Title
Modeling and Measuring Greenhouse Gas Reduction from Low Carbon Airport Access Modes

Author
Smirti, Megan

Publication Date
2008-07-01

Modeling and Measuring Greenhouse Gas Reduction from Low Carbon Airport Access Modes

Megan Smirti

Graduate Student Researcher
Institute of Transportation Studies
National Center of Excellence for Aviation Operations Research
University of California, Berkeley
109 McLaughlin Hall, Berkeley, CA 94720-1720
415-816-0925(O), msmirti@berkeley.edu

Submitted: July 28, 2008

ABSTRACT

The warming of the Earth's temperature due to human activities, known as anthropogenic climate change, is a threat to the environment and human health. The transportation sector is a major contributor to anthropogenic climate change, being responsible for 27 percent of all domestic greenhouse gas (GHG) emissions in 2003. Within this sector, urban surface travel has been the major focus of researchers and policymakers. To broaden this focus to include interregional travel, the proposed research focuses on the aviation sector. Airport access modes are shown to be a large proportion of aviation system GHG emissions; due to their share and political and engineering realities they are targeted for aviation system GHG reduction. Discrete choice models are used to study the entry of clean airport access modes into the market, and it is found that the entry of a subsidized electric vehicle door-to-door van could reduce GHG emissions by 36 percent.

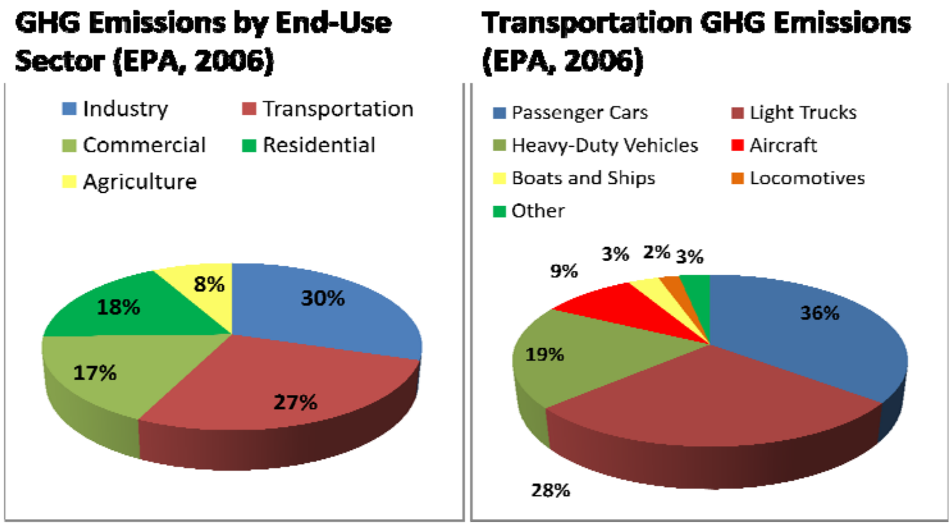
KEY WORDS: Aviation, Airport Access, Greenhouse Gas Emissions, Discrete Choice Model

INTRODUCTION

It is well known that the operation of transport vehicles is a major component of anthropogenic climate change – the warming of the Earth's temperature due to human activities. The use of transportation fuels increases levels of greenhouse gases (GHG), the gases which cause climate change (EPA, 2007). In the United States (US), the transportation sector is responsible for 27 percent of all GHG emissions, making it the second largest end use sector after electric power generation. Furthermore, of human produced GHG emissions in the US, Carbon Dioxide (CO_2) accounts for 85 percent of the radiative forcing, or perturbation to the earth-atmosphere energy system (EPA, 2006). The transportation sector is the largest sector contributing to domestic CO_2 emissions, producing 30 percent. These figures are similar worldwide (International Energy Agency, 2004).

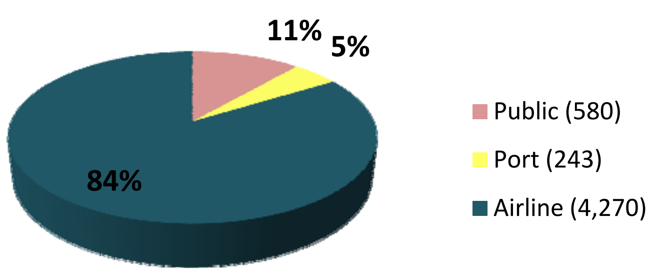
Reducing GHG emissions, CO_2 in particular, has become an initiative for many transportation modes. For surface transportation, new vehicle emission standards and the incorporation of GHG emissions into the Clean Air Act are two major policy movements towards GHG reduction from vehicle movements (EPA, 2006; Supreme Court of the United States, 2006; Winston, et al., 1999). It is no surprise that the surface sector is the focus of transport GHG reduction. Not only does the surface sector emit the largest share of transportation GHG emissions, there is also abundant precedent and experience in regulating and otherwise reducing road vehicle emissions in order to attain air quality standards mandated by the Clean Air Act. Surface vehicle modes, including passenger cars, light trucks, and heavy-duty vehicles are also the three modes with the largest share of Transportation GHG emissions, as can be seen in Figure 1.

FIGURE 1. GHG EMISSIONS BY END-USE SECTOR AND BY TRANSPORTATION MODE.



Aircraft operations are nine percent of transportation GHG emissions (Figure 1). However, this is not reflective of the distributional impacts of the aviation system. As trips do not begin or end at the airport, a more complete picture of the aviation system would include vehicles that access the airport. The Port of Seattle (2008) GHG inventory provides an interesting perspective on GHG emissions from airports. To date, it is the state of the practice in the development of GHG emissions inventories at the airport level. The Port of Seattle divides GHG emissions from the airport it operates, Seattle Tacoma International Airport (SEA), into ownership categories. Emissions owned by the port include those produced from hotel and parking lot shuttles (while on airport grounds) and facility power. Airline or tenant emissions are those from aircraft. Emissions owned by the public include passenger vehicles and hotel and parking lot shuttles (while not on airport grounds). The distribution of emissions found at the found in Figure 2.

FIGURE 2. PORT OF SEATTLE GHG EMISSIONS DISTRIBUTION BY OWNER.



Source: Port of Seattle, 2008

Figure 2 shows that public emissions from ground access vehicles traveling to the airport are 11 percent of the total, and therefore a substantial component of aviation system related CO_2 emissions. Because there is more political experience for GHG reduction from surface vehicles, this could be a natural place to start reducing emissions from the aviation system. This finding provides the motivation for the next segment of this study, which will assess the potential of "green" airport access modes. The method that will be employed is a discrete choice model, through which travel to the airport will be modeled and the introduction of green access modes can be studied.

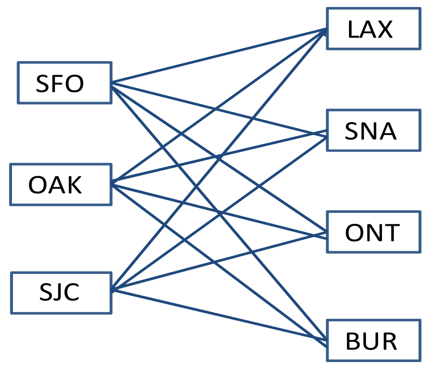
AIRPORT ACCESS MODE CHOICE MODEL

The following section will present different formulations of airport access mode discrete choice models. Discrete choice modeling is a powerful method to model and forecast consumer behavior, and airport choice in particular. Train (1978) used a standard logit model to model commute choice before a heavy rail system is developed and to forecast heavy rail ridership post-development. Harvey (1986; 1987) uses a discrete choice model to examine airport access choice in the Bay Area, and also airport choice along with airport access choice. Pels et al. (2003) investigated the impact of airport access and other airport attributes in the competition between airports in a multiple airport region using a discrete choice model. Recently, a guideline for best practices in airport access choice modeling was released, where Gosling (2008) presents the state of the practice in airport access mode choice modeling and suggestions for model improvements.

Study Corridor for Airport Access Mode Choice Study

The scope of this study will include passengers originating at three Northern California airports who are destined for four Southern California airports. The Northern California airports are San Francisco International Airport (SFO), Oakland International Airport (OAK), and Mineta San José International Airport (SJC). The Southern California airports are Los Angeles International Airport (LAX), John Wayne Airport, Orange County (SNA), Ontario Airport (ONT), and Bob Hope Airport, Burbank (BUR). This network is shown below in Figure 3.

FIGURE 3. GEOGRAPHIC SCOPE OF VEHICLE MOVEMENTS FOR AVIATION STUDY.



California is chosen for case study because in 2005, California Governor Arnold Schwarzenegger signed an executive order to establish statewide GHG emission reduction targets. The target is to reduce GHG emissions enough so that in 2020, the total GHG emission levels are at or below those from 1990. This requires of reduction of 145 million tons, and about 25 percent of those projected under the Business as Usual scenario (Governor of the State of California, 2005). Furthermore, in 2007, the state of California was successful in its law suit against San Bernardino County. In People of California v. San Bernardino County, San Bernardino was found to be not in compliance with the Clean Air Act, as its local government land use plan did not fully account for increased GHG emissions from new developments (People of California v. San Bernardino Count, 2007). The state government can now use this ruling to encourage and potentially compel local governments to incorporate GHG emissions forecasting into their regional planning. These events make airport access behavior for passengers traveling on the California corridor a particularly interesting case study.

Logit Model for Airport Access Mode Choice

A logit model allows for the calculation of the probability that a choice maker will choose alternative *i* given a choice of all alternatives *j*. The logit model presents a probability model which calculates the ratio of probabilities of choice maker utilities to capture the probability of a particular choice being made in the face of a complete, exhaustive list of choices. A utility function measures the dimensionless utility a choice maker derives from choosing a given alternative.

The utility function is formulated as a sum of observed utility V_{ni} and unobserved utility ϵ_{ni}, as shown in equation 0.2. The observed utility is a function of the attributes of a choice and the attributes of a choice maker which a researcher can observe. The unobserved utility is a function the attributes of a choice and of the choice maker that the researcher cannot observe. The probability that a choice maker n chooses alternative i is based on the observed utility V_{ni} (equation 0.3). A complete description of the logit model can be found in Train (2003).

$$U_{ni} = V_{ni} + \epsilon_{ni} \tag{0.1}$$

$$V_{ni} = B' X_{ni} \tag{0.2}$$

$$P_{ni} = \frac{e^{\beta x_{ni}}}{\sum_j e^{\beta x_{nj}}} \tag{0.3}$$

In this study, many data sources were used to ultimately estimate the different logit model formulations that will be presented. The main survey data which captures access mode choices is from the 2001/2002 Metropolitan Transportation Commission Airline Passenger Survey (MTC, 2003). The MTC survey was conducted in August and September 2001 and 2002 at SFO, OAK, and SJC. The total number of passengers surveyed was 14,851, of which 1197, or eight percent, were traveling on the study corridor.

To construct a standard logit model of airport access mode choice, airport access mode choices and attributes were defined as well as demographic attributes of the choice makers. An exhaustive alternative list must be formulated for the choice model estimation. The alternatives for airport access in the Bay Area were aggregated into five alternatives. These alternatives are: private auto, public rail transit to an airport shuttle with walk access or drive access, a, a scheduled airport bus with walk access or drive access, a private vehicle for hire (taxi/limo) or a shared ride door-to-door van. In this model formulation, a choice maker has already chosen their origin and destination airports and it is assumed that the access mode choices they face are based on their origin airport.

The airport access mode choices considered in this model include alternative cost (C) and alternative time (T). The alternative descriptions are below, along with how their costs and time were collected and/or calculated.

1. **Private Auto** includes rental car; drop off by private vehicle; and drive a private vehicle and park short-term, long-term, or off-airport. The attributes of private vehicle and park long-term was used to generalize the private auto mode. The time in auto was collected using GIS using Traffic Analysis Zones. Auto trips were loaded on the shortest path driving configuration and the travel time was calculated. Additional time was added based on the distance of the long-term lot to the airport terminal, based on the airport chosen. The distance traveled was multiplied by the AAA cost of driving. This was $0.51/mile in 2001 and $0.502/mile in 2002. The cost to park in 2001/2002 in a long term lot for one day for the three airports was added to the cost, depending on which year the choice was made and which airport was chosen.

2. **Walk to Public Transit** incorporates walking to a public transit mode (excluding a scheduled airport bus), and then connecting to a transit airport connector shuttle. Because this data is from 2001 and 2002, the three airports did not have a direct transit connection to the regional rail system, but rather required a rider to connect to an airport connection shuttle. To calculate the cost and time of this alternative, each rider was assigned the most likely transit mode based on their origin and destination. Passengers bound were assigned a transit mode based on distance from trip origin. If the rider could either use the VTA light rail or the Caltrain for SJC

access, transit mode was assigned based on distance from trip origin. The cost of this alternative was the sum of the fares of the public transportation system used. The time was calculated using the following equation:

$$T_{alt2} = \sum_{i=1}^{tr}(.5 * headway_i + in\ vehicle\ time_i) + transit\ mode\ distance * \frac{20\ min}{mile} + .5 * airport\ connection\ shuttle\ headway + in\ vehicle\ shuttle\ time \quad (0.4)$$

Where "i" is the transit segment number in a transit trip "tr" is the number of transfers necessary on the line-haul transit mode. Walk pace is assumed to be 20 minutes per mile.

3. **Drive to Public Transit** is similar to alternative 2 except the choice maker uses an auto mode to access public transit. The fare is the same as alternative 2 except. The cost of driving was calculated the same as alternative 1, between trip origin and public transit station.

4. **Drive to scheduled bus** includes auto access to a scheduled bus (a bus which travels directly between the origin station and an airport). The cost and time for this mode were calculated as alternative 3 was calculated. However, headways were multiplied by ¼ instead of ½. This is because transit literature notes that if the headway is sufficiently long, riders view a schedule and do not randomly show up at a station (Maguier and Ceder, 1984). Arrival times at the station are therefore more clustered around the departure time.

5. **Walk to scheduled bus** includes walk access to a scheduled airport bus. Cost and time are calculated in the same method as alternative 4, with walking time calculated using the same method as alternative 2.

6. **Taxi and limo** modes include hiring a door-to-door taxi or limousine for airport access. The time calculated this mode is the same as alternative 1, with parking time eliminated. The cost was based on the taxi flat and per mile rates quoted from taxis which serve the three airports.

7. **Door-to-door shared-ride van** (Super Shuttle, for example) is a hired van which picks independent passengers up at their origins in the same van. The time was calculated as the quoted circulation time of a van to pick up other passengers; half of the time window a rider is quoted as wait time; and the driving time from alternative 1. There was no cost data available for shuttle services in 2001 and 2002. To get the shared ride costs, an equation was estimated with data mined for the SF Bay Area in 2008. This linear model was estimated with shared ride costs as a function of time. The results of the equation estimation were the following equation: $C_{alt7} = 21.1579 + .2579 * shuttle\ time$. The results were significant at the .01 level. This equation was used to estimate shared ride costs based on 2001/2002 shared ride times.

The demographic variables entered into the utility function are as follows:

- Resident (R) (Binary, 1 if yes, 0 if no)
- Business traveler (B) (Binary, 1 if yes, 0 if no)
- Income (I) (average of range from 2001/2002 MTC Survey)
- Travel Party Size (Pt)

This information was collected directly from the 2001/2002 MTC survey.

The utility function estimated in this model includes choice specific coefficients for each of the seven alternatives. The utility functions for all alternatives were estimated in the following form, where *i* is the alternative number.

$$U_i = \alpha_i + \beta_{1i} * \frac{C}{Pt} + \beta_{2i} * (T * I) + \beta_{3i} * \frac{C * B}{Pt} + \beta_{4i} * \frac{C * R}{Pt} \tag{0.5}$$

MATLAB was used to estimate this model, and the code used is an adaptation of Train (2008). The estimated coefficients for the logit model are in Appendix A. The results in the left-hand section of the table are with the full model (each alternative is estimated as in equation 0.6), the right-hand section is when the model was re-run with insignificant coefficients of equation 0.6 eliminated. Note that time for alternative 7 was also dropped, because it was insignificant after the first round of coefficient elimination. Table 1 shows the actual mode shares from the data and the predicted mode shares from the logit model.

The resulting utility functions from the logit model are as follows. Note that all coefficients have negative values, representing that increased cost and time decrease utility.

$$U_1 = -0.0165\,\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) - 0.0126\,(\mathrm{T} * \mathrm{I})$$
$$U_2 = -1.7953 - 0.0165\,\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) - 0.0126\,(\mathrm{T} * \mathrm{I})$$
$$U_3 = -2.0591 - 0.0165\,\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) - 0.0192\,(\mathrm{T} * \mathrm{I}) - 0.4453\left({}^{\mathrm{C} * \mathrm{B}}/_{\mathrm{Pt}}\right)$$
$$U_4 = -0.2587\,\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) - 0.0126\,(\mathrm{T} * \mathrm{I}) + 0.157\left({}^{\mathrm{C} * \mathrm{R}}/_{\mathrm{Pt}}\right)$$
$$U_5 = -0.0165\,\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) + -0.0642\,(\mathrm{T} * \mathrm{I})$$
$$U_6 = -2.1557 - 0.0165\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) - 0.0126\,(\mathrm{T} * \mathrm{I}) + 0.0088\,\left({}^{\mathrm{C} * \mathrm{B}}/_{\mathrm{Pt}}\right) - 0.0167\,\left({}^{\mathrm{C} * \mathrm{R}}/_{\mathrm{Pt}}\right)$$
$$U_7 = -0.1203\left({}^{\mathrm{C}}/_{\mathrm{Pt}}\right) - 0.0126\,(\mathrm{T} * \mathrm{I})$$

TABLE 1. ACTUAL AND PREDICTED SHARES OF LOGIT MODEL.

Alt	Actual	Predicted
1	0.7912	0.7755
2	0.0577	0.0576
3	0.0204	0.0308
4	0.0161	0.0257
5	0.0068	0.0047
6	0.0874	0.079
7	0.0204	0.0266

This logit model could be used to forecast the introduction of “green” or lower-CO_2 airport access modes. However, drawbacks exist to using logit models for such purposes. While originally considered a strength and condition for discrete choice modeling, the logit model makes it so that an improvement in one alternative will draw customers proportionally from all other alternatives to the improved alternative. The logit model presents what is called Independence from Irrelevant Alternatives (IIA) (Train, 2003). This is because the ratio of two logit probabilities, in which the denominator of equation 0.4 is eliminated, becomes simply the ratio of the exponentiated observed utility of the two alternatives in question. While proportional substitution was considered a condition for logit modeling, it presents challenges for forecasting. For example, it is realistic to think that the transit alternative and the scheduled bus alterative have correlation in their unobserved utilities. If an attribute of transit changed to make it more desirable, it is reasonable to think scheduled bus users would switch to transit more than taxi users. Because of this interpretation, the following section will explore the use of a nested logit model.

Nested Logit Model for Airport Access Mode Choice

The nested logit model provides for a solution to the IIA problem. The utility functions of a subset of alternatives may have correlated unobserved utilities, as described in the transit/scheduled bus and taxi anecdote described above. Nested logit allows for those alternatives to be placed in the same nest; IIA holds for alternatives which are in the same nest but does not hold across nests. Using notation described in Train (2003), a nested logit model will have *k* nests, where B_k denotes the nest.

In the nested model, the utility is decomposed into two functions of the independent variables. This is noted in equation (0.6). The group of variables denoted W_{nj} are those that describe a certain nest *k*. The other variables, those that are unique to an alternative, are denoted Y_{nj}. The nested logit model captures the probability of choice maker *n* choosing choice *i*, termed P_{ni}; it is the product of two probabilities (equation (0.7)). The probability P_{nB_k} is the probability that choice maker n chooses nest B_k as can be seen in equation (0.8). Equation (1.0) is referred to as the “upper model” because the choice of nest precedes the choice of alternative. Equation (1.1) is called the “lower model”, which is $P_{ni|B_k}$. Here, a choice maker chooses the alternative *i* conditional on the chosen nest B_k.

$$U_{nj} = W_{nk} + Y_{nj} + \epsilon_{nj} \tag{0.7}$$

$$P_{ni} = P_{nB_k} \tag{0.8}$$

$$P_{nB_k} = \frac{e^{W_{nk}+\lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{W_{nl}+\lambda_l I_{nl}}} \tag{0.9}$$

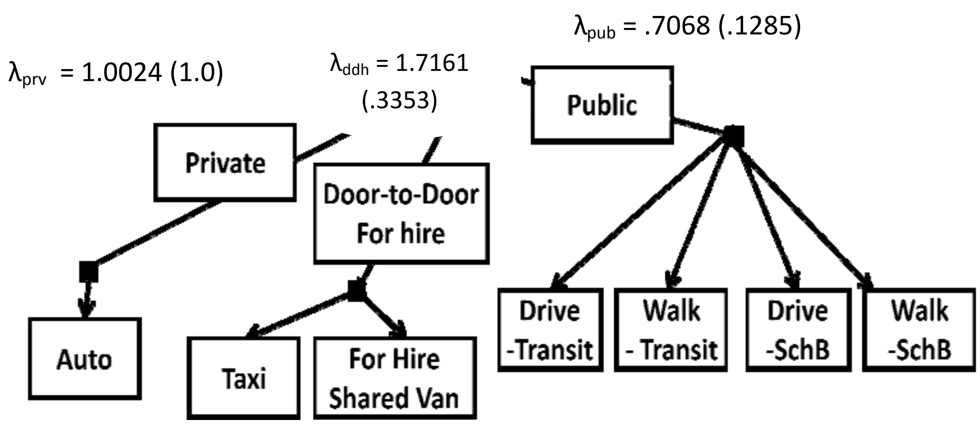
$$P_{ni|B_k} = \frac{e^{Y_{ni}/\lambda_k}}{\sum_{j \in B_k} e^{Y_{nj}/\lambda_k}} \tag{1.0}$$

$$I_{nk} = ln \sum_{j \in B_k} e^{\frac{Y_{nj}}{\lambda_k}} \quad (1.1)$$

Important things to note about the sequence presented in equations 0.7 through 1.1 are the role of λ_k and I_{nk}. The parameter λ_k is known as the nesting parameter. This parameter describes the degree of correlation between the unobserved utility for alternatives within a nest. The parameter I_{nk} is termed the inclusive utility of a given nest, and it multiplied by the nesting parameter is the expected utility that a choice maker has for choosing a particular alternative in nest B_k. The details of the nested logit model are well described in Train (2003).

In an effort to develop a model which can more accurately forecast mode choice changes due to incentives or changes, a nested logit model was estimated with the structure shown in Figure 4. The nests are Private (prv), Door-to-Door For hire (ddh), and Public (pub). Each nest was estimated with its own nesting parameter; in this instance K=3 and there are three unique values of $\lambda_{k.}$ Three unique nesting parameters were estimated because it is believed that the unobserved utilities of a subset of alternatives are correlated to a different degree than the unobserved utilities of a subset of alternatives from a different nest. For example, it is believed that the transit alternatives will exhibit a higher correlation in their unobserved utility than modes in another nest.

FIGURE 4. NESTING STRUCTURE FOR AIRPORT ACCESS MODEL.



The model was estimated using MATLAB. The baseline code can be found in Train (2008). A table of results is in Appendix B.

The following are the utility functions which resulted from the estimation:

$U_1 = -0.0271\ ({}^{C}/_{Pt})\ -0.0091\ (T * I\ )$

$U_2 = -2.0848 - 0.0271\ ({}^{C}/_{Pt})\ \ -0.0091\ (T * I)$

$U_3 = \ -3.1915 - 0.0271({}^{C}/_{Pt}) - 0.0091(T * I) - 0.1828({}^{C\,*\,B}/_{Pt})$

$U_4 = \ -2.0982\ -0.1074(\ {}^{C}/_{Pt}\ )\ -0.0091\ (T * I) + 0.0786\ ({}^{C\,*\,R}/_{Pt})$

$U_5 = \ -0.0146(\ {}^{C}/_{Pt}\ )\ -0.0551\ (T * I)$

$U_6 = \ -2.0409 - 0.0271(\ {}^{C}/_{P}\ )\ -0.0091(T * I) + 0.0137\ ({}^{C\,*\,B}/_{Pt}\ ) - 0.0181\ ({}^{C\,*\,R}/_{Pt})$

$U_7 = -0.1799\ (\ {}^{C}/_{Pt}\ )\ \ -0.0091(T * I)$

Estimated nesting parameters are also shown in Figure 4. Table 2 details the predicted shares for each alternative from the model. As can be seen, the predicted shares are fairly close to the actual shares.

TABLE 2. ACTUAL AND PREDICTED SHARES OF NESTED LOGIT MODEL.

Alt	Actual	Predicted
1	0.7912	0.7859
2	0.0577	0.0646
3	0.0204	0.0304
4	0.0161	0.0228
5	0.0068	0.0074
6	0.0874	0.0757
7	0.0204	0.0128

The nesting parameters, shown in Figure 4, must now be interpreted. According to Train (2003), a nesting parameter equal to one represents a standard logit model, which is seen for auto, as there is only once alternative nested as auto. The value of λ_{pub} is less than one, and by viewing the standard error, we can see that the value is statistically different than one. The interpretation is that substitution between the public modes is greater than it is from public modes to another nest. This is consistent with utility maximization. However, λ_{ddh} is greater than one and a hypothesis test shows that it is statistically different than one at the 1% level. This indicates that these two alternatives have negatively correlated unobserved utility, and that substitution across nests is greater than substitution within nests. Train, et al (1987) note that such a situation is not always consistent with utility maximization and that testing must be performed. Herriges and Kling (1996) note that there are certain ranges of data for which a nesting parameter greater than one can be consistent with utility maximization.

A simple test can, at the minimum, confirm that utility maximization is occurring for a range of values of interest. It is important to ensure that choice makers are not disproportionally switching from alternative 7 (Shared Ride Van) to other modes outside the nest if the attractiveness of alternative 6 (Taxi) is increased or vice versa. A simple test was employed to determine if this was the case. The price of alternative 6 was modified to see the effect on alternative 7. The shares of alternative 7 were observed to see if they decreased. By modifying the MATLAB code, the price of taxi was decreased by 40 percent to see if those who chose shared ride van dropped significantly because they from switching to other modes outside the nest. By setting the model to only predict shares, the share of alternative 7 did not decrease when the price of alternative 6 decreased, and therefore there is some confidence that the value of λ_{ddh} is consistent with utility maximization (Table 3).

TABLE 3. PREDICTED SHARES OF NESTED LOGIT MODEL: NESTING PARAMETER EXPLORATION.

		Predicted	
Alt	Actual	Before	After
1	0.7912	0.7859	0.7609
2	0.0577	0.0646	0.0619
3	0.0204	0.0304	0.0291
4	0.0161	0.0228	0.0218
5	0.0068	0.0074	0.0069
6	0.0874	0.0757	0.1062
7	**0.0204**	**0.0128**	**0.0133**

Using the nested logit model illustrated in this section, the introduction of strategies to decrease GHG emissions from airport access is explored.

GREEN AIRPORT ACCESS STRATEGIES

The purpose of developing the models which have been the focus of this study is to forecast the impact of future GHG reduction policies on airport access behavior. These models will now be used to forecast GHG emission reduction in the study corridor due to the introduction of two strategies: subsidized electric vehicle (EV) transit shuttles and subsidized door-to-door EV shared ride.

GHG emissions for each of the 1197 passengers traveling on the study corridor for the entire airport access trip were calculated. Each respondents' distance traveled was multiplied by the CO_2 emission factors per Passenger Mile Traveled (PMT) (transit) or per Vehicle Mile Traveled (VMT) for auto (Chester and Horvath, 2007). Passengers were separated by their mode choice, and a single average values for CO_2 emissions per access mode were determined. These averages were then multiplied by the share of passengers utilizing that mode. Baseline GHG emissions per alternative are presented in Table 4. Baseline GHG emissions are calculated based on the actual mode shares of passengers as defined in the data, and based on the estimated share of passengers estimated by the nested logit model. To generalize these results to a day, the total number of passengers traveling on the California corridor was estimated from BTS data based on a 379 flights per day, a 75 load factor, and an average of 115 seats per aircraft.

TABLE 4. BASELINE GHG EMISSIONS FROM AIRPORT ACCESS MODES (PER DAY).

Alt.	Average CO_2 Emissions /Passenger (lbs)	Actual Share of Passengers	Actual Number of Passengers	Actual CO_2 Emissions (lb)	Estimated Share of Pax	Estimated Number of Pax	Estimated CO_2 Emissions (lb)
1	17.25	0.7912	25788	444905	0.7859	25616	441924
2	5.12	0.0577	1881	9628	0.0646	2106	10780
3	9.82	0.0204	665	6529	0.0304	991	9730
4	27.97	0.0161	525	14678	0.0228	743	20787
5	12.03	0.0068	222	2667	0.0074	241	2903
6	13.58	0.0874	2849	38680	0.0757	2467	33502
7	13.35	0.0204	665	8876	0.0128	417	5569
			SUM:	525963		SUM:	525194

The difference in GHG emissions from the actual shares to the estimated shares is 769 lbs, or a relative error of 0.15 percent.

Electric vehicles have a large potential to reduce GHG emissions from surface transportation in California. California has comparatively clean electricity, which can be seen from the low Greenhouse Gas emission coefficients for electricity generation in California compared to other states (EIA, 2002). However, it is important to note that a reduction in CO_2 emissions from mode shift to an electric vehicle will involve both a loss of CO_2 emissions (from the mode shift to electric vehicle) and an increase in CO_2 emissions because electric power generation creates CO_2. To calculate the emissions generated from EVs, California has an electricity generation CO_2 emission factor of 289 grams per kilowatt hour (kWh) which translates to 3.3 lbs of CO_2 per VMT and 0.21 lbs of CO_2 per PMT traveled in an electric vehicle (Deru and Torcellini, 2007).

Electric Vehicle Transit Connection

The introduction of a fully subsidized transit airport connection shuttle is introduced in this section. Such a service would replace the vehicles that transport passengers between the regional rail systems and the airport. It is reasonable to assume that despite any personal strong environmental considerations among travelers, price and travel time are the main drivers of choice, as shown in the strong fit of the nested logit model. Therefore, it is reasonable to assume that an electric vehicle transit connection shuttle on its own will not shift passengers to transit, but rather a decrease in price in the transit mode as a whole will entice travelers to switch their travel modes. Therefore, to investigate the impact of an EV transit connection bus, the assumption will be that such a bus would be completely subsidized.

To investigate the impact of such a service, the price for the walk to transit (2) and drive to transit (3) alternatives were altered. In the data gathering section, it was noted that the costs for these alternatives were calculated by adding any additional shuttle costs. These costs in 2001/2002 were

$1.10/trip for a shuttle from transit to SFO and $2.00/trip for the AirBART shuttle from BART to OAK.[1] The average miles a choice maker would travel on a transit shuttle is calculated to be 3.26 miles. These prices were eliminated from the price of transit. Then, the nested logit model was set to "predict only," which predicts shares using the utility functions outlined in the nested logit model section. The resulting shares can be seen below in Table 5.

TABLE 5. ACTUAL AND PREDICTED SHARES FOR ALL MODES UNDER SUBSIDIZED TRANSIT CONNECTION STRATEGY.

		Predicted	
Alt	Actual	Before	After
1	0.7912	0.7859	0.7827
2	0.0577	0.0646	0.0657
3	0.0204	0.0304	0.0328
4	0.0161	0.0228	0.0224
5	0.0068	0.0074	0.007
6	0.0874	0.0757	0.0759
7	0.0204	0.0128	0.0135

TABLE 6. CHANGE IN GHG EMISSION FROM SUBSIDIZED TRANSIT CONNECTION STRATEGY.

	Before Transit Cost Reduction			**After Transit Cost Reduction**		
Alt.	Share of Passengers	Number of Passengers	CO_2 Emissions (lb)	Share of Passengers	Number of Passengers	CO_2 Emissions (lb)
1	0.7859	25616	441924	0.7827	25511	440125
2	0.0646	2106	10780	0.0657	2141	8740
3	0.0304	991	9730	0.0328	1069	8770
4	0.0228	743	20787	0.0224	730	20422
5	0.0074	241	2903	0.007	228	2746
6	0.0757	2467	33502	0.0759	2474	33590
7	0.0128	417	5569	0.0135	440	5873
		SUM:	525194		SUM:	524218

The CO_2 emissions savings from the transit cost reduction is 3,768 lbs, a savings of 0.19 percent of the total daily CO_2 emissions. Depending on the cost of this strategy, it may not be a worthwhile investment for a small reduction.

Electric Vehicle Door-to-Door Shuttle

This strategy involves the deployment of airport-based EV vans for door-to-door passenger airport transportation. One could envision that a passenger reserves a ride on such a van similar to current door-to-door van service (for example, Super Shuttle, where one calls or uses the internet to reserve a

[1] The shuttle to SJC was already free of charge. Also, as of 2008 there direct rail service to SFO; however, this example includes the SFO shuttle which was operational in 2001 and 2002 for illustrative purposes.

pick-up time for a specific airport). The adoption of such a service by the individual airports could be motivated by many sources: the airports could collude to reduce GHG emissions; they could be compelled by a Metropolitan Planning Origination (MPO) such as the MTC to offer such a service; or the state government could step in and encourage such a service for GHG reduction. Future study could involve airport and access mode choice in the face of such a strategy; this is introduced in the following section. To investigate the impact of such a service, the price for the DDV option was set to zero and the "predict only" function was employed in the nested logit model. The new shares can be seen below in Table 7.

TABLE 7. ACTUAL AND PREDICTED SHARES FOR ALL MODES UNDER FULLY SUBSIDIZED DOOR-TO-DOOR VAN STRATEGY.

		Predicted	
Alt	Actual	Before	After
1	0.7912	0.7859	0.3923
2	0.0577	0.0646	0.031
3	0.0204	0.0304	0.0136
4	0.0161	0.0228	0.0103
5	0.0068	0.0074	0.0028
6	0.0874	0.0757	0.0413
7	0.0204	0.0128	0.5087

The CO_2 emissions from powering such electric vehicle were added to the emission total of the DDV mode. This is done using the 0.21 lbs of CO_2/PMT multiplied by the number of passengers choosing this mode and the calculation that the average user travels 21.6 miles in a DDV currently. The calculation of GHG emissions before and after this mode is introduced are in Table 8.

TABLE 8. CHANGE IN GHG EMISSION FROM FULLY SUBSIDIZED DOOR-TO-DOOR VAN STRATEGY.

	Before Shared Ride Van Cost Reduction			**After Shared Ride Van Cost Reduction**		
Alt.	Share of Passengers	Number of Passengers	Actual GHG Emissions	After	Number of Passengers	Actual Emissions
1	0.7859	25616	441924	0.3923	12787	220597
2	0.0646	2106	10780	0.031	1010	5173
3	0.0304	991	9730	0.0136	443	4353
4	0.0228	743	20787	0.0103	336	9391
5	0.0074	241	2903	0.0028	91	1098
6	0.0757	2467	33502	0.0413	1346	18278
7	0.0128	417	5569	0.5087	16581	75211
		SUM:	525194			334100

The change in GHG emissions from this strategy is 191,094 lbs, a 36.4 percent reduction. This is a substantial reduction in CO_2 emissions. While such a strategy would be very costly, the payoff as far as CO_2 emission reduction is large. An interesting continuation of this study would be to determine the cost of such a strategy and the service attributes needed to reduce CO_2 emissions by a targeted amount employing this strategy.

ROUTE CHOICE MODEL

A strong addition to the model will be to include a third nesting structure. Such a structure would include an upper model in which a choice maker chooses a route (origin-destination pair), termed nesting level B_m. The choice maker would then choose an airport access modal group (B_k), and then choose an access mode. The upper model would include 12 combinations of airport route choices, shown in Table 9.

TABLE 9. ORIGIN AND DESTINATION CHOICES.

Origin	Destination
SFO	LAX
SFO	ONT
SFO	BUR
SFO	SNA
OAK	LAX
OAK	ONT
OAK	BUR
OAK	SNA
SJC	LAX
SJC	ONT
SJC	BUR
SJC	SNA

The following formulation for such a model is an adaptation of that described in Gil-Moltó and Hole (2003).

$$P_{ni} = P_{ni|B_k(B_m)} P_{B_k|B_m} P_{nB_m} \tag{1.2}$$

Similar to the formulation described in equations 0.7 through 1.1, choice maker *n* is choosing alternative *i*. Here, there are two upper models. The first is $P_{ni|B_k(B_m)}$ which is the conditional probability that alternative *i* is chosen by choice maker *n*, given that route choice nest B_m and access mode choice nest B_k is chosen.

While the three-level nested logit model is not estimated in this study, and instead reserved for future research, a standalone logit model for route choice was estimated to begin such a process. The utility function included three explanatory variables described below.

1. **Flight frequencies** on the dates that 2001/2002 MTC surveys were taken at each airport were collected. These were collected from the FAA ASPM Database. Frequency was divided by 100 for scaling purposes.
2. **Average fare of flights** in the third quarters of 2001/2002 was gathered from the Bureau of Transportation Statistics DB1B database, which records origin, destination, and fare information

for every 10th ticket booked domestically. For each of the 12 airport pairs the average fare was calculated using this data. Average fare was divided by income (in thousands).

3. Shortest path **distance from origin airport** (in miles)

The estimation of the model resulted in the following utility function:

$$U_{Route} = -0.093 * \text{Dististance} + 0.785 * \left(\frac{\text{Frequency}}{100}\right) - 0.0315 * \left(\frac{\text{Fare}}{\text{Income}}\right) \tag{1.3}$$

All coefficients are significant at the .05 level. The log-likelihood of the model is -2310.0101.

Future research will involve the development of a three level nested logit model with the route choice model as the upper model.

CONCLUSIONS

As GHG emission reduction becomes a focus of local, state, and federal policy, all forms of transportation emissions will share the task of reducing GHG emissions. This study investigated GHG emissions from the aviation system and pinpointed airport access modes as an area of both political and engineering realities for reduction. Additionally, this study furthered the use of nested logit models applied to environmental transportation issues. In particular, this study has shown how this method can be used to investigate the adoption of "green" airport access modes. In this particular case, it is found that green airport access modes are possible and could influence GHG reduction. Challenges to such reduction, such as the cost of reduction initiatives, were briefly explored.

There are many directions for future study with such a model. First, performing a similar estimation in Southern California, so the entire corridor could be viewed as a system, would be a strong step. Incorporating access mode choices from the Southern California Region could assist in gaining a bigger picture of airport access modes. It would also further the investigation of regional issues. This model could also be used to investigate changes at the flight level. If not all 12 airport pairs were available, and instead flights from, for example, SFO, were limited to just LAX and ONT, the three-level nested model could be used to determine how passengers would change their route choice and their related access mode. This would allow for an investigation of changes in CO_2 emissions from flights and from access modes.

Acknowledgements

The author would like to acknowledge and thank the University of California Transportation Center for providing opportunities for interaction with experts and for funding support. This research greatly benefited from the expertise and enthusiasm of Kenneth Train of the Department of Economics at University of California, Berkeley. The author would like to thank University of California, Berkeley Professor Mark Hansen and graduate students Mikhail Chester and Yoonjin Yoon for providing guidance, environmental knowledge, and technical expertise. Helpful comments on previous versions were provided by University of California, Berkeley undergraduates Elaine and Irene Kwan.

REFERENCES

Chester, M., Horvath, A. (2007) *Environmental Life-cycle Assessment of Passenger Transportation: A Detailed Methodology for Energy, Greenhouse Gas, and Criteria Pollutant Inventories of Automobiles, Buses, Light Rail, Heavy Rail and Air*. WORKING PAPER, UCB-ITS-VWP-2007-7. Available at: http://www.its.berkeley.edu/publications/UCB/2007/VWP/UCB-ITS-VWP-2007-7.pdf, accessed February 19, 2008.

Deru, M., Torcellini P. (2007) Source Energy and Emission Factors for Energy Use in Buildings, *Technical Report.* NREL/TP-550-38617. Available at: http://www.nrel.gov/docs/fy07osti/38617.pdf, accessed May 5, 2008.

Energy Information Administration, U.S. Department of Energy (2002) Updated State-level Greenhouse Gas Emission Coefficients for Electricity Generation 1998-2000. Available at: ftp://ftp.eia.doe.gov/pub/oiaf/1605/cdrom/pdf/e-supdoc.pdf, accessed May 5, 2008.

Environmental Protection Agency (EPA) (2007) *Climate Change: State of Knowledge*. Available at: http://www.epa.gov/climatechange/science/stateofknowledge.html, accessed October 12, 2007.

Environmental Protection Agency (EPA) (2006) *Greenhouse Gas Emissions from the U.S. Transportation Sector, 1990–2003*. Office of Transportation and Air Quality (6401A), EPA 420 R 06 003. Available at: http://www.epa.gov/otaq/climate/420r06003.pdf, accessed October 12, 2007.

Environmental Protection Agency (EPA) (2004) UNIT CONVERSIONS, EMISSIONS FACTORS, AND OTHER REFERENCE DATA. Available at: http://www.epa.gov/appdstar/pdf/brochure.pdf, accessed February 19, 2008.

Gil-Moltó, M. J., Hole, A. R. (2003) Tests for the consistency of three-level nested logit models with utility maximization. Discussion Paper Series, No.0313, Department Of Economics St. Salvator's College, Scotland.

Gosling, G. (2008) Airport Ground Access Mode Choice Models. ACRP Synthesis 5, Transportation Research Board, Washington, DC.

Governor of the State of California. EXECUTIVE ORDER EXECUTIVE ORDER S-3-05. Available at: http://gov.ca.gov/executive-order/1861, accessed May 4, 2008.

Harvey G. (1997) Airport Choice in a Multiple Airport Region. *Transportation Research Part A*, Vol. 21, No. 6, pp. 439 – 449.

Harvey, G. (1986) A study of airport access mode choice. *Journal of Transportation Engineering,* Vol. 112, No. 5.

Herriges, J. A., Kling, C. L. (1996) *Testing the Consistency of Nested Logit Models with Utility Maximization*. Economics Letters 50 33-39.

International Energy Agency (IEA) (2004) *CO_2 emissions from fuel combustion: 1970-2002*. Paris: IEA/OECD.

Maguier, P. H., Ceder A. (1984) “Passenger Waiting Strategies for Overlapping Bus Routes,” Trans. Sci. 18, pp. 207-230.

Metropolitan Transportation Commission (MTC) (2003) Available at: http://www.mtc.ca.gov/maps_and_data/datamart/survey/airpass1.htm, accessed March 6, 2008.

Pels E., P. Nijkamp, and P. Rietveld. Access to and Competition between Airports: a Case Study for the San Francisco Bay Area, *Transportation Research Part A*, Vol. 37, No. 1, 2003, pp. 71 – 83.

People of California v. San Bernadino County (2007) Available at:ag.ca.gov/globalwarming/pdf/SanBernardino_complaint.pdf, accessed on April 27, 2008.

Port of Seattle (2008) Greenhouse Gas Emissions Inventory. Available at: http://www.portseattle.org/downloads/community/environment/greenhousegas08.pdf, accessed on July 28, 2008.

Supreme Court of the United States (2007) Massachusetts et al. V. Environmental Protection Agency et al. Certiorari to the United States Court of Appeals for the District of Columbia Circuit. No. 05–1120. Argued November 29, 2006—Decided April 2, 2007. Available at: http://www.icta.org, accessed February 21, 2008.

Train, K. (2003) Discrete Choice Methods with Simulation. Cambridge University Press, New York.

Train, K. (2008) Economics 244: Discrete Choice Methods with Simulation. Problem Sets: Problem Set 3. Available at: http://elsa.berkeley.edu/users/train/ec244ps.html, accessed February 21, 2008.

Train, K. (1978) “A Validation Test of a Disaggregate Mode Choice Model,” Transportation Research, Vol. 12, pp. 167-174.

Train, K., McFadden, D., and Ben-Akiva, M. (1987) “The Demand for Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices,” RAND Journal of Economics, Vol. 18, No. 1, pp. 109-123.

Winston, C., Gomez-Ibanez, J. A., and Tye, W. B. (1999) Essays in Transportation Economics and Policy A Handbook in Honor of John R. Meyer. Brookings Institution Press.

Appendix A: Standard Logit Model Output

	Full model			Reduced Model		
	Coefficient Estimate	Std Err	t-stat	Coefficient Estimate	Std Err	t-stat
c/ptALL	-0.0003	0.0143	-0.0221	-0.0165	0.0039	-4.2227
c/pt2	0.2027	0.1350	1.5020			
c/pt3	0.0554	0.0705	0.7854			
c/pt4	-0.1736	0.0587	-2.9571	-0.2422	0.0441	-5.4880
c/pt5	-0.0146	0.0156	-0.9314			
c/pt6	-0.0037	0.0105	-0.3528			
c/pt7	-0.1116	0.0258	-4.3252	-0.1038	0.0086	-12.0934
t*inALL	-0.0128	0.0024	-5.4276	-0.0126	0.0016	-7.8801
t*in2	-0.0019	0.0019	-0.9968			
t*in3	-0.0048	0.0026	-1.8440	-0.0066	0.0028	-2.3637
t*in4	-0.0017	0.0024	-0.7022			
t*in5	-0.0443	0.0173	-2.5620	-0.0516	0.0106	-4.8559
t*in6	-0.0007	0.0017	-0.4128			
t*in7	0.0033	0.0016	2.0820			
cost*bus/ptALL	-0.0150	0.0155	-0.9688			
cost*bus/pt2	0.0304	0.1081	0.2816			
cost*bus/pt3	-0.4572	0.1681	-2.7191	-0.4453	0.1500	-2.9690
cost*bus/pt4	0.0033	0.0228	0.1465			
cost*bus/pt5	-0.3327	0.8189	-0.4063			
cost*bus/pt6	0.0163	0.0098	1.6733	0.0088	0.0041	2.1637
cost*bus/pt7	0.0234	0.0174	1.3439			
cost*res/ptALL	0.0010	0.0146	0.0674			
cost*res/pt2	0.0547	0.1054	0.5187			
cost*res/pt3	0.0154	0.0688	0.2238			
cost*res/pt4	0.1256	0.0484	2.5935	0.1570	0.0453	3.4650
cost*res/pt5	-0.0007	0.0149	-0.0456			
cost*res/pt6	-0.0157	0.0094	-1.6652	-0.0167	0.0054	-3.1231
cost*res/pt7	0.0031	0.0169	0.1808			
Alternative specific constant (a) 2	-2.1123	0.3754	-5.6260	-1.7953	0.1631	-11.0068
a3	-2.4257	0.3577	-6.7815	-2.0591	0.2796	-7.3640
a4	-0.5680	0.5747	-0.9883			
a5	0.0468	0.9936	0.0471			
a6	-2.3524	0.2099	-11.2086	-2.1557	0.1563	-13.7899
a7	-0.7122	0.4797	-1.4845			
log-likelihood	-919.965			-945.7083		

Appendix B. Nested Logit Model Estimation Results.

	Coefficient Estimate	Std Error	t-stat
c/ptALL	-0.0271	0.0055	-4.9527
c/pt4	-0.0803	0.042	-1.9095
c/pt5	0.0125	0.006	2.0756
c/pt7	-0.1528	0.0272	-5.6202
t*inALL	-0.0091	0.0014	-6.3297
t*in5	-0.046	0.0089	-5.1752
cost*bus/pt3	-0.1828	0.0811	-2.2541
cost*bus/pt6	0.0137	0.0046	2.9954
cost*res/pt4	0.0786	0.0364	2.1577
cost*res/pt6	-0.0181	0.0054	-3.3816
a2	-2.0848	0.1622	-12.8559
a3	-3.1915	0.2476	-12.8877
a4	-2.0982	0.4632	-4.5299
a6	-2.0409	0.181	-11.2784
nestparam0	1.0024	1	1.0024
nestparam1	1.7161	0.3353	5.1181
nestparam2	0.7068	0.1285	5.5022
log-likelihood		-918.6491	