A Destination Choice Model for Commercial Vehicle Movements in the Metropolitan Area

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Abstract

This paper describes the development of a destination choice model for modeling commercial vehicle movements in the metropolitan area. The proposed model has two major differences from other regional commercial vehicle models in the US, which include that: 1) the model is stratified by commercial vehicle type and trip purpose jointly, instead of by vehicle type only; and 2) the model employs the discrete choice modeling technique, instead of using a traditional gravity model. With this technique, non-impedance variables were able to be tested for inclusion in the utility function of the model. The study found that, besides travel time being a strong predictor, inter-area-type dummy variables are statistically significant in truck related sub-models, which push truck trips to less developed areas. Inter-county dummy variables were attempted as a proxy for inter-county economic interaction and found statistically significant in several sub-models. Both the inter-area-type and inter-county dummy variables add additional explanatory power to the model. The model estimation results indicate the model fits the data well with likelihood ratio index (ρ^2) values ranging from 0.24 to 0.32. This research effort demonstrates that a destination choice model stratified by both vehicle types and trip purposes can be successfully developed and employed for modeling commercial vehicle trip distribution.

INTRODUCTION

Trip-making characteristics of commercial vehicles (both goods- and service-related) are quite different from those of persons. They are often not as well represented in MPO regional models as person travel, while an increasing number of metropolitan planning organizations (MPOs) are attempting to model freight and commercial vehicle travel. Commercial vehicles, especially trucks, have considerable (but usually negative) impacts on traffic conditions, pavements, safety, and air quality. On the other hand, efficient freight and service flows are important to the local economy. Tradeoffs between the two-fold aspects often have to be made and capable planning tools and reliable data are essential to making right decisions.

The traditional four-step modeling approach has been widely used in MPO models (*1*,*2*), including modeling the commercial vehicle and truck travel component, if there is one. While it has been criticized that four-step model approaches lack the structure to account for the tour-based travel patterns of commercial vehicles and trucks, they are still the most readily available modeling techniques at the moment, that are manageable by MPO staff. With respect to trip distribution models for commercial vehicle movements, it is found that the state of practice in North America is still the gravity model (*3*,*4*,*5*,*6*,*7*,*8*). No discrete choice modeling techniques have been found to model commercial vehicle trip distribution in the metropolitan planning models. Discrete choice model structures offer several advantages over the gravity model, including allowing for explicit inclusion of socio-economic, geographic, and political-boundary variables in the utility function. A formal statistical process can be used to estimate coefficients on those variables. By including variables other than travel impedance in determining the probability of making a trip between two locations, the discrete choice model is expected to have stronger prediction power.

It has also been found that most of the MPO commercial vehicle models are stratified by vehicle type only, such as light vehicles, medium trucks and heavy trucks (*3*,*4*,*5*,*6*,*7*). None of them are stratified by trip purposes (or activity types), such as delivering goods, delivering services, or other purposes. It is expected that, similar to person trips, different trip purposes have different trip making characteristics, including trip making rates and trip distribution patterns.

Two types of data are usually deemed to be critical for developing commercial vehicle or truck models - vehicle classification count data and commercial vehicle travel survey data. While neither data are easy or inexpensive to acquire, travel survey data are more difficult and expensive. As a result, even some major MPOs base their models almost entirely on counts and tweak the borrowed trip rates, friction factor function coefficients, or even trip matrices directly to match traffic assignments with ground counts (*3*,4,6). However, in 2010 a commercial vehicle travel survey was conducted in the Triangle Region (Raleigh – Durham – Chapel Hill) in North Carolina. Information about 500 business establishments, commercial vehicles operated by those businesses, and travels made by the vehicles was collected. These data allowed for the development of a new commercial vehicle travel model for the Triangle Region.

This paper documents the trip distribution model component, which utilizes the discrete choice modeling technique and is stratified by vehicle type and trip purpose.

DATA

The 2010 Triangle Region commercial vehicle travel survey was conducted to collect commercial vehicle activity and travel data for developing commercial vehicle models for the Region. The data collection effort started on February 8, 2010 and ended on April 29, 2010. A rich set of data were successfully collected from 500 business establishments in the region. The major data items include:

- SIC code, number of employees, number of commercial vehicles by type, sales volumes, and locations for each surveyed business establishment;
- Vehicle type, number of axles, vehicle weight, and beginning and ending odometer readings for each surveyed commercial vehicle; and
- Arrival and departure times at each activity location, activity location coordinates, activity type/trip purpose, weight of goods delivered, and what goods are delivered for each trip record.

Excluding the 14 establishments that had buses only, a summary of the survey data is shown in Table 1 below.

TABLE 1 Summary Statistics of 2010 Triangle Region Commercial Vehicle Survey

Items	Statistics	Notes
Number of establishments that completed travel survey	486	
Number of vehicles garaged at non-residence locations and operated by the establishments completing the survey	2,793	
Number of vehicles surveyed	1,489	
Number of vehicles that made trips on assigned survey day	863	
Number of trips reported	5,669	
Number of trips recorded in detail in travel diaries	4,557	
Average vehicles per business establishment	5.75	Unweighted; = 2,793/486
Average daily trips per vehicle that completed the survey	3.81	Unweighted; = 5,669/1,489
Average daily trips per vehicle that made trips on assigned survey days	6.57	Unweighted; = 5,669/863

To improve model accuracy, it was decided that the new commercial vehicle model is first segmented into three markets based on trip end locations. The three markets are internal-to-internal (I-I) trips where both ends of a trip are within the region, internal-to-external/external-to-internal (I-E/E-I) trips where one of the trip ends is within the region and the other outside, and external-to-external (E-E) trips where both trip ends are outside the region. The I-E/E-I and E-E parts of the model are obtained from the North Carolina Statewide Model through an appropriate interface. Therefore, only the internal-to-internal (I-I) trips made by the business establishments within the Triangle Region were studied and modeled. In total, there are 3,139 I-I trip records in the survey dataset. Of these trips, 132 were found to serve people (such as picking up staff or dropping off children) and, therefore, removed from the dataset for model estimation. Moreover, since the number of observations of single-unit truck trips with "other purposes", multi-unit truck trips "delivering services", and multi-unit truck trips with "other purposes" is very low in the survey dataset, it is impossible to estimate corresponding models; those trip records were therefore removed from the dataset as well. The number of trip records by vehicle type and trip purpose that were finally used for model estimation can be found in Table 2. Classification of trip purposes is explained in detail in the Methodology section.

TABLE 2 Number of I-I Trip Records for Model Estimation

Vehicle Type + Trip Purpose	# of Trip Records
Light Commercial Vehicle - Delivery of Goods	487
Light Commercial Vehicle - Delivery of Services	945
Light Commercial Vehicle – Other Purposes	202
Single-Unit Truck - Delivery of Goods	520
Single-Unit Truck - Delivery of Services	526
Multi-Unit Truck - Delivery of Goods	241
Total	2,931

METHODOLOGY

Overall Model Design

Examination of the survey data in terms of trip making rates and trip lengths suggests that the commercial vehicle model be stratified by vehicle type and trip purpose. As can be seen from the trip generation models shown in Table 3, the coefficients of the same explanatory variable vary substantially among different models. This supports the decision of stratification of the commercial vehicle model. Also as Table 6 and Figures 1 and 2 show, average trip lengths and trip length frequency distributions vary a bit among different trip purposes even within the same vehicle type group. Therefore, estimation of destination choice models stratified by vehicle type as well as trip purpose was attempted. Vehicles were grouped into three vehicle types: light commercial vehicle (FHWA Classes 2 and 3), single-unit truck (Classes 5, 6 and 7), and multi-unit truck (Classes 8, 9, 10, 11, 12, and 13). Trips were classified into three trip purpose categories: delivery of goods, delivery of services, and other purposes. As indicated earlier, since the number of observations of single-unit truck trips with other purposes, multi-unit truck trips delivering services, and multi-unit truck trips with other purposes is very low in the survey dataset, these three models were not estimated. The following six models were finally estimated:

1) Light Commercial Vehicle (LCV) - Delivery of Goods
2) Light Commercial Vehicle (LCV) - Delivery of Services
3) Light Commercial Vehicle (LCV) - Other Trip Purposes
4) Single-Unit Truck (SUT) - Delivery of Goods
5) Single-Unit Truck (SUT) - Delivery of Services
6) Multi-Unit Truck (MUT) - Delivery of Goods

To have a good sample size for model estimation, models were not stratified by time of day. All trip records that fall into a vehicle-purpose category were used together to estimate the corresponding vehicle-purpose model. However, the time-of-day characteristics of the trips were not (and should not be) ignored in model estimation: the travel time variable in the model was fed with the value corresponding to the time of day when the trip was made. Therefore, the estimated models still have the capability to predict travel patterns for different time periods of the day. Travel times used for model estimation are from the existing Triangle Regional Model (TRM), which have been well calibrated and are more accurate than those reported in the survey. The TRM is a trip-based model stratified into three times of day: AM peak (6:00 am – 10:00 am), PM peak (3:30 pm – 7:30 pm), and off-peak (the rest of the day). Highway travel time skims of the three time periods from the model were used for model estimation.

Model Specification

The discrete choice modeling technique, specifically the multinomial logit form, was employed for modeling commercial vehicle trip distribution. The model has the following general form:

$$T_{ij} = O_i \times P_{ij} \tag{1}$$

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{k=1}^{N} e^{V_{ik}}} \tag{2}$$

Where,

T_{ij} = number of trips from origin TAZ i to destination TAZ j;

O_i = number of trip origin ends in TAZ i as estimated by the trip generation model multiplied by the time-of-day factor;

P_{ij} = probability of TAZ j being chosen as the destination by a trip from origin TAZ i;

V_{ij} = measurable utility of TAZ j as a destination perceived by a trip from origin TAZ i; and

N = total number of TAZs in the study area, which is 2,579 in this case.

The V_{ij} utility function is expressed as a function of a few factors and has a general form as follows:

$$V_{ij} = \alpha\, t_{ij} + \beta \ln(s_j) + \gamma\, z_{ij} \qquad (3)$$

Where,

t_{ij} = travel time from origin TAZ i to destination TAZ j by time of day;

s_j = number of trip destination ends in destination TAZ j as estimated by the trip generation model and multiplied by the time-of-day factor. This is used as the size variable in the model and takes the logarithmic form; and

z_{ij} = other explanatory variables, such as dummy variables indicating river crossing, border crossing, CBD related, and so on; and

α, β, γ = coefficients for corresponding explanatory variables. β can be constrained to 1, which is the case in this study.

Initial model estimation efforts only used travel impedance and size variables as input to the models. According to the goodness of fit of the models, measured by the likelihood ratio index (ρ^2), these two variables provided decent explanatory power. However, considering the complexity of commercial vehicle travel and the variety of influencing factors, local planners were consulted and the survey data was further examined. Two more explanatory variables were then included in the model for testing: a variable indicating if a trip is inter-county, which may reflect the strength of inter-county economic interaction, and a variable indicating the area types associated with the two ends of a trip, as it was found from the survey data that larger commercial vehicles tended to travel between less developed areas. As a result, a set of dummy variables were introduced to the model to account for inter-county movements. Since Wake, Durham, and Orange counties are the three major counties in the Triangle Region, one dummy variable was used to represent the interaction between each pair of them. Considering Johnston County produced the third largest number of commercial vehicle trips in the region (next to Wake and Durham) as revealed by the survey and conventionally has relatively strong interaction with Wake County, a separate dummy variable was used to represent the relationship between the two. All other cross-county movements were collectively represented by another dummy variable. When all the dummy variables aforementioned take a value of 0, it indicates the movement is intra-county.

With respect to area types, the TAZ area types as defined in the existing TRM were employed. If a trip has an end in a TAZ, the area type of that specific TAZ is used for that trip in the model. There are three area types defined in the existing TRM: urban, suburban, and rural. To fully cover the six possible combinations of area types associated with trip end pairs, five dummy variables were used, indicating if a trip was made between:

1) two rural areas (rural-rural);
2) a suburban area and a rural area (suburban-rural);
3) two suburban areas (suburban-suburban);
4) an urban area and a rural area (urban-rural);
5) an urban area and a suburban area (urban-suburban); or
6) two urban areas (urban-urban).

The rural-rural combination is used as the reference in this study and model results obtained for the other combinations should be interpreted relative to the reference. A trip falls into the reference category when all the five dummy variables take a value of zero.

As a summary, the improved model specification is shown in equation (4) below, which includes the terms in the utility function as discussed above, in addition to the travel impedance and size variables.

$$V_{ij} = \alpha\, t_{ij} + \beta \ln(s_j)$$

$$
\begin{aligned}
&+ \gamma_1 dummy_{inter-Durham-Orange} \\
&+ \gamma_2 dummy_{inter-Wake-Durham} \\
&+ \gamma_3 dummy_{inter-Wake-Johnston} \\
&+ \gamma_4 dummy_{inter-Wake-Orange} \\
&+ \gamma_5 dummy_{inter-Other-Counties} \\
&+ \gamma_6 dummy_{suburban-rural} \\
&+ \gamma_7 dummy_{suburban-suburban} \\
&+ \gamma_8 dummy_{urban-rural} \\
&+ \gamma_9 dummy_{urban-suburban} \\
&+ \gamma_{10} dummy_{urban-urban} \qquad (4)
\end{aligned}
$$

Where,

$t_{ij}, s_j, \alpha, \beta$ are the same as in equation (3);

$dummy_{inter-County1-County2}$ = a dummy variable, which has a value of 1 if a trip has one end in County 1 and the other end in County 2; 0, otherwise.

$dummy_{area\ type1-area\ type2}$ = a dummy variable, which has a value of 1 if a trip has one end in area type 1 and the other end in area type 2; 0, otherwise.

$\gamma_1, \ldots, \gamma_{10}$ = coefficients of corresponding dummy variables.

Model Estimation with Importance Sampling

It is not necessary to use all the TAZs as choice alternatives for estimation of a destination choice model for a study area with a large number of TAZs. Taking advantage of the Independence of Irrelevant Alternatives (IIA) property of the multinomial logit model, a subset of the full alternative set can be used to improve model estimation efficiency, while consistent estimation results are still preserved. Therefore, only a sample of TAZs was selected in this study for model estimation and the Importance Sampling with Replacement (ISwR) method described in Ben-Akiva and Lerman (*9*) was utilized for the sampling. The rationale behind Importance Sampling is that it is more efficient (than simple random sampling) to draw a sample of alternatives in which the alternatives more likely to be chosen by the decision maker have a higher probability of being selected.

Selection Weight and Selection Probability

Unlike simple random sampling where each TAZ is treated with an equal probability, Importance Sampling first assigns unequal selection probabilities to different TAZs and the probability of a TAZ being selected depends on the size of the TAZ and the travel impedance between the origin TAZ and this destination TAZ. First, the selection weight of destination TAZ j relative to origin TAZ *i*, is calculated using the following formula (*9*). The selection weight is computed by vehicle type and trip purpose.

$$
W_{ij} = A_j \times e^{\left(-2\times\frac{D_{ij}}{D_{avg}}\right)} \qquad (5)
$$

Where,

W_{ij} = selection weight of destination TAZ j relative to origin TAZ i.

A_j = size variable of TAZ *j*. In this study, trip attraction/destination ends by vehicle type and trip purpose are used as a size variable.

D_{ij} = highway distance in miles from TAZ i to TAZ j.

D_{avg} = regional average trip distance in miles. This value is computed by vehicle type and trip purpose.

The second step is to compute selection probabilities based on the weights using the following formula.

$$P_{ij} = \frac{W_{ij}}{\sum_{k=1}^{N} W_{ik}} \qquad (6)$$

Where,

P_{ij} = selection probability of destination TAZ j by a trip starting from TAZ i.
N = total number of TAZs in the study area, which is 2,579 in this case.

Selection Process

Based on the calculated selection probability P_{ij}, compute the cumulative selection probability cP_{ij} of destination TAZ *j* with *j* starting from TAZ 1 to TAZ 2579. The cP_{ij} of TAZ *j* has a range, with a lower limit equal to the sum of the selection probabilities from TAZ 1 to TAZ (*j*-1), i.e., $\sum_{k=1}^{j-1} P_{ik}$, and an upper limit equal to the lower limit plus the selection probability of itself, i.e. $\sum_{k=1}^{j} P_{ik}$. The upper limit of the last TAZ, $cP_{i,2579}$, is exactly 1.

Twenty random numbers between 0 and 1 were generated for each trip record in the survey. Then each random number was compared with the cumulative selection probabilities. If the random number fell in the range of cP_{ij}, TAZ *j* was selected into the sample set. This sampling process was repeated 20 times with replacement so that 20 TAZs were finally drawn into the sample set for each trip record. Then duplicate TAZs were deleted from the sample set and the actually chosen TAZ was added, if it was not sampled. Due to deletion of duplicates, this process ended up with different numbers of sampled TAZs for different trip records, with a maximum of 21 TAZs and a minimum of 1 TAZ (which is the chosen TAZ only).

Correction Factors

When sampling alternatives for model estimation, biases are introduced and correction factors are needed to obtain consistent estimates of the model parameters (*9*). With correction factors, model parameters estimated with a subset of alternatives are consistent with those as if estimated with all the alternatives. Using a subset of alternatives with correction factors makes model estimation more efficient, especially when there are too many alternatives (e.g., destination choice models). Correction factors take the following form:

$$CF_{ij} = -\ln q_{ij} = -\ln(P_{ij} \times n) \qquad (7)$$

Where,

CF_{ij} = correction factor of sampled TAZ j for a trip starting from TAZ i;
q_{ij} = overall probability of TAZ j being selected into the sample set for model estimation;
P_{ij} = selection probability of TAZ j for a trip starting from TAZ i; and
n = the number of selected TAZs in the sample set, which is 20 in this case.

Correction factors are only used in model estimation but not model application. Correction factors are added to the utility function as a linear additive term. The coefficient of the correction factor term is always constrained to 1.

Size Variable

Zonal time-of-day trip destination ends are used as the size variable in utility function (4). The trip generation models estimated and calibrated using the 2010 commercial vehicle survey data were first employed to estimate daily trip ends for each TAZ and then time-of-day factors were used to split the daily trip ends into the three time periods of the day: AM peak, PM peak, and off-peak. The trip generation models are shown in Table 3 below.

TABLE 3 Trip Generation Models by Vehicle Type and Trip Purpose

Model	Formula
LCV - Delivery of Goods	0.06115*(Industrial Employees + Retail Employees) + 0.0492*(Office Employees + Service Employees) + 0.06695*Households
LCV - Delivery of Services	0.0928*Industrial Employees + 0.03405*Retail Employees + 0.0144*(Office Employees + Service Employees) + 0.0644*Households
LCV – Other Purposes	0.1113*(Industrial Employees + Retail Employees) + 0.02035*(Office Employees + Service Employees) + 0.0614*Households
SUT - Delivery of Goods	0.0483*Industrial Employees + 0.02525*Retail Employees + 0.01165*(Office Employees + Service Employees) + 0.0367*Households
SUT - Delivery of Services	0.3840*Industrial Employees + 0.09175*Retail Employees + 0.0189*(Office Employees + Service Employees) + 0.05715*Households
MUT - Delivery of Goods	0.0830*Industrial Employees + 0.0182*Retail Employees + 0.0559*(Office Employees + Service Employees) + 0.00725*Households

MODEL ESTIMATION RESULTS

The free, open-source software package Biogeme (*10*) was utilized to estimate the destination choice models. Model estimation results are shown in Tables 4 and 5 below, stratified by vehicle type and trip purpose. The following criteria were used in the model estimation process to evaluate the explanatory variables and the model as a whole, decide if a variable is retained or removed from the model and if an estimated model is acceptable:

1) the coefficient of the variable has a logical sign;
2) the magnitude of the coefficient seems to be reasonable;
3) the variable has an acceptable *t* score, which is set as 1.0 in this study; and
4) the overall model goodness-of-fit measure, rho-squared, has an acceptable value.

As can be seen from Tables 4 and 5, all six estimated models have fairly high rho-squared values, ranging from 0.238 to 0.322, which indicates a good fit of the models to the data. The coefficient of travel time has a correct, negative sign across all the estimated models and is statistically significant at the 99% confidence level. The magnitude of the coefficient has a fairly narrow range between -0.113 and -0.267, indicating travel time has pretty consistent power in general in explaining commercial vehicle trip distribution across different vehicle types and different trip purposes. It is also noted that the absolute value of the travel time coefficients decreases with increasing vehicle size. This indicates larger vehicles are more willing to travel a longer time, which is consistent with what is observed from the survey data as shown in Table 6.

Inter-county travel dummies overall seem to be a significant explanatory variable. They have different (positive or negative) signs in different models, which work like adjustment factors to take care of the distribution patterns in the survey data that cannot be explained well by travel time alone, specifically, the intensity of commercial vehicle trip interchanges between counties likely caused by economic interaction. Table 4 shows that the inter-Orange -Wake dummy in the LCV-Other Purposes model has an unusually large negative coefficient of -8.65, compared with the other inter-county dummies. Closer investigation revealed that there are very few LCV-Other Purposes trips between Wake and Orange in the survey data. This dummy variable should be removed from the model later. The estimated coefficients for the inter-Wake-Johnston dummy do not seem to indicate stronger interaction between Wake County and Johnston County. The survey might not capture the reality adequately due to the small sample size.

From Table 4, it appears the inter-area-type dummy variables do not add much explanatory power to the light commercial vehicle models. In total only three inter-area-type dummy variables are retained in two of the three LCV models and none of them are significant at the 95% confidence level. However, when it comes to the truck models, these dummy variables play a much more important role. As can be seen from Table 5, all of the five inter-area-type dummies are significant at or above the 95% confidence level in the single-unit and multi-unit truck models, with the only exception being the Suburban-Rural dummy in the MUT - Delivery of Goods model. Moreover, the coefficients of these dummy variables display pretty similar patterns across the three truck models – all have negative signs and, the more developed the two trip end locations are, the more negative the coefficient is, which indicates fewer trip interchanges. Overall this pushes truck trips out of more developed areas and therefore increases trip lengths. This in general appears to make sense as larger trucks tend to travel in less developed areas (for example, between warehouses), as observed from the survey data.

TABLE 4 Estimated Destination Choice Models for Light Commercial Vehicle Movements

Variable	Models					
	LCV – Delivery of Goods		LCV – Delivery of Services		LCV – Other Purposes	
	Coefficient	*t* score	Coefficient	*t* score	Coefficient	*t* score
ln(trip ends)	1.0	-	1.0	-	1.0	-
Travel time	-0.220	*-20.47*	-0.183	*-25.78*	-0.267	*-15.25*
Inter-Durham-Orange			-0.502	*-1.97*	-1.05	*-1.58*
Inter-Durham-Wake	0.419	*2.04*	0.189	*1.36*	-0.598	*-1.28*
Inter-Orange-Wake			0.424	*1.36*	-8.65	*-13.26*
Inter-Wake-Johnston			-1.25	*-3.35*	1.36	*2.05*
Inter-Other-Counties			-0.922	*-3.82*	0.779	*1.70*
Suburban-Rural	0.643	*1.05*				
Suburban-Suburban			0.540	*1.73*		
Urban-Rural	0.647	*1.00*				
Urban-Suburban						
Urban-Urban					-0.897	*-1.16*
Initial log-likelihood	-1881.153		-3854.004		-820.406	
Final log-likelihood	-1401.269		-2737.629		-556.847	
ρ^2	0.255		0.290		0.321	

TABLE 5 Estimated Destination Choice Models for Truck Movements

Variable	Models					
	SUT – Delivery of Goods		SUT – Delivery of Services		MUT – Delivery of Goods	
	Coefficient	*t* score	Coefficient	*t* score	Coefficient	*t* score
ln(trip ends)	1.0	-	1.0	-	1.0	-
Travel time	-0.169	*-18.58*	-0.183	*-21.90*	-0.113	*-10.82*
Inter-Durham-Orange			-2.42	*-3.21*	-1.06	*-2.27*
Inter-Durham-Wake	0.241	*1.23*	-0.299	*-1.47*	-0.608	*-2.22*
Inter-Orange-Wake					-1.03	*-1.52*
Inter-Wake-Johnston	-0.605	*-1.96*				
Inter-Other-Counties	0.313	*1.30*	-0.533	*-2.25*		
Suburban-Rural	-0.924	*-2.49*	-0.901	*-3.11*	-0.669	*-1.74*
Suburban-Suburban	-1.19	*-2.94*	-1.38	*-4.02*	-1.66	*-3.43*
Urban-Rural	-1.56	*-3.88*	-2.29	*-5.58*	-1.98	*-3.66*
Urban-Suburban	-2.14	*-5.22*	-2.13	*-5.91*	-2.07	*-4.31*
Urban-Urban	-2.59	*-5.98*	-2.86	*-7.27*	-2.64	*-5.09*
Initial log-likelihood	-1992.442		-2128.121		-881.630	
Final log-likelihood	-1471.057		-1442.900		-672.093	
ρ^2	0.262		0.322		0.238	

MODEL PERFORMANCE EVALUATION

Performance of the estimated models is evaluated using the following three measures:

1) Average trip lengths;
2) Trip length frequency distribution; and
3) Coincidence ratios

Since the percent of commercial vehicle trips made in the PM peak period is very low in the survey, ranging from below 1% of LCV – Other Purposes trips to 11% of LCV – Delivery of Services trips, it is difficult to generate statistically reliable results for comparison with model output. Therefore, the PM peak period is combined with the off-peak period, and related statistics are computed for the two time periods jointly. Table 6 shows the average trip lengths in minutes by vehicle type, trip purpose, and time of day and compares the modeled with the observed. Trip length frequency distribution curves are shown in Figures 1 and 2 with the observed overlapped with the modeled.

Coincidence ratios are also calculated to measure how well the modeled distribution curve overlaps with the observed one. The formula used to compute the coincidence ratios is as follows. The coincidence ratios are summarized in Table 7.

$$CR = \frac{\sum_i \min(obs_i, mod_i)}{\sum_i \max(obs_i, mod_i)} \quad (8)$$

Where,

CR = coincidence ratio
obs_i = the percent of interval i in the observed total distribution
mod_i = the percent of interval i in the modeled total distribution

TABLE 6 Average Trip Lengths (in Minutes) by Vehicle Type and Trip Purpose

Vehicle + Purpose	AM Peak			Off-Peak & PM Peak		
	Observed	Modeled	% Deviation	Observed	Modeled	% Deviation
LCV-Delivery of Goods	16.39	14.51	-11.5%	14.23	14.53	2.1%
LCV-Delivery of Services	16.14	15.46	-4.2%	15.35	15.40	0.3%
LCV-Other Purposes	11.88	13.05	9.8%	13.54	13.14	-3.0%
SUT-Delivery of Goods	15.38	16.66	8.3%	17.28	16.57	-4.1%
SUT-Delivery of Services	12.85	14.99	16.7%	16.88	14.90	-11.7%
MUT-Delivery of Goods	22.21	19.12	-13.9%	22.73	18.65	-17.9%

TABLE 7 Coincidence Ratios by Vehicle Type and Trip Purpose

Vehicle + Purpose	AM Peak	Off-Peak & PM Peak
LCV-Delivery of Goods	0.59	0.69
LCV-Delivery of Services	0.57	0.58
LCV-Other Purposes	0.52	0.71
SUT-Delivery of Goods	0.74	0.82
SUT-Delivery of Services	0.73	0.74
MUT-Delivery of Goods	0.69	0.83

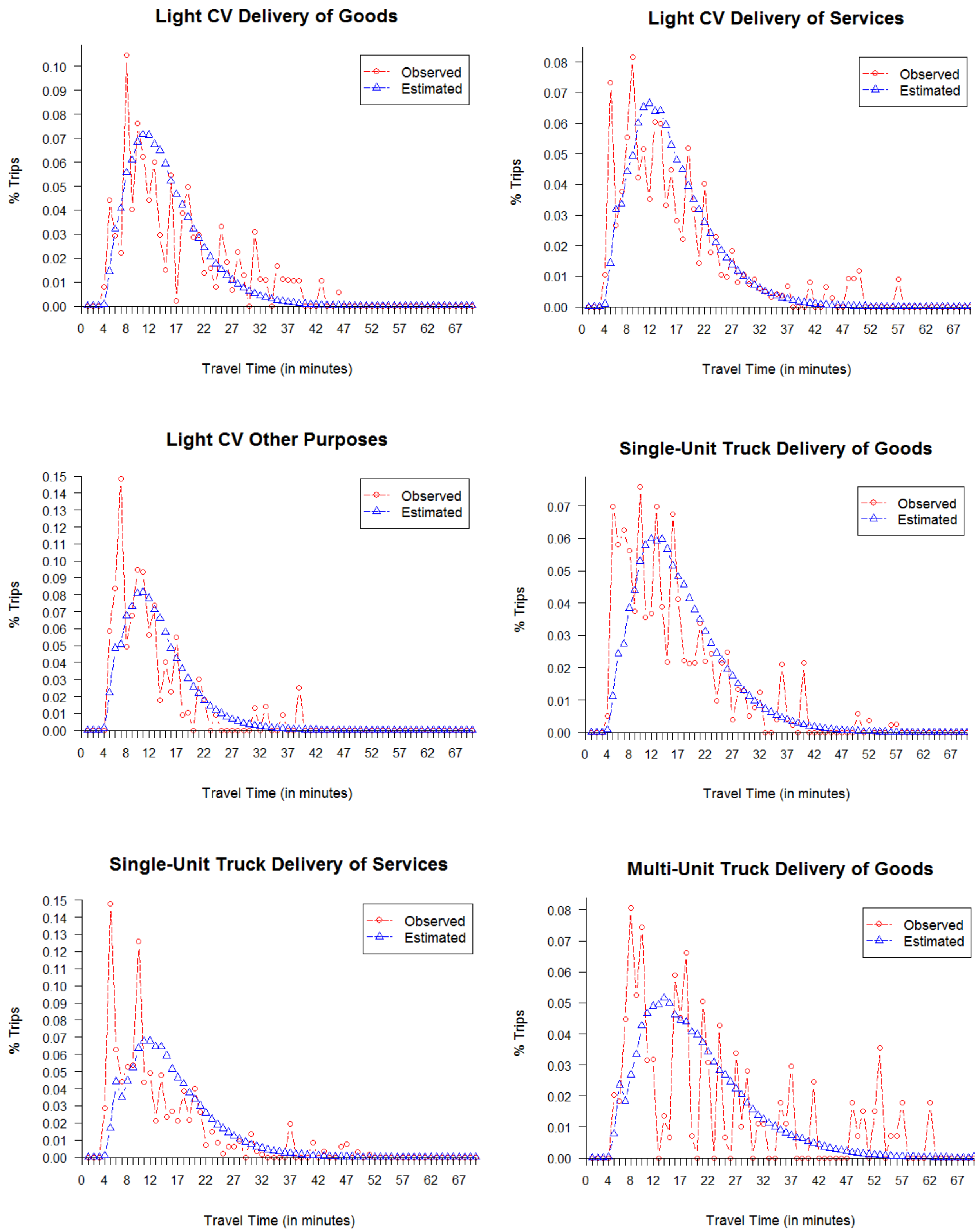

FIGURE1 Trip Length Frequency Distribution by Vehicle Type and Trip Purpose for AM Peak

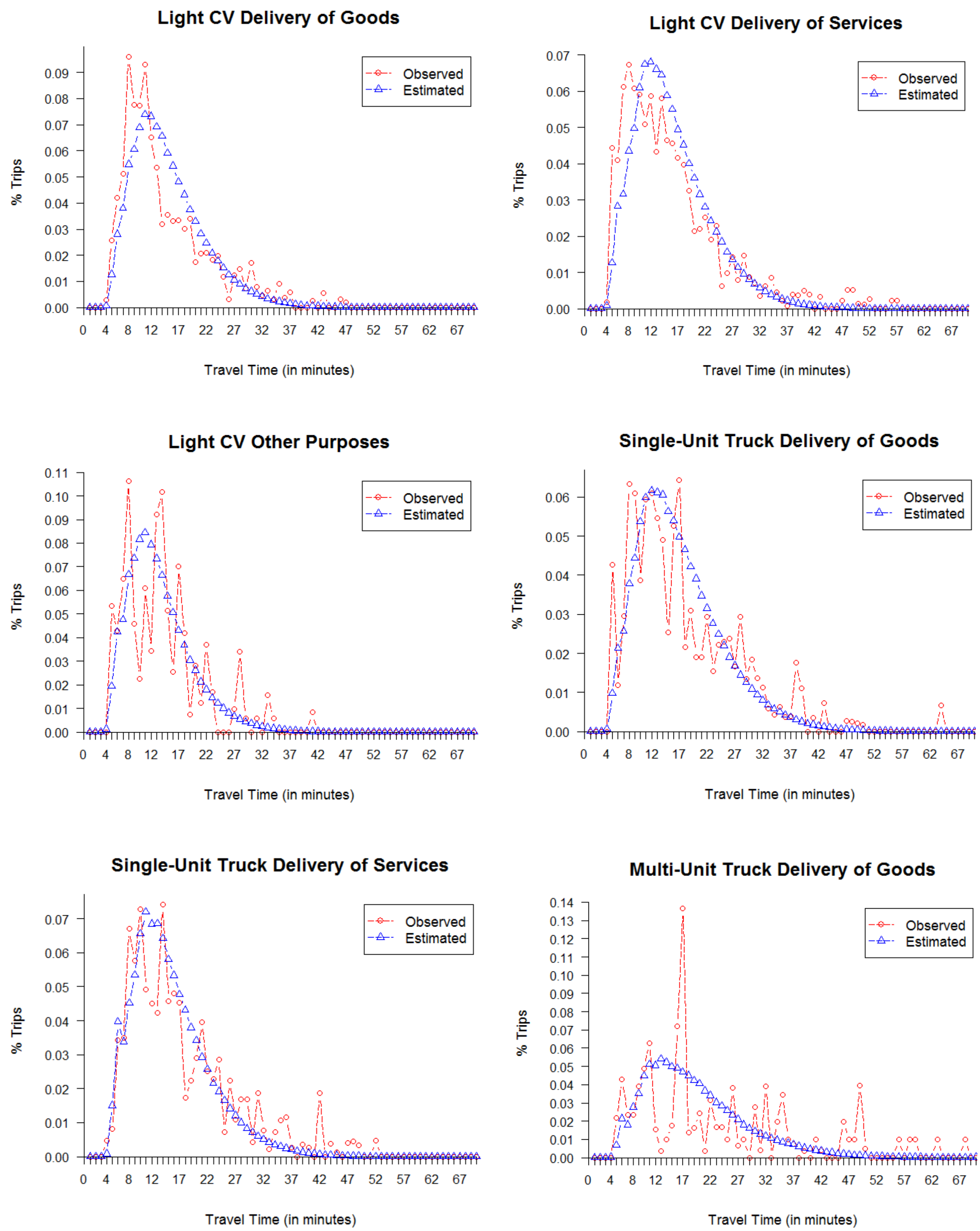

FIGURE 2 Trip Length Frequency Distribution by Vehicle Type and Trip Purpose for Off-Peak and PM Peak

As seen from Table 6, all of the 12 modeled average trip lengths are within +/- 20% of the observed average trip lengths, with seven of them even within the +/- 10% range. Figures 1 and 2 show that the trip length frequency distribution curves generated from the model output (the blue lines) overlap with those derived from the survey data (the red lines) fairly well. Some of the observed curves oscillate widely and have many high spikes due to the small sample size, for instance, the MUT – Delivery of Goods curves for both the AM peak period and the joint PM and off-peak period. This certainly has a negative impact on model estimation and calibration. Table 7 shows that the estimated destination choice models perform well overall with a coincidence ratio around or above 0.7, although a few of them will need some calibration work later.

CONCLUSION

This paper describes a research effort aimed at developing a destination choice model for distributing commercial vehicle trips in the metropolitan area. The intent was to explore the possibility of developing a model with the discrete choice model structure and stratified by both vehicle types and trip purposes for commercial vehicle trip distribution, based on commercial vehicle travel survey data. Considering the complexity of commercial vehicle travel, variables other than travel impedance were tested for inclusion in the utility function. Six sub-models, stratified by vehicle types and trip purposes jointl, were estimated. It was found from the study that 1) travel time is still the strongest determining factor for destination choice; 2) the inter-area-type dummy variables are statistically significant in all the single-unit truck (SUT) and multi-unit truck (MUT) sub-models, which push truck trips to less developed areas; 3) the inter-county dummy variables, intended as a proxy for inter-county economic interaction, are statistically significant in some sub-models, while not all; and 4) both the inter-area-type and inter-county dummy variables add additional explanatory power to the model. The model estimation results indicate the models fit the data well. The model performance evaluation results indicate that when put in application the estimated models are able to produce results within a reasonable range of the observed. The study proves that a destination choice model stratified by both vehicle types and trip purposes can be successfully developed and employed to model commercial vehicle trip distribution.

There is certainly room for improvement in many facets of the research. Among the critical priorities:

1) Explore the explicit inclusion of economic factors in the model to improve its explanatory power;
2) Investigate the use of more disaggregated employment categories that are more consistent with NAICS or SIC; and
3) Explore model stratification by NAICS or SIC sectors.

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