would be more constrained in terms of speed variability. Hence, the inter-modal variability will be quite high, while the intra-modal variability would be relatively low but varying depending on the mode type. Therefore, there is a need to calculate the *CV* for different modes separately. The speed would also vary differently according to different seasonal (temporal) periods of the study, that being; hourly, daily or monthly. Therefore, in the following section (section 3) we attempt to quantify the *CV* of the different transportation modes and the different seasonal divisions' effect on these values. Hence, we can identify the exact sample size and study duration required to conduct a GPS-based transportation mode inference study, based on the highest *CV* value calculated from the different transportation modes and seasonal divisions.

2.3. Survey Length vs Sample Size

Stopher et al. (2008) investigates the sample size implications of extending the survey (and whether an optimal or 'ideal' survey duration exists), and the potential cost savings of conducting multiday surveys over 1-day surveys, even accounting for the use of new technologies. The study takes different attributes (variables) into consideration such as the number of trips per day, the number of kilometres travelled per day, and the number of minutes of travel time per day, all measured at the level of individuals. And these variables are studied with respect to the mean values, variances, ratios of intrapersonal (each individual's) to interpersonal (across all individuals) variance, and resulting estimates of reductions in sample size afforded by 7 and 15 days of data in a form of 2 waves (2 weeks).

Concluding from this study, a reasonable assumption is that day-to-day variability in travel distances is about 4.75 times person-to-person variability. This means that multi-day data can result in significant sample size reductions (65% for a 7-day survey and 72% for a 15-day survey) and potential cost savings. More specifically, a 7-day survey using GPS would reduce the sample size to 35% of a one-day survey, and that a 15-day GPS survey would reduce the needed sample size to 28% of the one-day survey sample size. This empathizes the stress of having a more longitudinal study than a cross sectional type. However, cross sectional data might still be used for validation to account for the interpersonal variation. While extending the study duration in order to reduce the sample size, we need to understand how far this would affect the *CV* of speed. The highest *CV* will depend on the period that provides the highest variation (either hourly, weekly, or monthly). Therefore, after choosing the period division that would provide the highest *CV* (and sample size), we could apply the reduction proposed by Stopher et al. (2008) to the sample size computed for one day extending it into the chosen period division to account for that seasonal variation.

3. Coefficient of Variation for different Transportation Modes

Considering the two main variables (speed and acceleration) are calculated from the same parameters, then measuring the variability of either should apply to both similarly. In this section, we will consider calculating the *CV* of speed in order to calculate the sample size needed for each transportation mode separately. The train and tube modes however should theoretically have the lowest variation since they run according to schedules and their networks are more controlled and therefore not very much congestion-affected. However, from previous work of ours, the train and tube modes prove to be separated with almost an accuracy of 90% from other modes (Bolbol et al., 2012). This makes their variability a rather insignificant measure for calculating their sample sizes. This means in turn that other modes such as motorized and un-motorized vehicles using a road network should have more variation in their speed values; being affected by external factors such as congestion, number of lanes, road classification, precipitation, etc. This as a result would lead to the need of a higher sample size for other modes and therefore we will ignore calculating that of train and tube modes.

3.1. Cycling & Walking

Thompson et al. (1997) conducted a study on the typical cyclist speeds in a recreational population from self-reported speeds in Washington, US. The mean speed across genders and different age groups was found to be 4.11m/s with a standard deviation of ±1.16, which means a *CV* of 28%. Applying equation 2, a sample size of **85 participants** is found as a requirement for testing a cycling population.

$$\text{Sample Size (Cycle)} = n = (0.28)^2 * (1.645)^2 / (0.05)^2 = 85 \text{ participants}$$

Published in another research aimed at studying Pedestrian Level of Service design and impact on the quality of pedestrian life, Weidmann (1993) obtained a normally distributed average speed of 1.34 m/s and a standard deviation of 0.26 (*CV* = 19%) for pedestrians walking on the street (Pedestrian LOS Study, 2006). Similarly, applying equation 2, this would result in a sample size of **40 participants**.

This leaves us with the car and bus modes. These two modes are the two main motorized transportation modes that use the road network. The complexity of the road network and of the temporal variation in congestion dictates how difficult it is to detect the speed variability within such a network. The case of these two modes is more complex than that of walking and cycling because of the fact that they are motorized and hence varying in speed massively. They also obey the road network restrictions, unlike walking and cycling where the urban setting does not restrict the speeds as much. The following subsection discusses the nature of these modes and their associated speed variations.

3.2. Car & Bus

Yet the most problematic and variant modes are the motorised vehicles. Using data from its network of Automatic Number Plate Recognition (ANPR) cameras, TFL's LCAP project data of traffic counts is by far the best resource for understanding traffic congestion and speeds within London. The dataset consists of 5 minutes daily journey times for every link at the beginning and the end of each link.

The data was aggregated according to each link per different time durations of the day per the day of week per month. The data could be divided into two categories, assuming the bus lane users category is restricted to the bus mode while the non-bus lane users is restricted to the car mode. An average could be calculated for the speed data for each category, however, the all links are treated equally regardless their length. Therefore, a more realistic figure would be calculating the weighted average of the speed using each link's length using equation 3.

$$\bar{x}_w = \sum_{i=1}^{N} w_i x_i \Big/ \sum_{i=1}^{N} w_i \qquad (3)$$

where $\bar{x}_w$ is the weighted average, w_i is the length of road link i, x_i is the speed of link i and N is the total number of links. In order to calculate the *CV*, we need to calculate the standard deviation associated with these speeds. Traditionally, we would use the following formula to perform this calculation:

$$\sigma = \sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 / _{N-1}} \qquad (4)$$

where σ is the standard deviation for a population sample and the $\bar{x}$ is the sample's average. However, to calculate the weighted standard deviation σ_w the following formula could be used:

$$\sigma_w = \sqrt{\sum_{i=1}^{N} w_i (x_i - \bar{x}_w)^2 \Big/ (\acute{N} - 1) \sum_{i=1}^{N} w_i / _{\acute{N}}} \qquad (5)$$

where w_i is the weight for the i^{th} observation, $\acute{N}$ is the number of non-zero weights, and $\bar{x}_w$ is the weighted mean of the speeds calculated from equation 3. The *CV* then becomes the following:

$$CV_w = {}^{\sigma_w}/_{\bar{x}_w} * 100 \qquad (6)$$

where the CV_w is the weighted coefficient of variation computed from the division of the weighted standard deviation σ_w by the weighted mean $\bar{x}_w$. And then equation 2 becomes:

$$n = {}^{CV_w{}^2 Z_{\alpha}^2}/_{E^2} \qquad (7)$$

where the sample size becomes based on the weighted mean of the calculations. The difference between the weighted and un-weighted averages is illustrated in figure 1 for both categories of car and bus. As could be noted, the weighted mean values are higher for both the categories; where longer links are given a higher weight while in many cases they are more probable to have a higher speed limit, and therefore, raising the speed distribution to higher speeds.

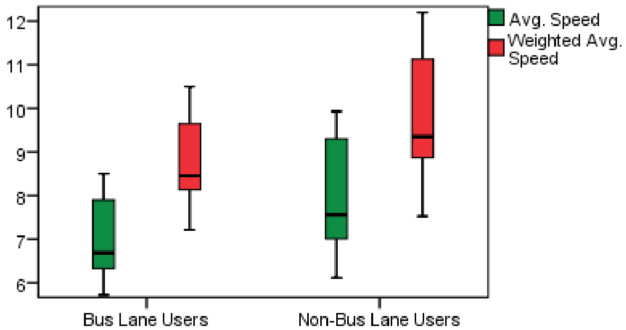

Fig. 1. Weighted and un-weighted means of the speed data

The next step is to identify the highest variability of speed according to different temporal divisions (hourly, daily and monthly). In the rest of this section, we compare these divisions by calculating the intra and inter temporal *CV*s of each the bus lane and non-bus lane users for each temporal division. We will then use the highest variability to apply it to equation 7 to identify the sample size required for each of these two modes.

3.2.1. Hourly Variation

Table 1 illustrates the results calculated for intra-hourly variability aggregated into significant periods of the day (identified by TFL) for bus lane users (assuming bus mode) and non-bus lane users (assuming car mode). Figure 2 illustrates the weighted average speed values by different time intervals along the day for the aggregated data period for both categories. It could be noted how differently the speed varies from relatively low speeds in the earlier half to the lowest values at the pm peak period of the day raising up again at the evening, night and pre-am periods again. One could also note that the difference in speed between cars and buses increases significantly in the late part of the day highlighting the fact that buses will not exceed certain speeds even in low congestion periods, being restricted by stoppage at bus stops and vehicle-acceleration limitations. The average intra-hourly variation is shown to be around 52% and 50% for bus lane and non-bus lane users respectively as shown in table 1. The inter-hourly variation however could be calculated from the average speeds giving 10.34% and 13.26% for each group respectively.

Table 1. Weighted average speed (m/s) according to inter-daily and intra-daily Temporal Variability from the LCAP Data

Period	Time	Bus Lane Users		Non-Bus Lane Users		Both	
		Mean	CV	Mean	CV	Mean	CV
All Day		**8.80**	**52.03%**	**9.83**	**50.10%**	**9.32**	**51.04%**
AM	07:00-09:55	8.43	51.66%	9.31	47.50%	8.87	49.48%
Inter-AM	10:00-12:55	8.28	54.62%	9.11	50.62%	9.61	50.16%
Inter-PM	13:00-15:55	8.02	54.57%	8.74	50.25%	8.70	52.52%
PM	16:00-18:55	7.66	51.78%	8.17	47.09%	8.38	52.32%
Evening	19:00-21:55	9.04	50.76%	10.19	49.51%	11.22	51.49%
Night	22:00-05:55	10.37	50.40%	12.07	52.03%	7.92	49.37%
Pre-AM	06:00-06:55	9.78	50.04%	11.25	48.75%	10.53	49.42%

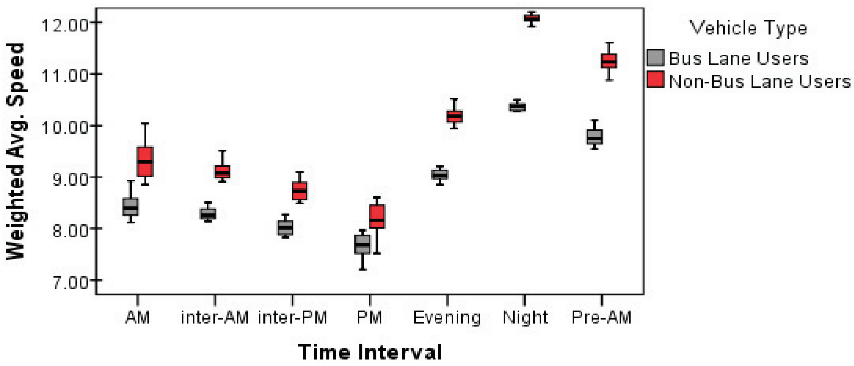

Fig. 2. Inter-daily and intra-daily results for the weighted mean speed data (m/s)

3.2.2. Daily Variation

Table 2 shows the results for the intra-daily variation and average speeds. Figure 3 also demonstrates this difference in the form of box plots. It could be noted that on Saturdays and Sundays the average weighted speed increases notably especially in the AM period, which illustrates the importance of this division. The inter-daily variation could be calculated from table 2 to give 3.36% and 4.05% for the bus and car modes respectively. The right side of table 2 shows the inter-daily variation for different periods of the day. A high average variation across days could be noted for the AM, Pre-AM and PM periods which could be attributed to the peak hour variation between weekdays and weekends.

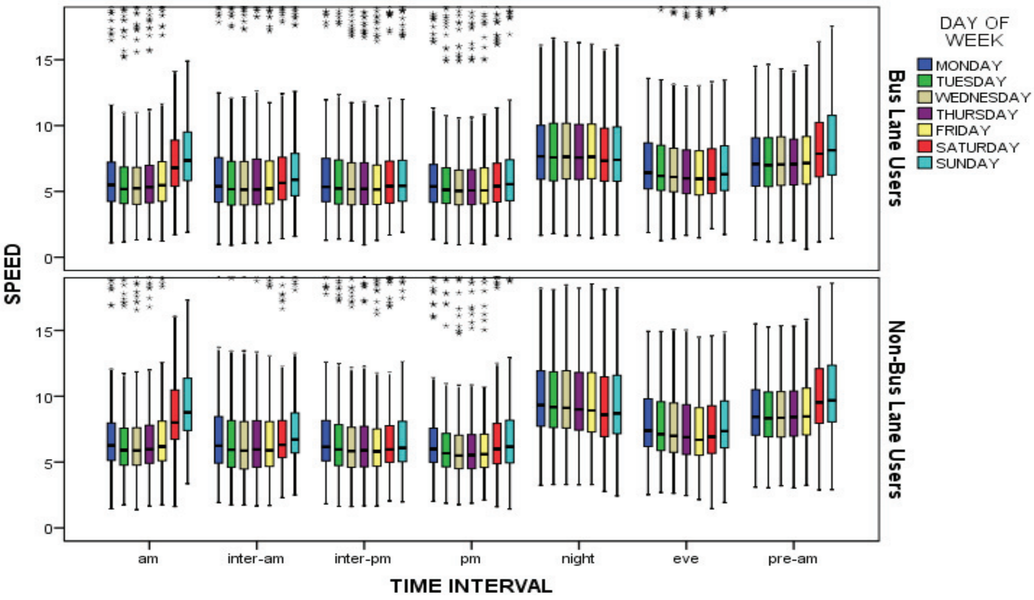

Fig. 3. Inter-daily variation in weighted speed data (m/s) by time interval for both categories for different time periods of the day

Table 2. Weighted Average Speed (m/s) According to Daily Temporal Variability from the LCAP Data

Week Day	Bus Lane Users		Non-Bus Lane Users		Both		Day of the week per diff periods	CV of $\bar{x}_w$	
	Mean	CV	Mean	CV	Mean	CV		Bus	Car
Monday	8.78	50.83%	9.89	48.93%	9.34	49.87%	AM	11.71%	15.25%
Tuesday	8.61	51.46%	9.62	49.46%	9.11	50.44%	Inter-AM	2.08%	2.56%
Wednesday	8.56	51.51%	9.52	49.65%	9.04	50.57%	Inter-PM	1.60%	2.08%
Thursday	8.60	51.23%	9.57	49.52%	9.08	50.37%	PM	4.23%	5.74%
Friday	8.59	51.28%	9.55	49.31%	9.07	50.27%	Evening	2.04%	2.63%
Saturday	9.13	51.59%	10.29	50.40%	9.71	51.02%	Night	1.14%	1.93%
Sunday	9.37	51.28%	10.62	50.30%	10.00	50.84%	Pre-AM	6.64%	8.81%

3.2.3. Monthly Variation

Table 3 illustrates the same results but for intra-monthly temporal variability for both user types all through the year, while figure 4 illustrates this variation visually. It could be noted that the night and pre-am periods contain the highest speed values for both cases, while the pm period contains the lowest speed values due to peak hour congestion. It is also seems to be a slight variation in August where values go a little higher expressing less congestion which could be attributed to holiday season, while having the opposite effect in November. This could inform us that some inter-monthly variation exists, however, is not significant enough to account for in the sample size analysis, calculating from table 3 an average variation of 1.43% and 1.75% for bus and car modes respectively; which is less than any other division.

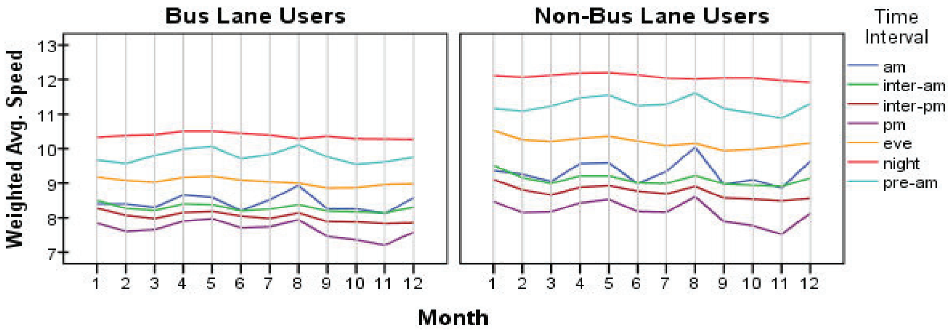

Fig. 4. Inter-monthly variation in weighted speed data (m/s) by time interval for both categories

Table 3. Weighted average speed (m/s) according to monthly Temporal Variability from the LCAP Data

Month	Bus Lane Users		Non-Bus Lane Users		Both	
	Mean	CV	Mean	CV	Mean	CV
All Year	**8.80**	**52.03%**	**9.83**	**50.10%**	**9.32**	**51.04%**
January	8.88	51.18%	10.03	48.96%	9.46	50.04%
February	8.76	51.77%	9.83	49.61%	9.30	50.66%
March	8.77	52.24%	9.78	50.37%	9.27	51.29%
April	8.97	51.68%	10.01	49.92%	9.49	50.79%
May	8.98	51.84%	10.06	50.28%	9.52	51.06%
June	8.77	52.45%	9.79	50.48%	9.28	51.44%
July	8.82	52.15%	9.80	50.36%	9.31	51.24%
August	8.96	52.14%	10.08	50.12%	9.52	51.10%
September	8.68	53.01%	9.65	50.93%	9.17	51.94%
October	8.62	52.65%	9.63	50.61%	9.13	51.61%
November	8.59	52.06%	9.53	50.18%	9.06	51.09%
December	8.75	51.15%	9.84	49.27%	9.30	50.19%

As a result the highest variation could obviously be nominated as of the hourly basis. We therefore use the CV of this temporal division to calculate the weighted sample size for both modes follows:

$$Sample\ Size\ (Bus) = (0.52)^2 * (1.645)^2 / (0.05)^2 = 289\ participants$$

$$Sample\ Size\ (Car) = (0.50)^2 * (1.645)^2 / (0.05)^2 = 271\ participants$$

4. Results

The figures calculated for each mode are listed in table 4 illustrating that the highest sample size required for 1 day surveys is that for car and bus modes as might be expected. However, adopting Stopher et al. (2008) results to extend the data collection period to 2-weeks (mentioned in section 2.3) would significantly decrease the sample size by 72%. The final figures are also shown in table 3 after applying this reduction. An important benefit of extending the survey length to 2 weeks is obtaining 2 waves of data for each individual accounting for the weekly-seasonality that is demonstrated in section 3.2.2. This would include any trips that the participant makes once a week twice within the survey length, where according to Simpson (2011), in most cases these one-off weekly trips take place.

Table 4. Sample sizes calculated for each mode from eq. 2 before and after applying Stopher et al. (2008) multi-day sample size reduction

Transportation mode	Mean	CV	Sample Size		Data Source
			1 Day Survey Sample Size	2 Week-Survey Sample Size	
Walk	1.34m/s	19%	40	11	Pedestrian LOS Study (2006)
Cycle	4.11m/s	28%	85	24	Thompson et al. (1997)
Bus	8.80m/s	52%	289	81	This research – TFL LCAP
Car	9.83m/s	50%	271	76	This research – TFL LCAP

According to table 4, it would mean that assuming that a user would undertake the bus mode in his/her weekly travel, a total number of 81 users would be sufficient to carry out a modal GPS-based survey study over 2 weeks. At least, 76, 24 and 11 users are also required to undertake the car, cycle and walk modes respectively. The train and tube modes can be assigned the maximum sample size (81 users) as that calculated for the bus mode.

5. Conclusions

In this paper, we use journey time data for London to measure the variability of different transportation modes in order to calculate the appropriate sample size for GPS-based surveys. We do this by calculating studying the variability of the variables to be used from GPS data such as speed. The study proves that motorised modes require a bigger sample size since they comprise of a higher variability. The study also discusses the inter-modal and intra-modal variability of the motorised data within London. The measure of variability is calculated and weighted according to each road link's length giving an accurate understanding of the variation in the context of London's network. The hourly, daily and monthly variability are also analysed to quantify their effect on the sample size calculation for bus lane and non-bus lane users. The hourly seasonal variation is found to have the highest variability, and hence its coefficient of variation is used to calculate the sample size for motorised modes. The study also proposes extending the sampling period into 2 weeks which was found to be significant combined with the hourly variation; and hence decreasing the sample size required (Stopher et al., 2008) as well as taking the weekly seasonality into account. Although these results are specific to Greater London, they could be very similar to other urban cities of a similar setting. Therefore, the sample sizes calculated here could be used as an example rather than a definite reference for any other city.

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