Using Household Survey to Forecast Household Mode Choice and Trip Sharing

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Abstract
The paper introduces a new method to forecast household travel mode choice and trip sharing behavior by using household socio-economic survey and trip table data. The method introduces spatial dimension in household travel mode choice analysis. It demonstrates how standard household survey data that are not specifically designed for use in a modal split model can be used to forecast household travel mode choice and estimate ridership for a mass transit mode. Using the sampled data of Bangkok household survey, the forecast reveals that trip sharing is predominant household mode choice, and mass transit is an attractive mode choice.

Keywords: household travel demand, trip sharing, Bangkok

1. Introduction

Urban travel patterns have become increasingly complex due to the interdependence of travel activities and complicated available mode choices. As such, traditional individual trip-based transportation models may be overly simplified and thus may not be appropriate to forecast urban travel demand because they cannot incorporate complexity in travel patterns, for example, shared household mode choices and trip chaining behaviors. In fact, many researchers have emphasized that the analysis of urban travel demand should be conducted at the household level—rather than at the individual level—since it can better incorporate complex travel patterns and interdependence of travel activities (Adler and Ben-Akiva, 1979; Dissanayake and Morikawa, 2002a; Dissanayake and Morikawa, 2010).

Household travel demand forecasting is complex because it is affected by dynamic household life cycle stages and interdependence in daily activities of household members. Analytically, however, due to data limitations, variables in household demand forecasting often use several socio-economic factors such as household income, vehicle ownership, and household demographics as indicators. Although much previous research on household travel behavior has been done in the context of cities in developed countries, little is known about household traveling patterns in developing countries, where daily trips of household members are highly interdependent (Dissanayake and Morikawa, 2002b). As public transportation in these developing countries tends to be insufficient for covering all metropolitan areas and meeting the needs of commuters, households in developing countries are often faced with complicated mode choices (Dissanayake and Morikawa, 2002b). Hence, a simple trip-based analysis may not be suitable for examining travel behavior in the context of developing countries.

Further, transportation analyses in developing countries are quite limited due to a lack of data availability. Generally, to analyze the household travel demand, researchers may choose to conduct their own travel survey, which can be very costly and time consuming. In a developing country like Thailand, where most data are not readily available to the public, ability to effectively use data sets that are regularly produced, yet underutilized, is highly beneficial.

This paper demonstrates an alternative analytical method to analyze travel mode choice of two-traveler households in the Bangkok Metropolitan Region (BMR) when trip sharing is one of the available mode choices, taking into account vehicle ownership. The proposed procedure combines a regularly produced household socio-economic survey and trip distribution tables to forecast household travel demand. To the best of our knowledge, this paper is one of the first few attempts that utilize a household socio-economic survey to forecast household travel mode choices when trip sharing is one of the alternative modes. The contribution of this study, therefore, is to demonstrate how standard household survey data that are not specifically designed for use in a modal split model can be used to forecast household travel mode choice and trip sharing as well as estimate ridership for a mass transit mode.

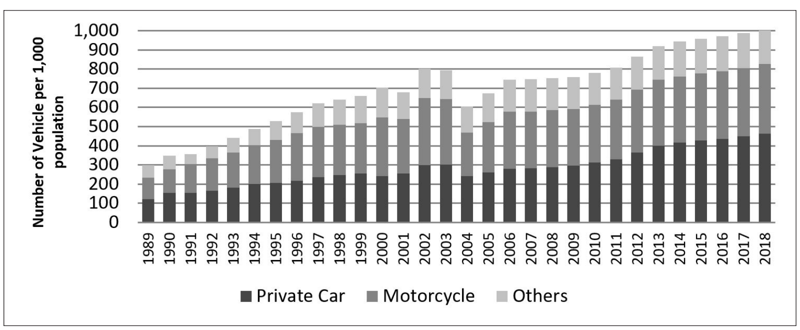
2. Literature Review

Trip sharing is generally defined as a linkage between two travelers in such a way that the first traveler accompanies the second traveler to the second traveler's destination and then continues to his/her final destination. This trip chain can be a linkage of different types of purposes, for example, work, shopping, school, personal business, or recreation.

In urban travel, trip sharing has increasingly become important in travel demand forecasting as it represents more realistically travel behaviors, and thus gives researchers a better understanding of the urban travel demand. In their seminal work, Adler and Ben-Akiva (1979) addressed theoretical and empirical issues in modeling complex travel patterns. Kitamura (1984) formulated an analytical framework to study the effect of trip chaining on destination choices, employing prospective utility of a destination zone as a measure of its attractiveness. He emphasizes that if interdependencies of trips across choices are neglected, the evaluations of effects of zonal attributes and travel time may be biased. Wegmann and Jang (1998) found that individuals who work in urban areas tend to develop trip sharing patterns. Commuters' socio-economic characteristics, workplace conditions, and traffic system characteristics also play an important role in trip sharing patterns (Jou and Mahmassani, 1997; Goulias and Kitamura, 1989). De Palma et al. (2001) found that compatible trip times contribute to trip chaining decisions of household members.

Although most studies have focused on trip chains created by individuals, little attention is paid to household-based trip chaining behaviors (for example, Golob, 2000; Lee et al., 2007; Oliveira et al., 2014), especially in the context of developing countries like Thailand. Travel decisions of households in developing countries often reflect joint decisions for individuals in the household (Zegars and Srinivasarn, 2007; Dissanayake and Morikawa, 2010). As households in developing countries are less likely to own multiple vehicles, travel decisions of household members are highly dependent, and trip sharing is an important component in the analysis of household urban travel demand.

Figure 1. Registered vehicle per 1,000 population, Bangkok, 1989-2018 (**Source:** Office of Transport and Traffic Policy and Planning) **Note:** Others include buses, trucks, vans, and other non-private vehicles



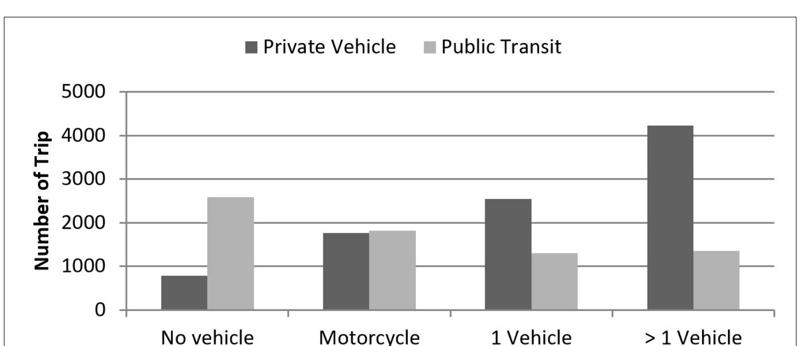


Figure 2. Number of daily trips by private vehicle and public transit, by vehicle ownership, Bangkok, 2009 (**Source:** Office of Transport and Traffic Policy and Planning 2009 Annual Report)

2.1 Previous empirical works on household travel demand

Additionally, since public transportation services in developing cities tend to be insufficient and of inferior quality, travelers in these cities are likely to own and use private vehicles. Bangkok, one of the most congested cities in Asia, is no exception. As shown in Figure 1, private car and motorcycle ownership in Bangkok has grown steadily since 1989. The number of registered vehicles in Bangkok has dropped in 2004-2005 due to changing statistical definition by excluding unutilized vehicles/ statistical procedure.

Vehicle ownership, among other things, can determine travel mode choices. Previous empirical work has shown that Bangkok households with more cars tend to use private automobile as a commuting mode (Fukuda et al., 2005). As shown in Figure 2, people who own more vehicles are less likely to use public transit. It reveals that vehicle ownership should be considered when conducting travel demand forecasting.

Although this stylized fact has shown that vehicle ownership in Bangkok has grown steadily since the 1980s, the level of vehicle ownership by household income is much less than those in developed countries. By comparing vehicle ownership of households in Bangkok and the United Kingdom by the level of household income, Dissanayake and Morikawa (2010) found that high-income households in the UK tend to own multiple vehicles as their income increases, while households in Bangkok are more likely to own only one car even though their incomes grow. In fact, this single-vehicle ownership is quite common in many developing countries where prices of car are relatively much higher than the income level. Zegras and Srinivasan (2007) also show that households in developing countries have higher propensity for trip sharing even though their incomes increase.

As households in Bangkok are likely to own a single vehicle, either one car or motorcycle, they tend to share their trips with other household members. As a result, traveling decisions of household members are closely interrelated (Dissanayake and Morikawa, 2010). Trip sharing, in fact, is very evident for households in Bangkok as a result of high purchase price of vehicle as well as severe traffic conditions in the city. Travel demand forecasting in Bangkok, therefore, should be conducted at a household level, rather than at an individual level, and should take into consideration explicitly this unique household trip sharing characteristic and household vehicle ownership.

Fukuda et al. (2005) examine the possibility of car sharing as both feeder and main mode of transportation for Bangkok commuters. The study found that the level of services and socio-economic attributes such as vehicle ownership, occupation, age, and income, play an important role in determining the usage of car sharing. Dissanayake and Morikawa (2010) examine household trip sharing in Bangkok, taking into consideration household vehicle ownership and traveler characteristics such as job industry, age, and income. The model jointly estimates parameters from both Stated Preference (SP) and Revealed Preference (RP), and thus can be used to forecast household travel demand of new public transit services in Bangkok.

In summary, a review of literature reveals that household trip sharing is important in travel demand forecasting, especially for the developing countries. Socio-economic factors that can influence household travel mode choices in Bangkok include household vehicle ownership, income, and travelers' occupation. The uniqueness of this research is to forecast household travel mode choice without conducting a survey but instead by integrating household socio-economic survey, the origin-destination table, and already calibrated SP/RP model from the previous work of Dissanayake and Morikawa (2010).

3. Study Area

Bangkok and its vicinity are officially called the Bangkok Metropolitan Region (BMR). The BMR consists of Bangkok and its five adjacent provinces, including Nakhon Pathom, Pathum Thani, Nonthaburi, Samut Prakan, and Samut Sakhon. As an automobile-dominant city, roads and highways are major components of Bangkok urban forms. Figure 3 illustrates a major road network as well as inner and outer ring roads, overlaying with BMR provinces and districts within each province. Most densely-populated urbanized areas are within the inner ring roads. Following Dissanayake and Morikawa (2010), the study areas are separated by inner and outer ring roads into three major analysis zones: inner city (1), inner suburbs (2), and outer suburbs (3).

4. Methodology & Data

The procedure of forecasting household travel mode choices involves three main steps: (1) selecting and sorting two-traveler households from household socio-economic survey (SES), (2) assigning travel destination to household members using information from the origin-destination table (O-D Table), and (3) forecasting household travel mode choices using parameters calibrated by Dissanayake and Morikawa (2010). The overall procedure is illustrated in Figure 4. Table 1 summarizes the data and model used in this study.

4.1 Selecting Two-traveler Households from the SES

The first step involves selecting the two-traveler households in the district of interest from the 2008 Household-Socio Economic Survey (SES) data, which contains information at both household and individual levels (see Figure 5). First conducted by Thailand National Statistical Office (NSO) in 1957, the SES has been produced biennially since 1986. The main purpose of the survey is to collect data on household income and expenditure, household consumption, changes in assets and liabilities, durable goods ownership, and housing characteristics. The survey covers all private, non-institutional households nationwide. Further, for the first time the households in the 2008 survey can be associated with the district in which they reside, thus allowing for home-based trip analysis.

After two-traveler households in the study area (the BMR) are selected, these households are then categorized into three groups by their vehicle ownership: car, motorcycle, and no vehicle owning. Households that own both cars and motorcycles are categorized as car owning group since cars are presumably a preferred mode of transportation for commuting trips.

In addition to vehicle ownership, other household characteristics are also extracted from the SES data, which will be used in the later stage. The variables include the number of children in the household, household expenditure, and characteristics of the household head, including gender, education, and marital status.

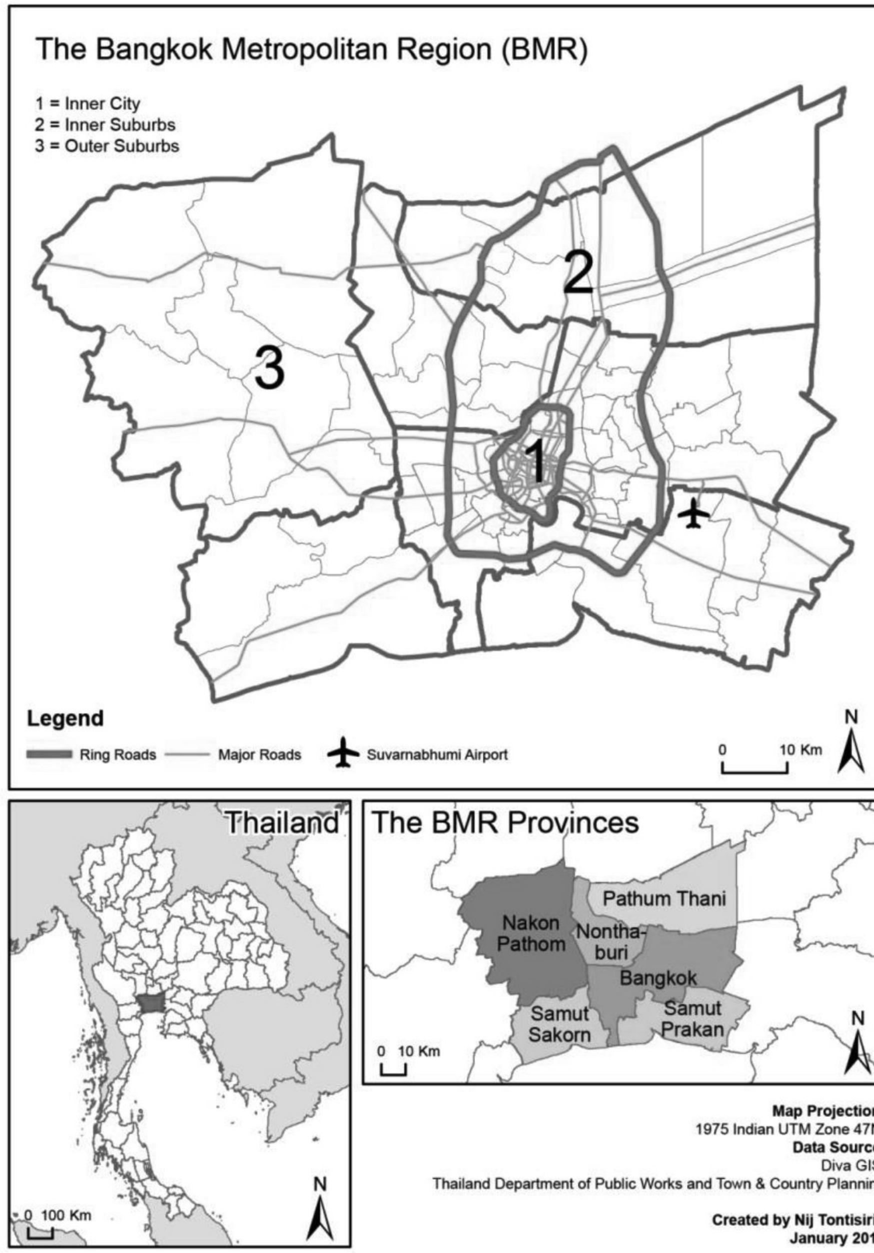


Figure 3. The Bangkok Metropolitan Region and major zoning configuration

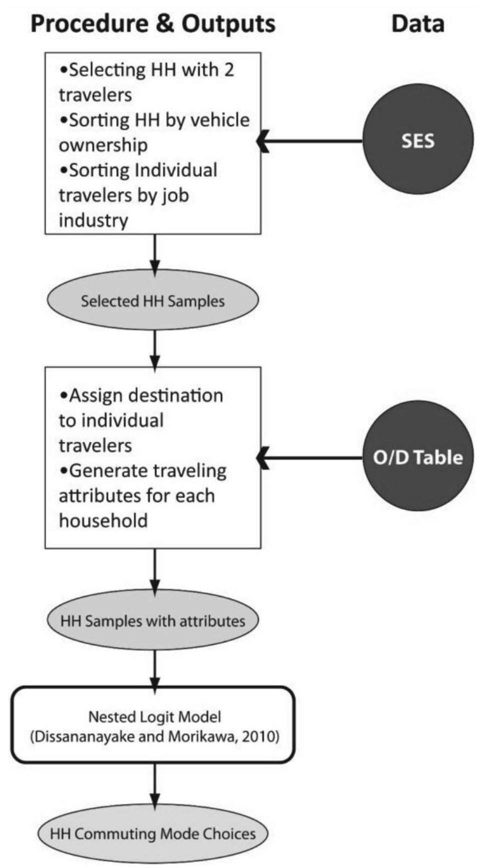


Figure 4. Overview of procedure to forecast two-traveler BMR households

Table 1. Data and model description

Data/Model	Description	Source
2008 Household-Socio Economic Survey (SES)	- Nationwide survey of household demographics, economic status, income and expenditure, housing, and property ownership - Produced biennially - Selected summary statistics available publicly through the website	Thailand National Statistical Office (2008)
Origin-Destination Table (O-D table) and Traffic Analysis Zone (TAZ) geography	- Trip flows between 737 internal traffic zones within the BMR as well as 24 external zones - Internal traffic zones available in a GIS shapefile - Number of school enrollment and jobs (by primary, secondary, and tertiary sector) also available in the attribute of each internal traffic zone	Office of Transport and Traffic Policy and Planning (2009)
Nested Logit Model	- Mode choice model of two travelers in the BMR, with vehicle ownership in the first level of a nested structure and trip sharing as one of alternatives - Using Stated Preference (SP) and Revealed Preference (RP) data	Dissanayake and Morikawa (2010)

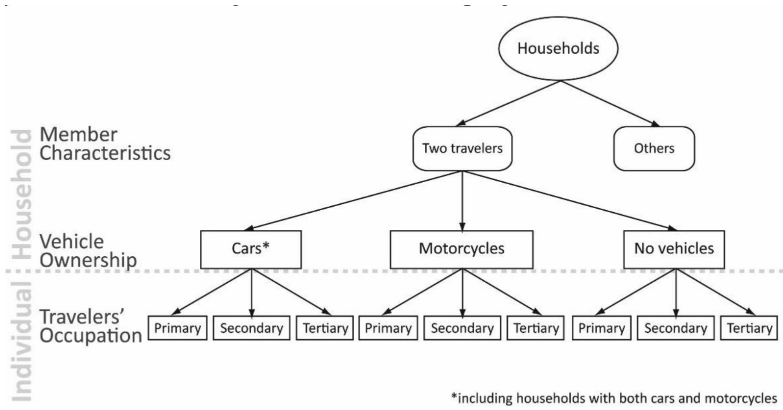


Figure 5. Procedure to select two-traveler Households from the SES

Since the 2008 SES survey is expenditure-based, it does not have information on household income. Yet, household income is needed to compute households' utilities in the forecasting household mode choices (this procedure is not necessary if the household survey contains household income data). Therefore, household income is estimated using the household average propensity to consume (APC), which is by definition the ratio of household consumption to income. The APCs of Thai households are derived from 2007 Thailand Social Accounting Matrix of which the households are categorized into ten percentile groups based on their incomes. The APCs range from 0.9076 for the lowest income group to 0.7688 for the richest. To compute household income (HH Income), the full, nationwide household samples are sorted into ten percentile groups based on their household expenditure (HH Exp). Household income is then computed by dividing household expenditure with the APC of its respective group as shown below.

$$HH\ Income=(HH\ Exp)/APC \qquad \text{(Eq.1)}$$

In addition to household characteristics, individual characteristics are also extracted from the SES, particularly work/study status and job industries, which are used in the next step to assign travel destinations of each traveler. The job industries of workers are categorized into three sectors: primary, secondary, and tertiary, while students are placed in a student category. From these individual job categories, dummy variables for executive and business-related jobs are also created.

4.2 Assigning Travel Destinations Based on Trip Distribution

Given that job industries of individual travelers are known from the SES data in the first step, in the second step each traveler is then assigned a travel destination based on the trip distribution from the Origin-Destination table (O-D table) and zonal attractions of each Traffic Analysis Zone (TAZ) in Geographic Information Systems (GIS).

The O-D Table gives the information of trip distribution among 737 TAZs. Travel modes of these trips include cars, motorcycles, low- and high-comfort public transit, taxis, and trucks. Generally, the low-comfort mode is non-air-conditioned bus trips, while the high-comfort represents air-conditioned bus trips as well as mass transit trips. Since this study examines household travel patterns of commuting trips, truck trips as well as external trips are excluded from the analysis.

In addition to the trip table, the TAZs also show the number of school enrollments as well as employment by primary, secondary, and tertiary sectors in each corresponding TAZ. These school enrollments and employment representing school and job locations are considered to be zonal attractions of commuting trips. Figure 6 depicts spatial distribution of school enrollment and sectorial employment as a percent of total in the BMR, yielding the generalized travel cost for each O-D pair.

Figure 6. Employment by sector and school enrollment by traffic analysis zones in the BMR as a percent of total

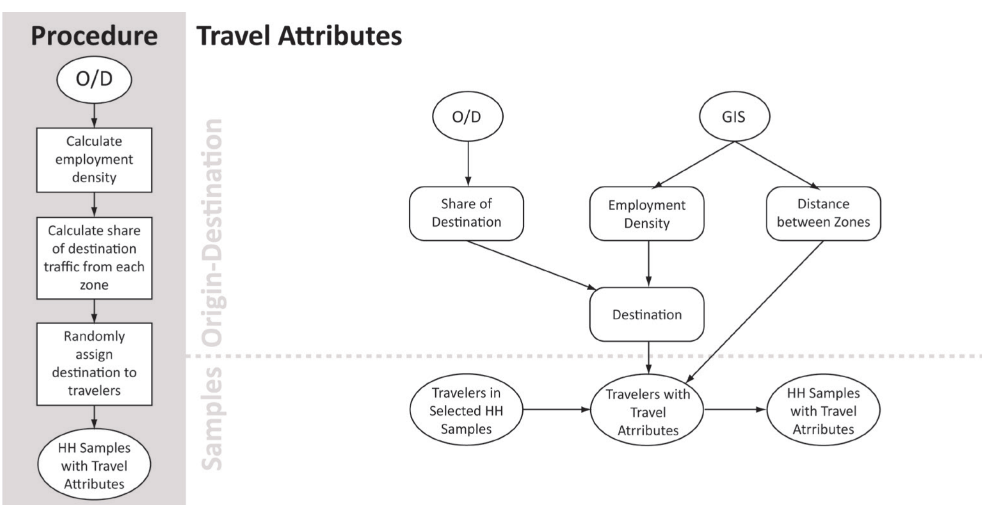


Figure 7. Procedure to assign travel destination

With the information from the O-D table and TAZ zonal attractions, the trip distribution is defined as the joint probability of trip distribution from the O-D table and percent share of total employment in the BMR (or percent share of school enrollment) from the TAZs attributes. The procedure is shown in Figure 7.

Formally, the trip distribution from TAZ i to destination j is defined as:

$$\mu_{ij}=T_{ij} \,/\, \textstyle\sum_j T_{ij} \;, \qquad \text{(Eq.2)}$$

where μ_{ij} = probability of trips originated in zone i to destination j, and
T_{ij} = number of trips originated in zone i to destination j.

Similarly, the percent share of total employment, or school enrollment, in the BMR represents zonal attractions and is defined as:

$$\theta_j^k = H_j^k \,/\, \textstyle\sum_j H_j^k \;, \qquad \text{(Eq. 3)}$$

where θ_j^k = share of employment in a k sector in destination zone j, and
H_j^k = number of employment or enrollment in k sector in zone j, where k{Prim,Scnd,Tert,Sch}.

Assuming that trip distribution is independent of zonal attractions, the joint probability of trip distribution by the percent share of sectorial employment or school enrollment is defined as:

$$p_{ij|k}= \mu_{ij}*\theta_j^k \,/\, \textstyle\sum_j \mu_{ij}*\theta_j^k \;, \qquad \text{(Eq. 4)}$$

where $p_{ij|k}$ = probability of trips from zone i to j given a traveler engaged in a k sector activity, where k {Prim,Scnd,Tert,Sch},
μ_{ij} = probability of trips originated in zone i to destination j, and
θ_j^k = share of employment in a k sector in destination zone j.

From these joint probabilities of trip distribution and zonal attraction, the cumulative frequency distribution can be derived and thus used to assign travel destinations. Let $P_{i|k}$ denotes cumulative frequency distribution of trips in k sector originated in zone i. The cumulative frequency distribution is defined as:

$$P_{i|k}(n) = \textstyle\sum_{j\le n} p_{ij|k} \;, \qquad \text{(Eq. 5)}$$

where n = the number of internal TAZs.

The destination assignment procedure begins by generating a uniformly-distributed random number, ranging between zero and up to one, for each traveler. This random number is then looked up through the derived cumulative frequency distribution, and a traffic zone with the same range of cumulative distribution is assigned to a traveler. Figure 8 graphically illustrates the destination assignment procedure of a traveler working in the secondary sector as an example.

Let x denotes a generated random number, depicted on the y-axis. The generated random number x is matched against the cumulative frequency of the corresponding sector k to find a destined TAZ n. A traveler is destined in zone n when:

$$P_{i|k}(n\text{-}1) < x \le P_{i|k}(n) \qquad \text{(Eq. 6)}$$

One caveat worth mentioning here is that travel destinations of each traveler in a household are assumed to be independent. We acknowledge that our assumption may not be realistic as travel destinations of household members may be interrelated. However, due to the absence of empirical data, we are unable to test this correlation structure. Thus, for this study, we are assuming that destinations of each traveler are independent. Another assumption we make is that households living in the same district share similar characteristics. In other words, the same set of households is used across traffic zones within the same district.

Once travel destinations are assigned, household travel distances, which have direct implication on travel time and costs, can be calculated. Due to insufficient quality of the road network data, Euclidean distances among TAZs are used instead of network distances. With geographical boundaries of TAZs, Euclidean distances between each TAZ are calculated from a centroid of each zone using Geospatial Modeling Environment (GME) by Beyer (2011) and ArcGIS.

Since we do not know whether household members choose trip chain or not, two types of distances are calculated. As shown in Figure 9, point A depicts a household's residential location, while point B and C represent a workplace or school location of each traveler. The first type of household distance—the distance AB and AC—is calculated for non-trip sharing. On the other hand, the second type of distance—the distance AB and BC—is generated for trip sharing. Based on these calculated distances, travel time in hour is first calculated, assuming that average travel speed is 15 kilometer per hour (Office of Transport and Traffic Policy and Planning, 2009). Travel costs are then calculated by multiplying travel time by the value of time (VOT) parameter from Dissanayake and Morikawa (2010). The VOT parameter is 42 Thai Baht per hour (around US $1.5 per hour). The entire mechanism of this destination assignment and household attribute formatting is done using Visual Basic Application in Microsoft Excel.

4.3 Forecasting Household Commuting Mode Choices

After both types of household travel distances, travel time, and travel costs are computed in previous steps, the last procedure is to forecast household travel mode choices using a nested model calibrated by Dissanayake and Morikawa (2010). The model combines Revealed Preference (RP) and Stated Preference (SP) and considers explicitly BMR household vehicle ownership in the first level of a nested logit model. Two models are presented in Dissanayake and Morikawa (2010); one is calibrated from RP data, and the other from the combined RP/SP data.

In the RP model, the upper level of the nested structure represents three basic choices of vehicle ownership, that is, car, motorcycle, and no vehicle. The lower level consists of 17 mode choice combinations of two travelers, of which trip sharing is considered one of the options as shown in Figure 10.

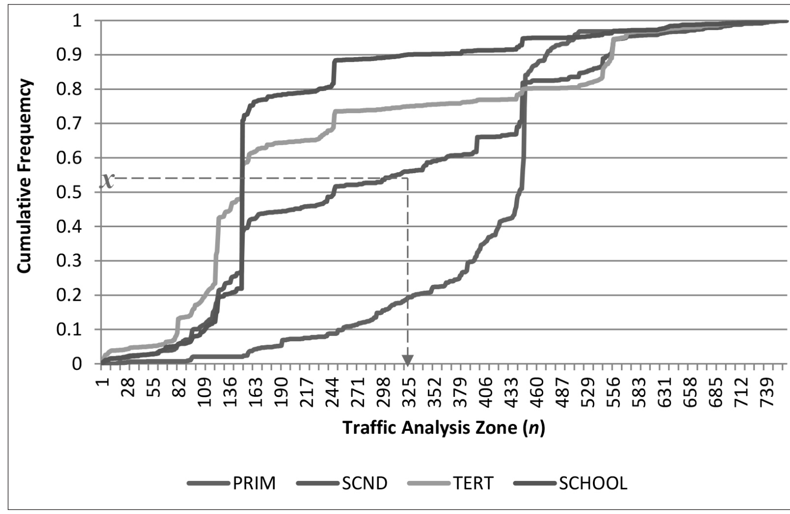


Figure 8. Cumulative frequency distribution of primary (PRIM), secondary (SCND), tertiary (TERT), and school sectors from a TAZ in the BMR

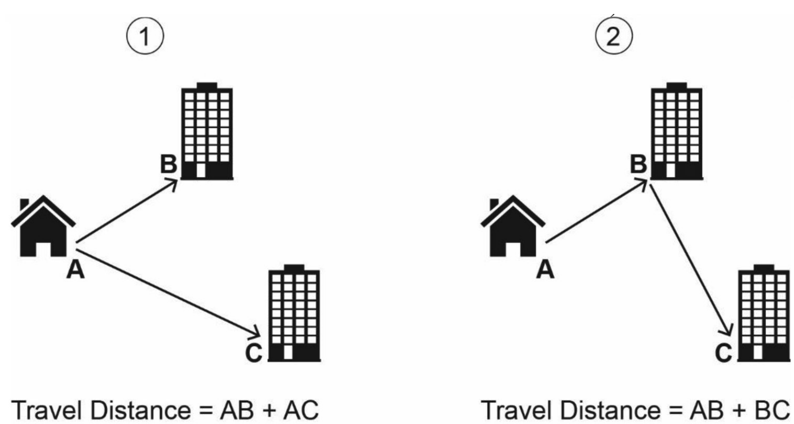


Figure 9. Two types of household travel distances: (1) without trip sharing and (2) with trip sharing

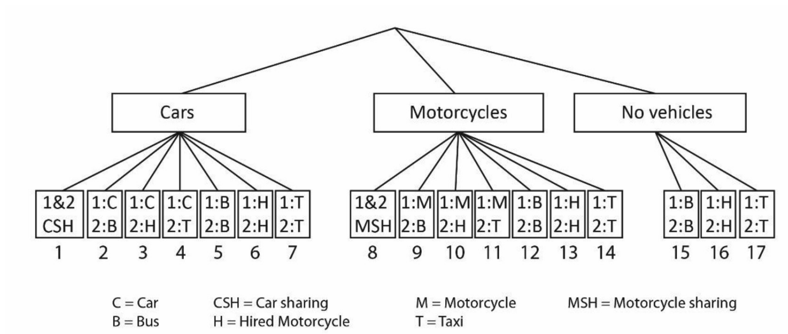


Figure 10. The nested structure of Revealed Preference (RP) model (**Source**: Dissanayake and Morikawa (2010)

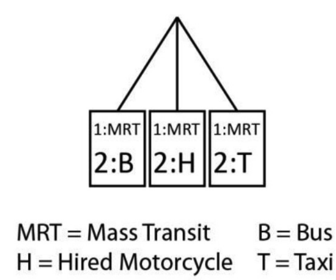


Figure 11. Additional mode choices in the combined Revealed and Stated Preference (RP/SP) model

For RP/SP model, the analysis of the mass transit uses of commuter (first traveler) is introduced. The SP model was calibrated from a multinomial model of Dissanayake and Morikawa (2010) with three choices available for the first traveler, which are car, bus, and MRT. As such, for each group of vehicle ownership, three additional mode choices are available in the combined RP/SP model. In addition to 17 mode choice combinations in the RP model, the nested structure of the combined RP/SP model includes nine other household mode choices—three choices for each vehicle ownership group—of which MRT is the first traveler's alternative in combination with bus, hired motorcycle, and taxi of the second traveler respectively (see Figure 11). The table reporting parameters of both RP and RP/SP models is shown in the Appendix.

Based on the RP and RP/SP model structure, vehicle ownership defines available travel mode choices for each household. Households' travel mode choices are predicted based on estimated utility level of each available mode choice. A household is expected to select a mode choice that gives the highest utility level.

Following Dissanayake and Morikawa (2010), the household utility for each alternative is calculated as follows:

Estimated utility of household i in car ownership group if choosing mode choice m:

$$\hat{U}_{im,car} = \alpha_m + (\beta * LOS_i) + (\gamma_{m,car} * DUMMY_i) \quad \text{(Eq.7)}$$

Estimated utility of household i in motorcycle ownership group if choosing mode choice m:

$$\hat{U}_{im,mc} = \alpha_m + \delta_{mc} + (\beta * LOS_i) + (\gamma_{m,mc} * DUMMY_i) \quad \text{(Eq.8)}$$

Estimated utility of household i in no-vehicle ownership group if choosing mode choice m:

$$\hat{U}_{im,no\_veh} = \alpha_m + \delta_{no\_veh} + (\beta * LOS_i) + (\gamma_{m,no\_veh} * DUMMY_i), \quad \text{(Eq.9)}$$

where

LOS_i = a matrix of level-of-service variables = {travel time (h), travel cost/income},

$DUMMY_i$ = a matrix of alternative specific dummies,

α_m = mode specific constants for both travelers,

$\delta_{mc}, \delta_{no\_veh}$ = vehicle ownership constants for motorcycle and no-vehicle,

β = coefficients of level-of-service variables, and

$\gamma_{m,car}, \gamma_{m,mc}, \gamma_{m,no\_veh}$ = coefficients of alternative specific dummies

5. Results and Discussions

In this analysis, we will demonstrate the forecasting procedure by selecting six TAZs—with varying degree of household sample sizes and vehicle ownership—and examining mode choices of two-traveler households in these TAZs. For simplicity, six TAZs are selected to represent variation in locations and mass transit availability. Within each major zone—inner city, inner suburb, and outer suburb—two TAZs are selected: one with the existence of mass transit (both in the present or future) and the other without mass transit.

Figure 12 shows the locations of selected TAZ, called by their identifier number for convenience, overlaying with major highways, ring roads, and locations of mass transit stations. As can be seen, the zones within the inner city includes zone 150 and 87; within the inner suburbs are zone 677 and 240; within the outer suburbs are zone 613 and 461. Overall, out of the selected 236 households, 86 (36 percent) are categorized in car-owning group, while both motorcycle owning and no vehicle owning group each equally has 75 households or 32 percent.

The number of household samples is shown by their vehicle ownership and TAZ in Table 2. As can be seen, vehicle ownership in these selected TAZs varies considerably. Household samples in outer suburb TAZs have less share of car ownership, while around 50% of household samples in the inner city and inner suburb are car owning group.

Figure 12. Six selected Traffic Analysis Zones in the BMR

Table 2. Vehicle ownership of two-traveler households by selected Traffic Analysis Zones

	Location					
	Inner City		Inner Suburb		Outer Suburb	
Mass Transit	**With**	**Without**	**With**	**Without**	**With**	**Without**
Traffic Analysis Zone	**150**	**87**	**677**	**240**	**613**	**461**
Vehicle Ownership (HH)						
Car owning	17 (46%)	10 (56%)	39 (37%)	14 (67%)	2 (6%)	4 (18%)
Motorcycle owning	8 (22%)	3 (17%)	32 (30%)	4 (19%)	13 (41%)	15 (68%)
No Vehicle owning	12 (32%)	5 (28%)	35 (33%)	3 (14%)	17 (53%)	3 (14%)
Total Households	**37**	**18**	**106**	**21**	**32**	**22**

Table 3 shows the forecasted household travel mode choices of these selected TAZs using RP model. The RP model predicts some extent of trip sharing in both car owners and motorcycle owners; around one-third of car-owning households share their trips. Car-owning households are also slightly less likely to share their trips compared to motorcycle-owning ones. The RP model also predicts that both travelers in no-vehicle households tend to use buses; these results are quite reasonable since bus fares in Bangkok, ranging from $0.25 to $0.75 a ride in 2008, are considerably cheaper than any other modes of transportation. The results are also consistent with the fact that buses are major public transportation mode of transportation in Bangkok at that time (Office of Transport and Traffic Policy and Planning, 2009).

Table 3. Forecasting results of RP model

	Traffic Analysis Zone						
Household mode	**150**	**87**	**677**	**240**	**613**	**461**	**Total**
Car owning	17 (100%)	10 (100%)	39 (100%)	14 (100%)	2 (100%)	4 (100%)	**86 (100%)**
car sharing	5 (29%)	1 (10%)	12 (31%)	6 (43%)	0 (0%)	1 (25%)	25 (29%)
1: car, 2: bus	12 (71%)	9 (90%)	27 (69%)	8 (57%)	2 (100%)	3 (75%)	61 (71%)
Motorcycle owning	8 (100%)	3 (100%)	32 (100%)	4 (100%)	13 (100%)	15 (100%)	**75 (100%)**
MC sharing	2 (25%)	3 (100%)	11 (34%)	2 (50%)	5 (38%)	7 (47%)	30 (40%)
1: mc, 2: bus	6 (75%)	0 (0%)	21 (66%)	2 (50%)	8 (62%)	8 (53%)	45 (60%)
No Vehicle owning	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	**75 (100%)**
1: bus, 2: bus	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	75 (100%)
Total households	**37**	**18**	**106**	**21**	**32**	**22**	**236**

Table 4. Comparison of forecasted modal share to the RP data

	Forecasted		RP Data
Household mode	**HH**	**%**	**%**
Car owning	**86**	**36%**	
car sharing	25	11%	13.2%
1: car, 2: bus	61	26%	12.0%
Motorcycle owning	**75**	**32%**	
MC sharing	30	13%	16.3%
1: mc, 2: bus	45	19%	13.4%
No Vehicle owning	**75**	**32%**	
1: bus, 2: bus	75	32%	37.1%
	236	**100%**	

Note: RP data from Dissanayake and Morikawa (2010)

The forecasting model yields the modal share results that are also consistent with the RP data in Dissanayake and Morikawa (2010) (Table 4). Our procedure predicts five modes (car sharing, car & bus, MC sharing, motorcycle & bus, and bus & bus), which are major modal share in the RP data. Car sharing mode, for example, is 11% while the modal share of car sharing in the RP data is 13.2%. Trip sharing for both car and motorcycle is predominant mode choice. However, we acknowledge that the forecasting model may overestimate car & bus mode due to the absence of other predicted model.

As shown in Table 5, the forecasting results from the combined RP/SP model suggest that modal shift of first travelers to MRT (See Table 4). Clearly, the result is strongly biased toward MRT, and small sample sizes may be contributing to these results. In particular, the model predicts that the first traveler in car-owning and no-vehicle households tend to use MRT. A closer inspection of the predicted household utilities reveals that the MRT mode gives much higher utility than other modes, suggesting that, when available, MRT is a very attractive mode of transportation for both car and bus users.

The results are in fact consistent with the previous empirical study that most MRT users are previous bus riders (Hayashi et al., 1998). In addition, one caveat worth mentioned here is that structure of SP model only takes into account the use of MRT by the first traveler and does not capture the attractiveness of trip sharing. Hence, we can forecast the MRT uses only by the first traveler and the results may be highly biased toward MRT.

Household Mode	Traffic Analysis Zone 150	87	677	240	613	461	Total
Car owning	17 (100%)	10 (100%)	39 (100%)	14 (100%)	2 (100%)	4 (100%)	**86 (100%)**
1: car, 2: bus	1 (6%)	0 (0%)	3 (8%)	2 (14%)	2 (100%)	2 (50%)	10 (12%)
1: MRT, 2: bus	16 (94%)	10 (100%)	36 (92%)	12 (86%)	0 (0%)	2 (50%)	76 (88%)
Motorcycle owning	8 (100%)	3 (100%)	32 (100%)	4 (100%)	13 (100%)	15 (100%)	**75 (100%)**
MC sharing	2 (25%)	1 (33%)	5 (16%)	1 (25%)	5 (38%)	6 (40%)	20 (27%)
1: MRT, 2: bus	6 (75%)	2 (67%)	27 (84%)	3 (75%)	8 (62%)	9 (60%)	55 (73%)
No Vehicle owning	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	**75 (100%)**
1: MRT, 2: bus	12 (100%)	5 (100%)	35 (100%)	3 (100%)	17 (100%)	3 (100%)	75 (100%)
Total households	**37**	**18**	**106**	**21**	**32**	**22**	**236**

Table 5. Forecasting results of RP/SP model

This household forecasting methodology has demonstrated how households commuting mode choices can be predicted from the regular socio-economic household survey. This method enables the researchers to examine household mode choices without necessarily conducting a time-consuming and costly household traveling survey. This method can be applied to other TAZs to gain mode share of the entire BMR households, which would be further steps of the study.

6. Conclusion

This study demonstrates how one can fully utilize the household socio-economic survey—the data set not designed for analyzing household travel patterns—with the trip distribution table (O-D table) to examine traveling patterns. By combining household attributes and vehicle ownership, the BMR trip table, and the Revealed Preference and Stated Preference forecasting model, this methodology allows for examining travel mode choices of urban subpopulation in the BMR. Specifically, this study examines mode choices of two-traveler households in the BMR when trip sharing is one of the mode alternatives.

The forecasting results of sampled households in the BMR suggest that this method can be used as an alternative estimation method for household travel demand analysis when travel data are limited. The results also highlight the utilization in analysis of household trip sharing as well as in predicting demand for future public transportation services. The results suggest that most MRT users are converted from bus users, which conforms to the results of previous study by Hayashi et al. (1998). The proposed method can be further extended by incorporating route choices with network travel distances, time, and travel costs if such data are available.

With mass transit systems in the BMR are currently being expanded, this household mode choice forecasting model can be used in the planning of transit services to quickly estimate household travel demand as well as mass transit ridership in the area around the new mass transit. In addition, this method can be combined with other calibrated mode choice models to validate to estimated results.

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Table A.1 Coefficients from Revealed Preference estimation model of Dissanayake and Morikawa (2011)

Parameters	Car-owning Mode Choice							Motorcycle-owning Mode Choice							No Vehicle Mode Choice		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Mode Specific Constant	3.4	4.69	3.49	1.52	2.61	0.81		3.8	4.71	3.51	1.54	2.61	0.81		2.61	0.81	
Alternative Specific Constants								0.69	0.69	0.69	0.69	0.69	0.69	0.69	2.23	2.23	2.23
Level-of-service parameter (LOS)																	
Travel Time (h)	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55
Travel Cost/Income/100	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15	-2.15
Dummy variables (DUMMY)																	
Male commuter	1.63							1.63									
Travel distance for both travelers > 30km		1.61															
Distance between destinations ≥ 10km									1.1								
Distance between destinations ≤ 15km	0.83							0.83									
Second travelers travel distance > 5km			-2.02														
Distance share of both travelers > 75%								0.58									
Commuter's job (executive)								-1.00									
Commuter's job (executive or business)	1.29	1.29	1.29	1.29	1.29	1.29	1.29										
Travelers jobs are not executive															0.51	0.51	0.51
Commuter's age > 50yrs															0.59	0.59	0.59
School children in the household ≥ 1	0.95	0.95	0.95	0.95	0.95	0.95	0.95										
Household income ≤ 25000 Baht															1.67	1.67	1.67
Trips touching CBD		0.82															
Trips within CBD	-0.8	-0.8	-0.8	-0.8	-0.8	-2.62	-0.8	-1.1					-1.82			-1.82	

Table A.2 Coefficients from Revealed/Stated Preference estimation model of Dissanayake and Morikawa (2011)

Parameters	Car-owning Mode Choice										Car-owning Mode Choice										No vehicle					
	1	2	2.1	3	3.1	4	4.1	5	6	7	8	9	9.1	10	10.1	11	11.1	12	13	14	15	15.1	16	16.1	17	17.1
Mode Specific Constant	2.86	4.53	6.53	3.31	5.31	1.43	3.43	2.55	0.71		2.92	4.56	6.53	3.34	5.31	1.46	3.43	2.55	0.71		2.55	6.53	0.71	5.31		3.43
Alternative Specific Constants											0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	2.1	2.1	2.1	2.1	2.1	2.1
Level-of-service parameter (LOS)																										
Travel Time (h)	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57	-0.57
Travel Cost/Income/100	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51	-2.51
Dummy variables (DUMMY)																										
Male commuter	1.65										1.65															
Travel distance for both travelers > 30km		1.8																								
Distance between destinations ≥ 10km												1.6														
Distance between destinations ≤ 15km	0.79										0.79															
Second travelers travel distance > 5km				-2.3																						
Distance share of both travelers > 75%											0.56															
Commuter's job (executive)											-1.4															
Commuter's job (executive or business)	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37	1.37																
Travelers jobs are not executive																					0.54	0.54	0.54	0.54	0.54	0.54
Commuter's age > 50yrs																					0.63	0.63	0.63	0.63	0.63	0.63
School children in the household ≥ 1	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2																
Household income ≤ 25000 Baht																					1.75	1.75	1.75	1.75	1.75	1.75
Trips touching CBD																										
Trips within CBD	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85	-2.67	-0.85	-1.4								-1.82				-1.82			
RP mode, Bus, Car: SP	2.48	2.48	2.48	2.48	2.48	2.48	2.48	2.48					2.48		2.48		2.48	2.48			2.48					
Car ownership or Car and Motorcycle ownership	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89	-0.89						