Using GPS Data to Understand the Day-to-Day Dynamics of the Morning Commute Behavior

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ABSTRACT

This paper examined the day-to-day variability of the journey-to-work trips, including the departure time, route choice, and trip chaining behavior, using GPS-based disaggregate morning commute data of 56 drivers during a one-week period. Data were collected from the ongoing instrumented vehicle projects in Atlanta sponsored by NHTSA and FHWA. The paper examines alternate measurements of the day-to-day variability of the commute pattern. While commuting trips are often thought to be highly repetitious and therefore highly predictable trips, research results of this paper show that commuters change departure times more frequently than routes, and trip chaining significantly impact commuters' departure time and route choice behavior. This paper begins to explore definitions and relationships that will be necessary to the better understanding of the day-to-day commute dynamics.

INTRODUCTION

Urban transportation researchers have put great attentions in the research of commuting trips. Interest in the daily commute arises from the fact that the journey to work places great strain on the urban transportation system due to its temporal peaking. While researchers has investigated travel distances, travel times, modal and route choices associated with commuting trips, comparatively less research has focused on the day-to-day dynamics of the commuting behavior. Since commuting trips are often thought to be highly repetitious and therefore highly predictable, past studies have usually ignored or suppressed the problem of dynamic behavior in conventional transportation studies by collecting and analyzing commute data of a common weekday or one-day's data of different weekdays to obtain averaged travel patterns across individuals and days of week, rather than comparing day-to-day difference in travel behavior (*1*). Another argument for ignoring this variability in behavior in the past was that variation in behavior could be fully explained based on one-day's data, given a sufficiently large random sample of travel behavior from individuals in the population. However, if interest lies in individual rather than averaged group behavior, limit exists how far statistical explanations of behavior can account for variations in the data, without allowing for intra-person variability (*1*).

As the focus of today's transportation planning increasingly moves away from transportation investments that meet unrestricted demand, to applications of new technologies that manage travel demand and achieve more efficient use of the systems, better understanding of variability is central to the modeling of travel behavior and the assessment of policy impacts. Specifically, the day-to-day dynamics of commuting decision is of considerable significance to the development and analysis of congestion management strategies, including those that rely on advanced information technologies. These solutions or mitigation strategies are critically dependent on the ability to influence the temporal and spatial characteristics of commuter behavior and decisions. A partial list of the motivating problems and opportunities in this research area includes travel demand management, peak-period congestion and peak spreading, ITS and information dissemination strategies, mobile emissions estimation, and others (*3*).

Mahmassani (*3*) presented a review of the developments in the research area of commuting behavior dynamics. Although the foundation for conducting research in this area has been forming slowly, this area is still under active development. Because of the inherent complexity of gathering and subsequently analyzing observations of the dynamic phenomena of interest, significant breakthroughs remain to be made both substantively and methodologically. One of the major impediments to developing a larger body of knowledge in the dynamic aspects of commuter behavior is the lack of sufficient data at the desired level of richness. The collection of such data requires much effort from the respondent, especially if the respondent is required to report detailed diaries. This is particularly true for network-path choice, a topic on which scant link-by-link data appear to be available (*4*). Despite the recognition of the presence of day-to-day variation in travel behavior, multi-day surveys are seldom used because of the potential ill-effects of survey fatigue and low response rates typically attributed to longer survey durations. In particular, very little empirical work is based on real world observations.

As the GPS technology becomes more accurate and less expensive, it is now increasingly utilized in transportation research. Advancements in GPS technology make multi-day data collection for travel diary studies and other transportation applications a reality. Based on the summary of Pendyala (*2*), GPS technology is able to better capture travel behavior during a long period of time and completely solve the survey fatigue problem of multi-day travel diary survey. GPS-based travel data can capture short and infrequent trips that may not be obtained in a traditional travel diary survey. It can also provide accurate temporal information on trips without round off, detailed route choice, spatial location, and other information currently not available in traditional travel surveys.

This paper examines the journey-to-work of 56 commuters using disaggregated GPS-based activity data collected during a one-week period. The main objective of this study is to better understand the key aspects of morning commute journeys including the departure time from home, intervening stops between home and work, the route followed through the network, and their inter-relationship. The remainder of this paper is organized as follows: section 2 presents data collection methods, and describes data source and sample statistics; section 3 presents empirical results of data analysis; the final section provides a summary of the research findings, and identifies possible extensions of the research.

DATA SOURCE AND COLLECTION

At present, more than 200 vehicles from 100 plus households in the Atlanta area are instrumented with an event data recorder (EDR) capable of collecting second-by-second GPS position and speed. The EDR that turns on and off automatically with the vehicle ignition and requires no human input provides an accurate itinerary of vehicle trips, including those short, intermediate, and infrequent stops that would otherwise be missed in traditional travel diary data collection methods. The recorded data are downloaded automatically over a cellular connection every day. These features make the EDR a practical option for undertaking multi-day travel behavior. The GPS receiver used in the EDR has 12 parallel channels with dead-reckoning equipment and software installed for signal acquisition under urban canyon and thick foliage environments. The GPS receiver that has a position accuracy of 4.9 meters at 95% significance level and a speed accuracy of 0.1 meters per second at 68% significance level is capable of acquiring satellite signal within 10 seconds under a hot engine start situation and 45 seconds under a cold engine start situation.

Participants of this undergoing research were selected from a sample of 8,000 households that have previously completed a two-day travel diary in the Atlanta SMARTRAQ program. The survey covers the 13 counties in the Atlanta region and is stratified by net residential density at the census block group level. Each participant must be the primary driver for one vehicle in the household 90 percent or better of the time. One-week worth of data of morning commuting activities for a total of 56 of drivers can be clearly identified from the current data available. An example of the commuting data of one of the drivers is shown in Figure 1. Selected socioeconomic and demographic information of the commuters including age, gender, household income and household size are available for analysis. The descriptive characteristics of the drivers are shown in Table 1.

A series of procedures were developed to differentiate the morning commute activity from the other vehicle activities during the day: First, the home and workplace locations of each participant are geo-coded into the latitude and longitude format using ArcGIS^{TM}. Next, potential morning commute trips are screened based on time and location. A series of trips with the first trip starts at home, the last trip ends at the work place, and all trips intermediate that take place during the morning commute time-period on a given day are considered a single morning journey-to-work. The morning commute time period is currently defined as from 5 a.m. to 10 a.m., Monday through Friday. Trips with starting position that falls within a 0.5 mile buffer of the home location or the ending position that falls within the 0.5 mile buffer of the workplace location are considered starting at home or ending at the workplace. Since it normally takes the EDR up to 60 seconds to start up in the cold-engine condition, the trip starting location provided by the GPS unit may have an error. In this study, the previous trip's last known position is used as the current trip's starting position since the vehicle is not supposed to move with the engine turned off.

DATA ANALYSIS

Departure time choice and route choice constitute the primary choices available to commuters on a daily basis in response to congestion, incidents, or other situations. In contrast, the time-frames for decisions of mode shifts, telecommuting, residence relocation, and change of work place are comparatively longer. Previous research (*4, 5, 8, 9, 10*) has also highlighted the impact of trip chaining along the commute on the variability of departure time and route choice decisions. In this section, findings on the day-to-day dynamics of commuting behaviors, including departure time choice, route choice and trip chaining behavior, and the extent of variability in these behaviors are discussed. Most methodological approaches adopted in the paper follow that presented in Mahmassani (*4*).

Trip Chaining

One integral component of a person's travel behavior is his trip chaining patterns. As the empirical evidence pointed out, that a secondary role of the commute journey is to provide an opportunity to link non-work travel with the commute itself (*5*), commuting trips are becoming more and more complex as workers incorporate personal, household, and child-care activities into their commutes (*6*). For example, Orski (*7*) found that more than 60 percent of office workers who drive their personal car to work made intermediate stops on the way to or from work at least three times a week. Davidson (*8*) also found that employees were twice as likely to make stops on their way home from work as on their way to work from home. Yalamanchili et al. (*9*) compared the trip chaining indications provided by the GPS data with those provided by the recall data. Results of their study shows that the GPS-based data performed in a superior manner to the recall data in capturing multi-stop chains in that the former captured more than twice as many multi-stop chains than the latter when comparisons were made in the context of a one-day travel period.

In this section, the GPS-based activity data that collected in the ongoing research are used to investigate the problem whether the non-work stops during morning commute is a common phenomenon, or a relatively inconsequential phenomenon. For the purpose of this study, every daily home-to-work commute journey is referred to as a trip chain starting at home and ending at work place that may or may not have intermediate stops. Stops have been divided into two types: Type I stops take place when the driver turns off the engine during the stop. Type II stops take place when the driver doesn't turn off the engine during the stop. Type I stops usually have longer duration than Type II stops.

The frequency of non-work stops during the morning commute is shown in Table 2, which shows a total of 87 out of 280 (31%) morning commute journeys having one or more stops. Similarly, Hanson found a 29.4 percent of passenger vehicle trips having one or more stops between home and work (*10*). In a survey of 164 respondents, Mahmassani (*4*) found 24.3 percent of morning commute trips have one or more stops. Compare of these numbers shows that GPS-based data collection methods may be more effective in capturing trip chaining behavior. Further analysis using the full fleet (1,600) of participants' vehicles equipped with EDRs is necessary to rule out the incidence of bias in the number of trips made for the present analysis. Currently, the sample is skewed slightly to higher income households due to recruitment criteria regarding car sharing. Two-thirds of the final sample will have no car-sharing restrictions, and a compare of trip-making will be undertaken at that time.

For each commuter, a stops-ratio was calculated by dividing the number of commute journeys with stops by the total number of commute journeys for each driver. The stops ratio of the 56 commuters in the sample is shown in Figure 2 that shows approximately 60% commuters stop on their way to work at least one day during their 5-day commute period and more than 15% of the drivers stop every day during their morning commute journey. These results indicate that the existence of the non-work stops during the morning commute is a common phenomenon among a large percent of commuters.

A former study shows a large percent of households' total travel is undertaken in conjunction with the journey to and from work. The growth of non-work vehicle trips made during the commute contributes to the traffic congestion (*11*). Work trips with non-work stops contribute to the vehicle-miles and vehicle-hours traveled in an urban area (*4*). Findings in this study are consistent with these statements. A T-test of paired two sample means was performed to test the null hypothesis that commute with intervening stops has the same travel time and travel distance compared to commute without intervening stops of the same driver. Both null hypotheses are rejected at the 0.05 significance level (see Table 3).

If we divide the stops into two groups: routine stops which appear at least twice during the 5-day commute period for a certain driver, and non-routine stops which appear only once during the 5-day commute period for a certain driver, 35 out of the 109 stops are non-routine stops, and the remaining 74 are routine stops. The drivers that make routine stops average 0.87 non-routine stops during 5-day period. On the other hand, the drivers who make zero routine stops average 0.54 non-routine stops. 7 out of 15 drivers who make routine stops also make non-routine stops. 14 out of 41 drivers who do not make routine stops make non-routine stops. A statistical test on correlation between routine and non-routine stopping behavior of commuters is not significant at the 0.05 significance level.

Departure Time & Arrival Time

In order to study the variability of departure times and arrival times, the time-of-day was converted to a continuous clock time. For example, 8 a.m. is equal to 28,800 seconds starting at 12 midnight. Two types of time variation are studied. The median switch is used to study the deviation from driver's usual behavior. The current commute is considered a departure/arrival time switch from the median whenever the absolute value of the difference between the departure/arrival and their medians are larger than the criteria. The median instead of the mean is used in order to avoid the influence of outliers. The day-to-day switch is used to capture driver's variation in behavior from the previous day's departure/arrival time. The current commute is considered a departure/arrival time switch from the previous day whenever the absolute values of the difference between the departure/arrival times of the two continuous days are larger than the criteria.

The number of the commute journeys that switch based on the definitions above are listed in the Table 4. The result shows that considerable variability exists in the departure time and arrival time decisions. Even at the 30-minute threshold level, around 20 percent of the 280 commute journeys in the sample are switched based on the median switch definition. Note that the above results correspond to actual driver decisions in an uncontrolled environment, and the particular underlying reasons for the changes of departure/arrival time are unknown. A large percent of the switch decision may be due to reasons other than the desire to avoid congestion. Similarly, during a commuter phone survey in Seattle, Mannering found that users reported making average of only 2.32 departure-time changes from their normal departure time per month with the intent of avoiding traffic congestion (*4*). Based on all the different switch criteria, a Chi-square test of correlation between departure time switch frequency and stop behavior is not statistically significant. The reason for this finding may be that work start time was not controlled in this sample, and over-representation of commuters with flexible work start time may exist in the sample. A survey of flexible work schedules or other alternative work programs currently underway will help to discern if this is indeed the case.

Route Choice

The results of this study show that route switching by morning commuters is not as frequent as departure-time changing. A usual route exists and can be identified for most commuters. As shown in Table 5, only around 13.5% trips utilized a non-mode route or a route that differed from the most frequently taken route. This result is consistent with the findings of Mahmassani (*4*) and Mannering (*12*). The null hypothesis, that the same proportion of commute trips with or without stops uses a mode route, is rejected by the Chi-square test for difference in two proportions at the 0.05 significance level. The result shows that commuters that stop during the home to work journey have a higher likelihood of choosing a non-mode route.

The results in Table 6 report the observed dominance of one route for most commuters, as 33 out of 56 commuters use only one route during their 5-days commutes. These drivers do not even deviate from their route. Only 4 out of 56 commuters have two primary routes (routes that appear more than twice in the 5-day commutes). The other 9 commuters who used routes other than primary routes during a single trip did so to make a non-routine stop on their way to work. The null hypothesis, that commuters who make stops on their way to work have the same tendency to use an alternative route compared to commuters who do not make stops on their way to work, is rejected by Chi-square test for difference in two proportions at the 0.05 significance level. The result shows a correlation between stop and route choice behavior such that commuters with stops on their way to work have a higher likelihood of using alternative routes.

Commuters' Characteristics and Travel Behavior

Pas and Koppelman *(16*), using the total trip rates as the behavior unit, found out that the level of intra-personal variability varies significantly across the demographic segments. On the other hand, in the study carried out by Hanson and Huff (*14*), the ability to explain difference in travel using social-demographic variables was rather disappointing. The descriptive summary of the travel behavior based on the commuters' characteristics is listed in Table 10. The differences of the mean values among different characteristic groups are not statistically significant. This result could be due to the problem of small sample size, mis-categorization issues, or misunderstandings of the nature of the travel behavior as mentioned by Hanson and Huff (*14*); that several characteristic travel-activity patterns exist for each individual instead of one. Further research with a larger sample size is needed to answer this question.

CONCLUSION

In this study, the day-to-day variation in the morning commute behavior is measured using the GPS-based data collected from a sample of 56 commuters during the period of one week. The study, which analyzed the intra-personal and inter-personal variability in behavior, has provided insight into the morning commute scheduling, trip chaining, and route choice behavior using the observations of the behavior in the real world situation. About 60% of the commuters in this study have at least one non-work stop during their way to work, which underscore the importance of trip chaining in commute behavior. Furthermore, the trip chaining aspect of the commute emerges as a major feature of commuter decision making. Trip chaining, a key determinant of the day-to-day variability in trip scheduling and route choice, significantly impacts commuters' route choice behavior in that commuters who have stops or drop-offs on their way to work are more likely to have more than one route compared to commuters who never make stops on their way to work.

One limitation of the study is that the results are based on a small sample size within a restricted geographic area during short time period, so they cannot be extrapolated directly to larger samples and other urban areas. Another limitation of this study is that although traffic information systems play an important role in driver's decision-making both before and during travel and day-to-day evolution of these decisions, the study does not consider the impact of traffic information on commuter's decision making process. Nevertheless, the study has provided valuable insight into the actual behavior of commuters observed over a one-week period, rather than self-reported behavior based on a traditional travel diary covering a one- or two-day period, which is borned to lead to inaccuracy. That is, the study data permit the observation and understanding of the day-to-day dynamic decisions of actual commuters in real traffic networks.

With the increasing accuracy and the decreasing cost, GPS technology can now be applied to large-scale multi-day travel behavior data collection, especially route choice data collection. However, large data volumes require highly automated data processing methods that can extract meaningful information more effectively. This paper has begun to explore the definitions and relationships that will be necessary to develop these processing routines.

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TABLE 1. Sample descriptive characteristics

Characteristic	Range	Observation
Age		
	16-29	2 (3.57%)
	30-44	22 (39.29%)
	45-60	24 (42.86%)
	Over 60	5 (8.93%)
	Unknown	3 (5.36%)
Gender		
	Male	23 (41.07%)
	Female	31 (55.36%)
	Unknown	2 (3.57%)
Income		
	Less than $29,999	2 (3.57%)
	$30,000 to $ 59,999	13 (23.21%)
	$60,000 to 99,999	19 (33.93%)
	$100,000 or more	13 (23.21%)
	Unknown	9 (16.07%)
Household size		
	1 person hhld	8 (14.29%)
	2 person hhld	19 (33.93%)
	3 person hhld	10 (17.86%)
	4 person hhld	10 (17.86%)
	4+ person hhld	6 (10.71%)
	Unknown	3 (5.36%)
Average commute time (include stop time)	28.65 min	
Average commute time (exclude stop time)	24.78 min	
Average commute time standard deviation (only for trips without stop)	2.53 min	
Average commute distance	12.29 mile	

TABLE 2. Number of morning commute journey with stops

Number of Stops on Commute Journey	Frequency of Type I Stops	Frequency of Type II Stops	Frequency of Type I and Type II Stops Combined
None	226 (80.71%)	237 (84.64%)	193 (68.93%)
One	49 (17.50%)	37 (13.21%)	74 (26.43%)
Two and More	5 (1.79%)	6 (2.14%)	13 (4.64%)
Total	280 (100%)	280 (100%)	280 (100%)

Notes: Type I stops take place when the driver turns off the engine during the stop. Type II stops take place when the driver doesn't turn off the engine during the stop.

TABLE 3. T-test of paired two sample means of travel distance and travel time

	Without Stop	*With Stop*	*T Stat*	*P(T<=t) one-tail*
Mean Commute Travel Time (sec)	1783	2401	-3.51	0.0008
Mean Commute Travel Distance (mile)	13.27	15.87	-2.46	0.010

TABLE 4. Departure and arrival time switching

	5 min switch threshold	10 min switch threshold	30 min switch threshold
Number of Median Switch of Departure Time	148 (53%)	116 (41%)	54 (19%)
Number of Median Switch of Arrival Time	151 (54%)	119 (43%)	57 (20%)
Number of Day-To-Day Switch of Departure Time	128 (46%)	92 (33%)	31 (11%)
Number of Day-To-Day Switch of Arrival Time	127 (45%)	95 (34%)	34 (12%)

TABLE 5. Route choice of morning commute journey

Category	No. of Commutes With Stops	No. of Commutes With No Stop	No. of Commutes Total
Mode route	64 (79.02%)	178 (89.44%)	242 (86.43%)
Mode route, small deviation	8 (9.87%)	8 (4.02%)	16 (5.71%)
Other routes	9 (11.11%)	13 (6.53%)	22 (7.88%)
Total	81(100%)	199 (100%)	280 (100%)

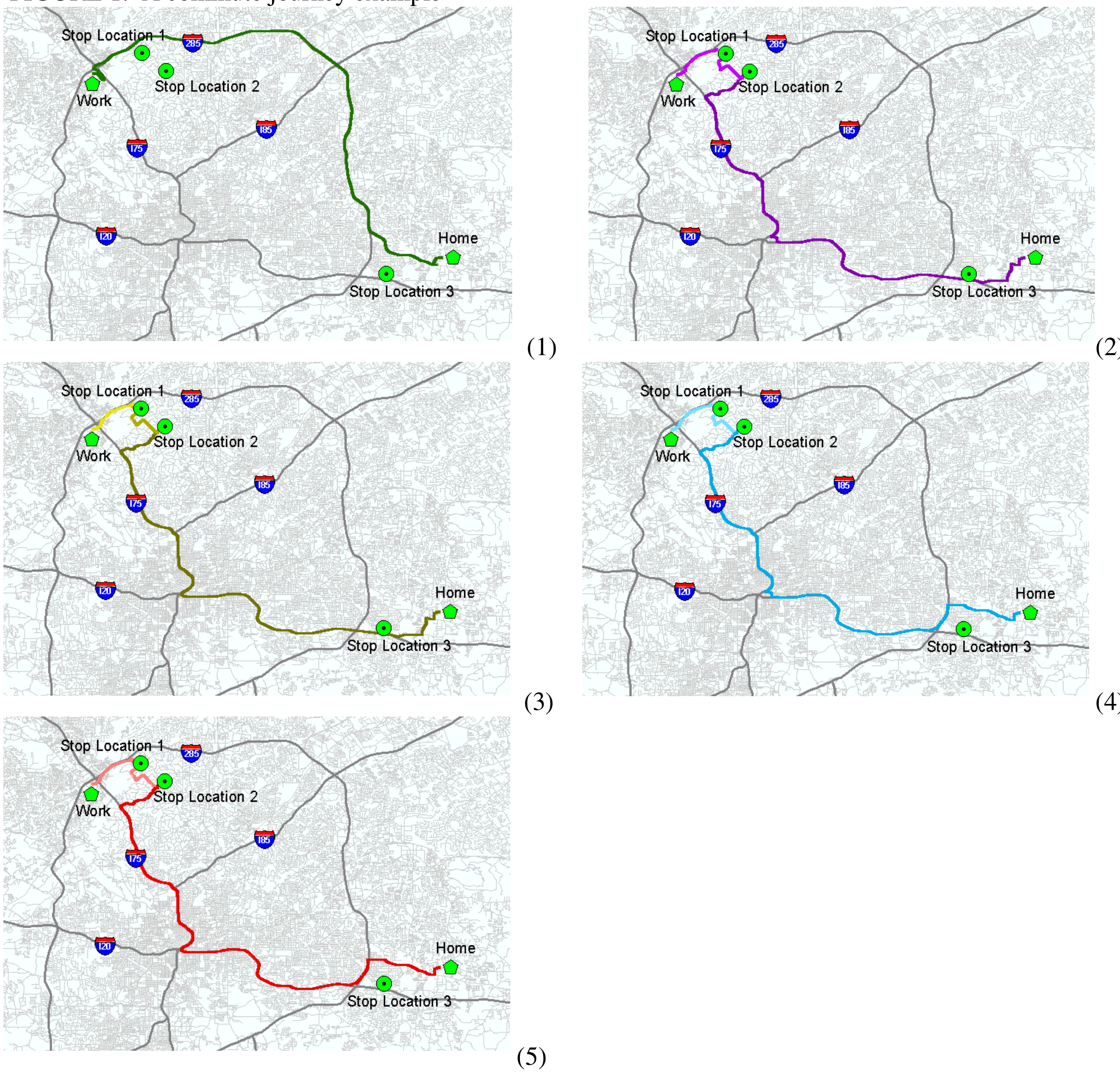
TABLE 6. Route choice pattern of morning commuters

Category	No. of Commuters (With Stop)	No. of Commuters (With No Stop)	No. of Commuters (Total)
One route	12 (40%)	21 (80.77%)	33 (58.93%)
One primary route, used other routes at least once	16 (53.33%)	3 (11.54%)	19 (33.93%)
Two primary routes	2 (6.67%)	2 (7.69%)	4 (7.14%)
Total	30 (100%)	26 (100%)	56 (100%)

TABLE 7. Commuters' characteristics and travel behavior

Characteristic	Range	Mean No. of Stops During 5-day commute	Mean Percent of drivers who stops at least once during 5-day commute	Mean Percent of driver who used other routes at least once during 5-day commute	Mean Percent of Trips have Departure Time Switch under Median 10 minute definition
Age	18-29	1	100.00%	50.00%	20%
	30-44	2.1	59.09%	45.45%	46%
	45-60	2.3	58.33%	41.67%	38%
	Over 60	1	40.00%	20.00%	56%
Gender	Male	2.5	65.22%	43.48%	40%
	Female	1.6	54.84%	41.94%	44%
Income	Less than $29,999	3.5	50.00%	50.00%	40%
	$30,000 to $ 59,999	2.3	61.54%	53.85%	48%
	$60,000 to 99,999	1.4	47.37%	36.84%	38%
	$100,000 or more	2.4	69.23%	38.46%	38%
Household Size	1 person hhld	0.6	37.50%	37.50%	48%
	2 person hhld	2.5	57.89%	36.84%	44%
	3 person hhld	2.2	60.00%	40.00%	28%
	4 person hhld	1.7	70.00%	40.00%	54%
	4+ person hhld	2.8	66.67%	66.67%	30%

FIGURE 1. A commute journey example



Day	Segment	Start Time	End Time	Travel Duration	Total Commute Time	Stop Duration	Route	Stop at location 1	Stop at location 2	Stop at location 3
1	1	08:36:34	09:10:34	34m	0h 34m 0s	0	1	no	no	no
2	1	08:40:02	09:26:58	46m 56s	1h 8m 40s	6minsec	2	no	yes	yes
	2	09:33:07	09:48:42	15m 35s						
3	1	07:34:09	08:16:00	41m 51s	1h 9m 44s	4min48sec	2	yes	yes	yes
	2	08:20:48	08:27:44	6m 56s		4min17sec				
	3	08:32:01	08:43:53	11m 52s						
4	1	07:20:55	08:07:18	46m 23s	1h 7m 59s	8min6sec	2, deviation	no	yes	no
	2	08:15:24	08:28:54	13m 30s						
5	1	08:26:36	09:04:54	38m 18s	0h 59m 55s	8min3sec	2, deviation	no	yes	no
	2	09:12:57	09:26:21	13m 24s						

FIGURE 2. Distribution of stops ratio for morning commuters