TRIP GENERATION MODELING FOR LONDON, ONTARIO, CANADA: A MICRO-ANALYTICAL APPROACH

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Introduction

The transportation planning process has been used intensively by estimating urban travel demand models since the mid-1950s. Researchers and policy makers have been using these models to make informed decisions on the future development and management of urban transportation systems. To date, the majority of the efforts in the literature have been focused on developing aggregate zone based models (TMIP, 2014). In this framework, the urban area is divided into a finite number of zones known as traffic analysis zones (TAZs) that form the units of analysis in the model. However, with the need to capture the travelers' behavior, there has been a shift towards developing micro-based models that make use of households and individuals as the unit of analysis. In general, the zone based approach has been criticized due to the lack of the realism needed to capture the actual travel behavior observed in the urban area. This paper strives to advance the micro-based paradigm by studying trip generation in the London Census Metropolitan Area (CMA). It does so by developing micro-based trip generation models using a household travel survey that was collected in the year 2009. The focus will be to compare various techniques that could be used to model trip generation (i.e., regression, cross-classification, discrete choice, and count models) at the micro-level.

Background

Factors Influencing Trip Generation

The current literature makes a persuasive case on the factors influencing trip generation for an average weekday. The reviewed studies highlight the relationship between trip frequency and the following measures: household size, employment, gender, age, household income, and mobility tools. In addition, some studies emphasize the importance of separating the generated trips based on the purpose of the trip. For instance, previous studies show that increase in household size has a positive impact on the total trip frequency for both all-purpose (Badoes & Chen, 2004) and non-work trips (Huntsinger et al., 2013; Jang, 2005). Similarly, employment has also shown to positively impact the total number of generated all-purpose trips (Badoe, 2007; Badoe & Chen, 2004; Roorda et al., 2010), work trips (Chang et al., 2014; Huntsinger et al., 2013; Páez et al., 2006) and non-work trips (Jang, 2005). Gender also shows to impact trip generation. Past studies have shown that males have a positive influence on total trips (Badoe, 2007; Badoe & Chen, 2004) while females have a positive impact on shopping and social trips (Fox & Patruni, 2015). This is expected as in a multi-person household, females are typically more likely to engage in shopping and social trips. Furthermore, a study conducted by Nobis et al. (2004) highlights that the gender difference in travel patterns is linked to employment status, household structure, child care, and maintenance tasks.

The current evidence on the relationship between age and trip generation is inconsistent (Badoe, 2007; Huntsinger et al., 2015; Jang, 2005; Páez et al., 2006; Roorda et al., 2010). For example, an examination by Badoe (2007) of the affect of age on total trip frequency shows that young people (11-17 years) are more likely to engage in more trips, and the number of generated trips decreases as age increases, with the lowest trips generated for seniors. Another study by Roorda et al. (2010) reports that the total trips generated per household in Hamilton, Toronto and Montreal is highest for the young age group (<20 years) and the working age group (36-50 years). Finally, Páez et al. (2006) highlights that for work trips, trip rate is relatively low for the young age group (<20 years), and increases with age reaching a peak for the working age group (34-50 years). The impact of age then decreases for the pre-retirement and senior age groups. As for the non-work trips, the number of generated trips decreases rapidly for individuals in the pre-retirement and senior age groups (Páez et al., 2006).

Finally, household income and mobility tools have a positive impact on the trip frequency of work and non-work trips (Badoe, 2007; Badoe & Chen, 2004; Chang et al., 2014; Jang, 2005; Páez et al., 2006; Roorda et al., 2010). Household income reflects the degree of economic activity by a household. Also, the availability of mobility tools (e.g. vehicle ownership, driver license and transit accessibility) reflects the degree of accessibility of a household. Therefore, increase in household income and accessibility (i.e. mobility tools) suggests that a household is actively participating in economic activities (increase in work trips). Consequently, a household then becomes more active in participating in shopping and social and recreational trips.

Modeling Techniques

The techniques used to model trip generation in past studies can be categorized in four groups; regression, category analysis, discrete choice, and count models. The traditional models that have been widely employed in empirical studies are linear regression models (Badoe, 2007; Chang et al., 2014) and category analysis (Chang et al., 2014). Although they have shown acceptable performance from a planning perspective, there are limitations to these methods. For example, regression models have three main limitations; 1) the likelihood of negative trip rates, 2) the continuous dependent variable, 3) and the lack in incorporation of traveler behavior theory (Chang et al., 2014). Although category analysis is seen to have an advantage over regression models (Chang et al., 2014), this technique requires large sample sizes to reduce uncertainty for the cell-by-cell calculation, hence incurring high cost and time.

The later limitations can be overcome using discrete choice and/or count data models; ordered logit/probit (Badoe, 2007; Chang et al., 2014; Huntsinger et al., 2015; Roorda et al., 2010; Páez et al., 2006), Poisson (Badoe, 2007; Chang et al., 2014; Jang, 2005), negative binomial (Badoe, 2007; Jang, 2005), and zero inflated models (Jang, 2005). Ordered logit and probit models are regression models that consider the ordinal nature of the dependent variable. On the other hand, count models like the Poisson regression model is often used for modeling count data when the data does not suffer from over-dispersion. To overcome over-dispersion in the count data, the negative binomial models can be used. A zero-inflated model is typically considered to correct for excess zeros in the dependent variable.

Badoe (2007) and Chang et al. (2014) show that the performance of the different modeling techniques differs from one dataset to the other. Some studies found that traditional modeling techniques do a better job predicting trip generation in the base-year. That is, predictions with these models were associated with less error compared to other complex technique (Badoe, 2007; Chang et al., 2014). On the other hand, one should keep in mind that although some approaches may lead to better replication of observed travel patterns, they might not necessarily lead to better forecasts. Accordingly, the predictive ability of various models must be validated by a comparison of the observed and predicted trip rates. Some validation techniques that have been used include; correlation index, root-mean-square error, and coincidence ratio, as will be explained in the methods of analysis section (see Chang et al., 2014).

Method of Analysis

Study Area & Data

The analysis in this research is focused on the London CMA located in Southwestern Ontario, Canada. London occupies approximately 2,665.62 km^2 of Canada's land (Statistics Canada, 2015). According to the most recent Canadian census, the population of London CMA in 2011 was 474,786 living in 195,055 dwellings and contributing to 214,545 jobs in the year 2011.

The data used in the analysis was acquired from two main sources: 2011 Canadian census and the London Household Travel Survey (LHTS). The Canadian census data provide demographic information such as the population and employment numbers, and information on family structure and household count by dwelling type for each census tract. The LHTS provides information on the traveler's socioeconomic characteristics such as age, gender, employment status, dwelling type, vehicle ownership, and transit accessibility. As for the trip-related information, it includes the locations of the trip's origin and destination. In addition, the travelers were asked to reveal the mode used to make the trip and the purpose of the trip. Here, nine travel modes; auto drive, auto passenger, London transit, chartered bus, school bus, taxi, motorcycle, bicycle, and walk are recorded. The survey also classifies the trip based on nine purposes; work, work related, school, pick up/drop off passenger, shopping, social and recreational, personal business, returning home, and other. For modeling purposes, these categories were collapsed into five main groups; work, school, shopping, social and recreational, and other. The "other" trip purpose category includes trips that are classified in the following subcategories: personal business, pick up/drop off passenger and other. The survey is expanded using data from the Canadian census and population synthesis techniques, as will be highlighted in the next sub-section.

Out of all the work and non-work trips in the dataset, over 51% were home-based work trips, while school trips accounted for 19%. On the other hand, shopping and other trip purposed accounted for about 15% and 10% respectively. As for social and recreational trips, they pertained to about 5%. Therefore, the non-work trips pertained to about 49% of the total trips for the London CMA. Moving to the travelers' socio-demographic characteristics, females account for about 51% of the sample. Travelers under the age of 20, and aged 35-49 each represent 24% of the total sample followed by travelers aged 20-34 with 20%, then those aged 50-64 with 17% and 65+ with about 15% of the total sample. More than twenty-seven percent of the surveyed travelers live in apartments. Households with three occupants constitute nearly 35% of the sample, while 28% of the dataset consists of households with two occupants.

Expanding the LHTS

The Combinatorial Optimization (CO) technique is used to synthesize a disaggregate list of households with attributes, when aggregated conform to predefined zonal totals provided by the 2011 Canadian census. To reach the optimal solution, the simulated annealing (SA) approach was employed. For more information on the simulated annealing approach in the context of CO method see Williamson et al. (1998). This process was repeated multiple times to confirm the consistency of these populations. To generate a representative aggregate cross-tabulation, as an input to the synthesizing process, zonal totals from the Canadian census were used. The cross-tabulations included information on gender, age category, and dwelling types per census tract. Next, a micro-sample of more than 6,200 households were extracted from the survey responses were information on gender, age, and dwelling type are stated. The CO method was then used to create a list of more than 195,000 households, where each household in the sample has information on the members of the household (gender and age category) and dwelling type. Each synthesized household was linked directly to a household in the micro-sample, and as such the information needed on vehicle ownership, employment, mode choice, etc. were assigned. A 5% sample (about 10,000 households) was randomly selected from the synthesized population of 195,000 households for modeling purposes using the stratified sampling technique. The population was divided into groups based on household size (1, 2, 3, 4, 5, and 6 or more members), and a random sample was obtained from each group based on their percentage in the entire population. This was done to ensure that the sample used is representative of all groups in the entire population.

Model Formulation

Table 1 lists the variables used in the analysis. These variables were inspired by the information found in the literature on the factors affecting work and non-work trip generation. Starting with socio-demographic variables, the young and senior age groups are expected to generate the least number of work trips compared to other population age groups. The highly economically active age group (35-49 years of age) is expected to generate the most work trips. As for non-work trips, it is expected that as age increases, the non-work trip rate will also increase but in a non-linear fashion. Therefore, five variables representing different age groups in a household are used and *Age1* is chosen as the reference category (RC). Besides age, gender is also expected to affect trip generation. Males are expected to generate more work trips, whereas females are expected to generate more non-work trips as they are more social active compared to males. In addition, by exploring the temporal distributions of the trips by trip purpose for an average weekday for London CMA, we concluded that like most metropolitan areas, the London CMA strains the transportation network during the peak periods. Work trips are found to take place in the AM peak period (6-9 am). Whereas for non-work trips, they mostly take place in the AM-off peak and in the mid-day period. As a result, dummy variables representing the hour of the day the trip took place in are also considered. Finally, a dummy variable representing the social trips are also used to distinguish the shopping from social trips in the non-work trips analysis.

Table1. List of variables used in analysis

Variable	Description	Expectation
Age 1	The population of less than 20 years in a household	RC
Age 2	The population of 20 to 34 years in a household	+
Age 3	The population of 35 to 49 years in a household	+
Age 4	The population of 50 to 64 years in a household	+
Age 5	The population of 65 years and older in a household	-/+*
Males	The population of males of 15 years and older in a household	+
Vehicles	The number of vehicles owned in a household	+
Social	1 if purpose of the non-work trip is social and recreational; 0 otherwise	+
Social × Females	An interaction term between non-work trip purpose (social and recreational) and the population of females of 15 years and older in a household	+
Dummy1	1 if the work trip took place between 6 and 7 am; 0 otherwise	+
Dummy2	1 if the work trip took place between 7 and 8 am; 0 otherwise	+
Dummy3	1 if the work trip took place between 8 and 9 am; 0 otherwise	+
Dummy4	1 if the work trip took place between 9 and 10 am; 0 otherwise	+
Dummy5	1 if the non-work trip took place between 9 and 10 am; 0 otherwise	+
Dummy6	1 if the non-work trip took place between 10 and 11 am; 0 otherwise	+
Dummy7	1 if the non-work trip took place between 11 am and 12 pm; 0 otherwise	+
Dummy8	1 if the non-work trip took place between 1 and 2 pm; 0 otherwise	+

*-/+ is the expected sign for the work and non-work models, respectively

Modeling Trip Generation

The techniques employed to model trip generation are documented below. The parameters estimates for the different models, except for the cross-classification approach, are performed in the NLOGIT 5.0 software.

1) Regression Modeling Approach
The ordinary least square (OLS) regression model can be used to capture the effect of different population characteristics on the number of trips generated per household/census tract in the study area. That is, given certain population characteristics, for instance age categories and information on vehicle ownership, this model predicts the number of generated trips per household/census tract *n* using the following linear formula:

$$y_n = \beta_1 x_{1_n} + \beta_2 x_{2_n} + \cdots + \beta_k x_{k_n} + \varepsilon_n, \quad n = 1,2,\cdots,N$$

where y_n is the number of generated trips, n indexes the nth observation (which is either the household or the census tract), β is the vector of the parameters that needs to be estimated, x is the vector of independent variables, and ε is a random disturbance that follows the normal distribution with a zero mean and constant standard deviation.

2) Cross-classification Approach
The cross-classification analysis separates the population in the study area into relatively homogenous groups based on certain socio-demographic characteristics. This is followed by empirically estimating the average production rates per household for each class. Hence, creating a lookup table that can be used to forecast trip production rates at the household level depending on which class category that household belongs to. The socio-demographic characteristics used in this study are vehicle ownership (number of vehicles owned by a household), gender (number of males/females in the household), and household size.

3) Discrete Choice Modeling Approach (Ordered Logit)
Ordered logit models are used when the dependent variable is ordinal. In each case of this project, the numbers of generated trips y^* by household are categorized as either 0, 1, 2, or 3 or more trips. Categories 0, 1, and 2 are assigned the same numerical values in the model. As for the category representing three or more trips, it is assigned a numerical value of 3 in the models. The model is used to predict the probability of generating 0, 1, 2, or 3 or more trips. From a practical perspective, the predicted number of generated trips for a given household *i* can be calculated using the following equation:

$$y_i^* = 0 * \Pr(0) + 1\,.\Pr(1) + 2\,.\Pr(2) + 3.2\,.\Pr(3^+)$$

where the 3.2 used in the weighted probabilities represent the average number of generated trips under the 3^+ category. See Train (2009) for a comprehensive overview of the ordered logit model.

4) Count Modeling Approach (Poisson Model)
Count data models are also considered in modeling trip generation as the dependent variable (trip frequency) is a positive integer variable. The most common technique employed to model count data is Poisson regression. This study considers both the Poisson and negative binomial regression models. However, since the dataset used in the modeling process does not suffer from over-dispersion, the negative binomial model was not preferred. In the Poisson model, the probability of specific household *i* making 0, 1, 2, or 3^+ trips (y_i), is given by:

$$P(y_i|X_i) = \frac{\exp(-\lambda_i)\,\lambda_i^{y_i}}{y_i!}; \text{where } \lambda_i = \exp(y_i) = \exp(\beta X_i)$$

Model Validation Techniques
The comparison between the trip generation models does not only depend on the goodness-of-fit for each model, represented by the R^2 and McFadden's ρ^2, but rather on the model's ability to predict future behavior. In addition, the models are estimated and calibrated using a 5% random sample consisting of 10,000 households from the London CMA synthesized population. As a result, to validate the models' predictive ability, another 5% random sample is selected from the remaining 95% of the synthesized

population. Using the 5% cross-validation sample, different validation measures are considered to check the correlation, accuracy, and coincidence ratio between the observed and predicted trip generation rates. A correlation coefficient (r) value close to 1 suggests strong positive relation between the predicted and observed values. The RMSE is a measure of accuracy of the trip rate measuring the average error between the observed and predicted trip rate. Typically, a RMSE close to 0 suggests a strong predictive ability. Since RMSE is measured on the same scale for all the observations, a scaling problem may arise. Hence, %RMSE is also considered as it normalizes the RMSE and eliminates the scaling effect. Again, %RMSE values close to 0 are the most favorable. The coincidence ratio (CR) is used to check the frequency distribution of trip rates. CR value close to 1.0 suggests a superior predictive ability of the utilized model.

Results and Discussion

Results for Micro-analysis

The results of the trip generation micro-models for work trips are summarized in tables 2. The models show that work trip generation is effected by the household structure (i.e., age categories and gender), vehicle ownership, and the hour of the day the trip took place. The relationship between age and work trip generation is non-linear. Taking *Age1* (>20 years) as the reference category, the results show that work trip frequency per household increases as age increases, reaching a peak for the working age group (*Age3*), and then decreases for the senior age group (*Age 5*). As expected, males, vehicle ownership, and AM-peak period have a positive impact on work trip frequency. These findings are consistent across all estimated models for work trips. The regression model's explanatory power of work trip generation is at an empirically acceptable level with an R-squared of 0.739. Similarly, the ordered logit and Poisson models have empirically acceptable explanatory powers with McFadden's rho-squared values of 0.421 and 0.238, respectively. As for the cross-classification model (not shown here for brevity), the values are presented as work trip rate per household, number of males, and vehicle ownership. The results follow the results in the previous models as work trip rate increases with increase of males and vehicle ownership in a household.

Table 2. Model Estimation Results

Variables	Work Trips						Non-Work Trips					
	Regression		Ordered Logit		Poisson		Regression		Ordered Logit		Poisson	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Constant	-0.01	-0.94	-2.76	-36.58	-1.00	-32.65	0.05	3.72	-2.28	-30.58	-1.52	-35.35
Age2	0.28	29.28	1.23	25.19	0.21	12.64	0.02	2.42	-0.05	-1.11	-0.15	-5.83
Age3	0.34	29.28	1.41	24.28	0.29	13.47	0.03	3.96	0.03	0.70	-0.13	-4.20
Age4	0.22	21.14	0.98	18.69	0.20	9.78	0.15	19.21	0.70	16.21	0.33	13.08
Age5	-0.03	-2.96	-0.36	-5.56	-0.62	-17.48	0.36	36.47	1.47	27.14	0.51	19.13
Males	0.03	3.10	0.14	3.21	0.03	1.57						
Vehicles	0.09	11.89	0.39	10.42	0.10	7.37						
Dummy1 (6AM)	0.66	42.40	3.01	36.58	0.47	17.88						
Dummy2 (7AM)	0.70	57.15	3.12	45.57	0.54	24.86						
Dummy3 (8AM)	0.70	57.58	3.13	45.94	0.53	24.46						
Dummy4 (9AM)	0.63	40.05	2.92	35.16	0.46	17.59						
Dummy5 (9AM)							0.66	26.64	2.65	21.39	0.65	13.59
Dummy6 (10AM)							0.73	46.22	2.99	36.77	0.86	25.36
Dummy7 (11AM)							0.69	32.57	2.86	27.36	0.79	17.94
Dummy8 (1PM)							0.76	37.35	3.12	30.79	0.83	20.08
Social Dummy							0.46	19.63	1.84	16.37	0.38	7.19
Social X Females							0.12	8.19	0.51	7.04	0.20	6.19
Mu(01)	--	--	3.61	65.13	--	--	--	--	3.43	54.78	--	--
Mu(02)	--	--	8.73	82.71	--	--	--	--	8.33	48.60	--	--
Sample Size	10,000		10,000		10,000		10,000		10,000		10,000	
Estimator	OLS		MLE		MLE		OLS		MLE		MLE	
R^2	0.739		--		--		0.612		--		--	
ρ^2	--		0.421		0.238		--		0.414		0.246	

All the coefficients in the non-work models have the expected signs. Similar to the work trip micro models, non-work trip generation is also affected by the household structure (i.e., age categories and gender) and the hour of the day the trip took place. For the three models presented in Table 2, the relationship between age and non-work trip generation is non-linear. Holding *Age1* (>20 years) as the reference category, the results vary slightly between the three models for *Age2* and *Age3*, but for the most part they show that non-work trip rate increases as age increases, reaching a peak for the senior age group (*Age5*). The hour dummies suggest a positive and highly significant impact for the periods between 9 am to 12 pm, and 1 pm to 2 pm. In addition, the *Social* dummy variable is positive and highly significant. That is, compared to shopping trips, social trips have a higher trip generation likelihood. The interaction term *Social* × *Females* also followed our expectations as females are more likely to generate social trips compared to males. The results show an acceptable goodness-of-fit for the ordered and Poisson models with McFadden's rho-squared values of 0.414 and 0.246, respectively. However, the R-squared value for the regression model is relatively low (0.612). Finally, for the cross-classification model for non-work trips are estimated using non-work trip rate per household, number of females, and vehicle ownership. The results vary considerably for the different household structures and vehicle ownership, but no clear pattern is observed.

Validation Results for Micro-analysis

The results pertaining to the cross-validation are shown in Table 3. For the work trip micro-models, the results do not vary significantly for the first two models. However, the four considered measures are in favor of the ordered logit model, followed by the regression, Poisson, and cross-classification models, respectively. On the other hand, the validation results for the non-work trip micro-models vary significantly for the cross-classification model. The later model performs very poorly proving that using household size, females, and vehicle ownership on their own is not very useful when predicting non-work trips in a household. As for the three other models, the validation results are similar and comparable. The ordered logit model has the most accurate predictions followed by the regression and Poisson models, respectively.

Table 3. Model Validation Results

Validation	Work Trips				Non-Work Trips			
	Regression	Ordered Logit	Poisson	Cross-Classification	Regression	Ordered Logit	Poisson	Cross-Classification
Correlation	0.831	0.840	0.765	0.607	0.766	0.766	0.639	0.300
RMSE	0.519	0.504	0.598	0.701	0.435	0.434	0.538	0.647
%RMSE	0.243	0.263	0.255	0.341	0.267	0.279	0.320	0.349
Coincidence Ratio	0.647	0.675	0.591	0.538	0.752	0.807	0.755	0.568

Conclusion

Trip generation is a critical step in the urban transportation modeling system. In this study, work and non-work trip frequency data for the London CMA, Ontario are analyzed with the use of advanced micro-based techniques. The analysis is based on two main data sources; the 2011 Canadian Census and a conventional Household Travel Survey conducted for London in 2009. Using the latter data, a complete list of over 195,000 households is synthesized using the combinatorial optimization population synthesis technique. For each trip purpose, four micro-based trip generation models (linear-regression, cross-classification, ordered choice, and count models) are estimated and compared.

Several socio-demographic factors including household size, age, gender, and vehicle ownership are used to estimate the models. Also, dummy variables for the hour of day when the trip took place are introduced. The results of the models show that trip generation differs by trip purpose, hour of day, and household characteristics. The estimates from the linear-regression, ordered logit and Poisson models are consistent in terms of behavior and predictive ability. Surprisingly, the cross-classification has the weakest results. The breadth of the conducted analysis is unique and has not been performed in past studies. The conducted analysis provides a benchmark for modeling trip generation of households at the micro-level. The results suggest that the ordered logit model is better suited for predicting trip generation of households.

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