Nationwide Estimate of Long-Distance Travel (NELDT)

Generating External Trips for Local Travel Demand Models

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SUMMARY

Though only a small share of trips cover long distances, these long-distance trips generate a disproportionally large amount of traffic and emissions. Therefore, local travel demand models require data on regional trips entering or leaving the study area. Such trips contribute to local congestion, and accounting for them is essential for modeling the full universe of urban travelers. This paper presents an approach to generate long-distance travel within the United States. Trips that enter, leave or go through a specific local study area can be extracted and added to the local model as external trips.

INTRODUCTION

Long-distance travel contributes a large amount of traffic to the highway network. Research in the U.K. suggests that while trips with a distance of more than 50 miles make up only 2 percent of all journeys, these trips account for 31 percent of all vehicle miles traveled (Dargay and Clark 2010: 8). A similar relationship was found for other European countries with 0.5 percent of all trips being more than 100 km long and contributing roughly 20 percent of total miles traveled (Axhausen 2001). Urban travel demand models often aim at simulating these long-distance trips by the same methodology as short-distance trips, regardless of infrequency and different travel sensitivities of long-distance trips.

Furthermore, trips that cross the border of an urban study area are commonly treated as external trips. In most cases, external trips are given exogenously and either remain constant over time or are growth-factored for future years. Roadside surveys can be used to generate external trip data with origin, destination, occupancy, vehicle type and other traveler characteristics, but often they are not done because of resource constraints or concerns about safety or inconveniencing the motoring public.

This paper presents an alternative approach for generating these external travel data. Nationally available data are used to generate long-distance trips throughout the United States, from which regional trips can be extracted for any local study area within the country.

STATE-OF-THE-ART

The simulation of long-distance travel is a relatively young field as most travel demand research has focused on urban traveling. One of the most comprehensive approaches has been developed by Baik et al. (2008). Based on the 1995 American Travel Survey (ATS) they developed a four-step long-distance travel demand model for the modes air taxi, commercial airline and auto. It is unclear how well the four-step approach that has been developed for urban model performs for long-distance travel. Particularly, the second step -trip distribution- may be difficult to calibrate covering heterogeneous distances from 100 miles to 3,000 miles and more.

Dargay et al. (2010) developed a long-distance travel demand model for Great Britain. Using a National Travel Survey from 2004-2006, they estimated demand for 5 different trip purposes by four modes for medium distances (50 to 150 miles) and long distances (> 150 miles). The elasticity for travel time and travel costs on travel demand by purpose, mode and distance were estimated. In scenarios, adjustments were made to rail fares, air fares, highway travel costs and fuel efficiency. The model is not geographically specific, as origin and destination are not simulated. While this paper provides a valuable analysis of long-distance travel data, it cannot be used for spatially explicit scenario analysis. Grimal (2010) analyzed long-distance travel defined as trips longer than 80 km in France. They found that people living in Paris make fewer long-distance trips that are more distant and longer in duration than people living in less urbanized areas. Dargay and Clark (2010: 17) support this view and show that London residents make fewer long-distance trips than other British residents. Apparently, living in a major metropolitan area provides as many opportunities that the need or desire for long-distance travel is reduced.

Talbot et al. (2011) estimated through trips (also called External-External trips) using road-side survey data at external stations for 13 MPO (Metropolitan Planning Organisation) areas across Texas. A through-trip model was developed that chooses an external station for every incoming trip by congested travel time through the study area and number of turns on links. Though this is a worthy example showing how to generate through trips beyond static assumptions, the model only creates External-External trips, omitting Internal-External and External-Internal trips.

Other papers explore the use of long-distance travel data. Haupt et al. (2004) developed a nationwide model for Germany for person travel and truck flows. Using data from navigation systems they were able to calibrate the model based on a large number of data records. Nevertheless, work trips were k-factored to match commuter trip tables provided by the federal employment agency. Finally, synthetic matrix estimation was used to tweak the trip tables to traffic counts. This paper provides an impressive example of how the vast data availability from navigation systems can be exploited in travel demand modeling. However, the use of k-factors and synthetic matrix estimation limits the application of this model for policy analysis.

The model to be developed here is intended to make use of publicly available data, ensuring that this work is reproducible without obtaining protected private data. While the 1995 ATS data is rich in content, it is also 16 years old and may not capture recent shifts in travel behavior. Furthermore, it only covers trips longer than 100 miles, and therefore, is likely to miss a significant share of external traffic for many urban areas. To overcome the limitations of a static gravity trip-distribution model, travel and socio-economic data shall be used to the maximum amount possible to resemble real-world origin-destination pairs in a simulation model.

DATA

In 2001/2002, the Federal Highway Administration conducted the National Household Travel Survey (NHTS), which collected data on both daily and long-distance travel within the U.S. (FHWA 2010). The survey consisted of 69,817 telephone interviews conducted from March 2001 to May 2002. Contestants were asked about their daily travel patterns (short distance) as well as any traveling within the past 28 days where the furthest destination was 50 miles or more away from their home (long distance). This data set offers a rich source of information for long distance trips by all modes of transportation within the U.S. A total of 45,165 (raw count) long-distance data records were available. In 2010, FHWA published a new NHTS conducted in 2008 (FHWA 2010). This time, however, interviews focused on daily traffic only, without a special survey for long-distance travel. From this dataset, a total of 28,246 records (raw count) with trip length over 50 miles are available. It is unclear to the authors why the NHTS data set contains only 2 percent trips made by the mode air, compared to 8 percent in the NHTS 2002. To avoid ambiguous usage of data, this research uses the 2002 NHTS. It is currently evaluated whether the NHTS 2009 may enrich the NHTS 2002 survey. Given the smaller sample size, the 2009 NHTS is unlikely to be able to replace the previous survey.

Air travel data are published by the Bureau of Transportation Statistics based on ticketed passengers (BTS 2009). These data provide a ten percent sample of passengers between all U.S. airports, distinguishing between passengers changing flights and passengers having their final destination at one airport. Data are available by quarter, and to ensure compatibility with the NHTS data, air travel data was retrieved for 3/2001, 4/2001, 1/2002 and 2/2002.

Given the shortage of reliable long-distance travel data, other data sources were explored. Gur et al. (2009) analyzed the usability of cellular phone data to travel demand modeling in Israel. The benefit of these data is the sheer number of observations. Even though Gur et al. had only access to one carrier covering roughly one third of all cellular phone users in Isreal, the team was able to collect over 280,000 tours within only 4 months. As mentioned above, Haupt et al. (2004) have suggested using GPS data from navigation systems to collect travel data. The authors contacted a major navigation system provider in the U.S. aiming to using such data. Today's market penetration of GPS devices covers a wide range of socio-economic groups, making these data more usable for travel demand modeling. For privacy reason, however, the raw data was not released. The navigation system provider is planning to develop algorithms to extract aggregate trip data from GPS signals in the future.

For this study, neither cellular phone data nor navigation system data were available. Though both data systems are impressive enrichments to travel patterns, they are unlikely to become the sole data source for travel demand modeling. Commonly, these data do not provide any information on trip purpose, mode, vehicle occupancy or the socio-demographic characteristics of the traveler. For privacy reasons, neither cellular phone providers nor navigation system providers match travel data with information they have about on single user accounts. These massive data are likely to be helpful in calibrating and validating travel demand models in the future, however, their use in model estimation is limited so far.

MODEL DESIGN

A Nationwide Estimate of Long-Distance Travel (NELDT) has been developed and implemented to simulate person long-distance travel. Figure 1 shows the workflow of NELDT. The key input data are the NTHS data records. The NHTS data records in combination with the synthesized records are considered to be a representative sample of long-distance travel in the U.S. Using the BTS air travel data, a nationwide control total for long-distance travel is developed for each mode. Subsequently, the NHTS records are expanded to match the national total of air travelers.

The NHTS provides long-distance trips by home state and destination state. To increase the resolution, state-to-state trips are disaggregated to county-to-county trips based on population density. Long-distance trips by auto are assigned to a multimodal U.S. network to define routing of trips. Finally, trips relevant for a particular study area can be extracted for a local travel demand model. Commonly, these include internal-external (I-E), external-internal (E-I) and through or external-external (E-E) trips.

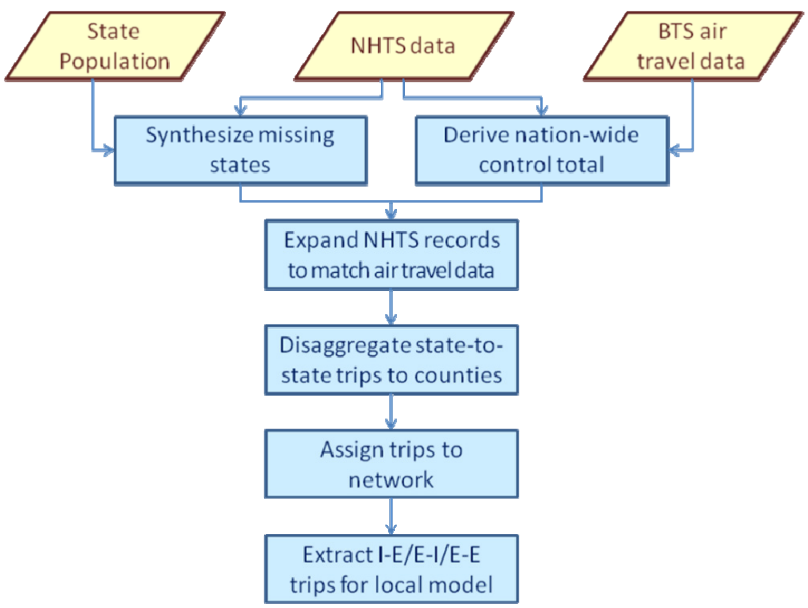


Figure 1: NELDT design

GENERATE MISSING NHTS RECORDS

For privacy reasons, the NHTS dataset only reports the origin state for trips from states with a population of 2 million or more. For smaller states, synthetic data records were generated based on travel data of surrounding states for which data are available. Figure 2 shows the number of data records of long-distance trips by state. Most states without data records have neighboring states that can be used to synthesize missing data records. Maine records were generated based on Massachusetts datasets, and Montana records were generated based on Washington and Oregon data.

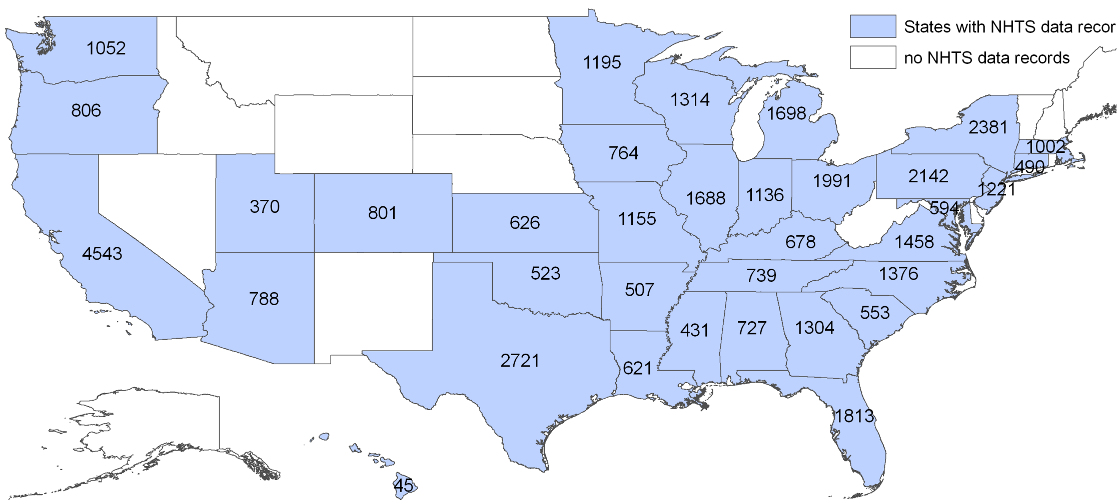


Figure 2: Number of NHTS long-distance travel data records by home state

For residents of 15 states and Washington D.C., the NHTS data set does not provide long-distance travel records for confidentiality reasons. To estimate the number of records that need to be synthesized for these states, a multiple regression is estimated. As explaining variables for long-distance travel, three independent variables were tested:

- Population
- Share of service employment of total employment
- GDP per capita

To avoid multicollinearity, not total service employment or total GDP were chosen, as each of those would have been highly correlated among themselves and with population. The selected three independent variables show close to none multicollinearity. Table 1 summarizes the results of this multiple regression by mode.

Table 1: Estimation of NHTS records per State

Auto	Estimate	Std. Error	t value	Pr(>|t|)	Air	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-109.2	513.2	-0.213	0.833	(Intercept)	-116.6	42	-2.776	0.00924 **
Population	0.000107	0.000006642	16.106	<2e-16 ***	Population	0.00001127	5.436E-07	20.738	< 2e-16 ***
Serv.Empl.Share	1285	2020	0.636	0.529	Serv.Empl.Share	277	165.3	1.676	0.10387
GDP per capita	-0.004354	0.01249	-0.349	0.73	GDP per capita	0.0004496	0.001022	0.44	0.66318
Adj. R-squared:	0.913				Adj. R-squared:	0.9479			
N:	36,790				N:	3,110			

Bus	Estimate	Std. Error	t value	Pr(>|t|)	Train	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-18.97	25.39	-0.747	0.461	(Intercept)	-46.82	47.01	-0.996	0.327
Population	0.000002541	3.286E-07	7.732	1.01e-08 ***	Population	0.000001472	6.084E-07	2.42	0.0216 *
Serv.Empl.Share	21.83	99.91	0.218	0.828	Serv.Empl.Share	12.39	185	0.067	0.947
GDP per capita	0.0004488	0.000618	0.726	0.473	GDP per capita	0.001239	0.001144	1.083	0.2873
Adj. R-squared:	0.7276				Adj. R-squared:	0.2643			
N:	833				N:	370			

Ship	Estimate	Std. Error	t value	Pr(>|t|)	Other	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.727	4.021	0.927	0.361	(Intercept)	-4.006	10.35	-0.387	0.701
Population	9.773E-08	5.204E-08	1.878	0.0698 .	Population	7.028E-08	1.339E-07	0.525	0.604
Serv.Empl.Share	-22.57	15.82	-1.426	0.1638	Serv.Empl.Share	19.99	40.73	0.491	0.627
GDP per capita	0.0001486	0.00009787	1.519	0.1389	GDP per capita	-0.0000597	0.0002519	-0.237	0.814
Adj. R-squared:	0.2289				Adj. R-squared:	-0.08008			
N:	36				N:	70			

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

A reasonable correlation was found for the modes auto, air and bus. Train and ship are sparsely available across the country and have a small sample sizes. They were expected to show less correlation. In all cases, no more than one independent variable turned out to be statistically relevant, namely population. Hence, the other two independent variables were dropped, and the estimation was done with population as the only relevant independent variable (Table 2). Furthermore, the intercept was forced to be 0 to ensure that if the population of a region was 0, the number of long-distance trips from that region would be 0 as well.

Table 2: Revised Estimation of NHTS records per State

Auto	Estimate	Std. Error	t value	Pr(>|t|)	Air	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)					(Intercept)				
Population	1.23E-04	4.35E-06	28.29	<2e-16***	Population	1.14E-05	3.31E-07	34.47	<2e-16***
Adj. R-squared:	0.9581				Adj. R-squared:	0.9714			
N:	36790				N:	3110			

Bus	Estimate	Std. Error	t value	Pr(>|t|)	Train	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)					(Intercept)				
Population	2.89E-06	1.81E-07	15.96	<2e-16***	Population	1.53E-06	3.35E-07	4.56	6.34E-05***
Adj. R-squared:	0.8788				Adj. R-squared:	0.3612			
N:	833				N:	370			

Ship	Estimate	Std. Error	t value	Pr(>|t|)	Other	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)					(Intercept)				
Population	1.37E-07	2.82E-08	4.864	0.0000258***	Population	1.69E-07	7.24E-08	2.336	0.0255*
Adj. R-squared:	0.393				Adj. R-squared:	0.113			
N:	36				N:	70			

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

These factors are used to estimate the number of trip records for states that were not reported in the NHTS survey as their population is below 2 Mio. An according number of trip records needs to be synthesized for these less populated states. Auto, air and bus trips are analyzed subsequently as the modes train and ship are only available in selected states and cannot be estimated with a general regression analysis.

Table 3: Number of NHTS records to be synthesized by state and Washington D.C.

State	Auto	Air	Bus
Alaska	79	7	2
Delaware	99	9	2
District of Columbia	70	7	2
Idaho	165	15	4
Maine	159	15	4
Montana	112	10	3
Nebraska	213	20	5
Nevada	267	25	6
New Hampshire	157	15	4
New Mexico	228	21	5
North Dakota	78	7	2
Rhode Island	132	12	3
South Dakota	94	9	2
Vermont	76	7	2
West Virginia	222	21	5
Wyoming	61	6	1

Up to four major neighboring states were chosen to select randomly NHTS records from those states. The destination of each synthesized record is set to ensure that the share of intrastate trips is the same as the average share of intrastate trips in neighboring states. For example, to generate records for New Mexico, NHTS records were selected randomly from the four states Arizona, Colorado, Oklahoma and Texas. The average share of intrastate trips by auto for these four states is 84.4%, thus for the 228 auto records synthetically created for New Mexico, 84.4% (or 192 records) were set to have a destination in New Mexico. This way, the characteristics of the travelers of neighboring states is copied, while the average trip length of neighboring states is approximately achieved. Alaska is particularly difficult as it has no neighboring US states, and – given its size– it has a very unique long-distance travel pattern. Though distances are big in Alaska, the absolute number of long-distance travelers is comparatively small given the small population. As Alaska long-distance travelers barely affect volumes in the contiguous 48 states and Hawaii, Alaska travelers were not included in this research.

Because the NHTS is a national survey that interviewed long-distance travelers in their home state, no international visitors are included in the NHTS data set. International travelers are synthesized based on air travel data and land border crossings from Canada and Mexico. Their characteristics are assumed to be comparable to American long-distance travelers, with the exception that all non-U.S. travelers are assumed to arrive by air or auto. Accordingly, data records from the national travelers are selected randomly to synthesize international visitors.

NATIONWIDE NUMBER OF LONG-DISTANCE TRAVELERS

Because the NHTS data set is a sample of long-distance travel, not all long-distance trips of the entire population are included. Even though the NHTS data set includes weights for every data record, simply expanding the records based on these weights is not recommended (FHWA 2005: 5-7). Long-distance travel is an event that is too infrequent to expand from single records. If, for example, a person reported two trips in a 28-day period, expanding this trip to

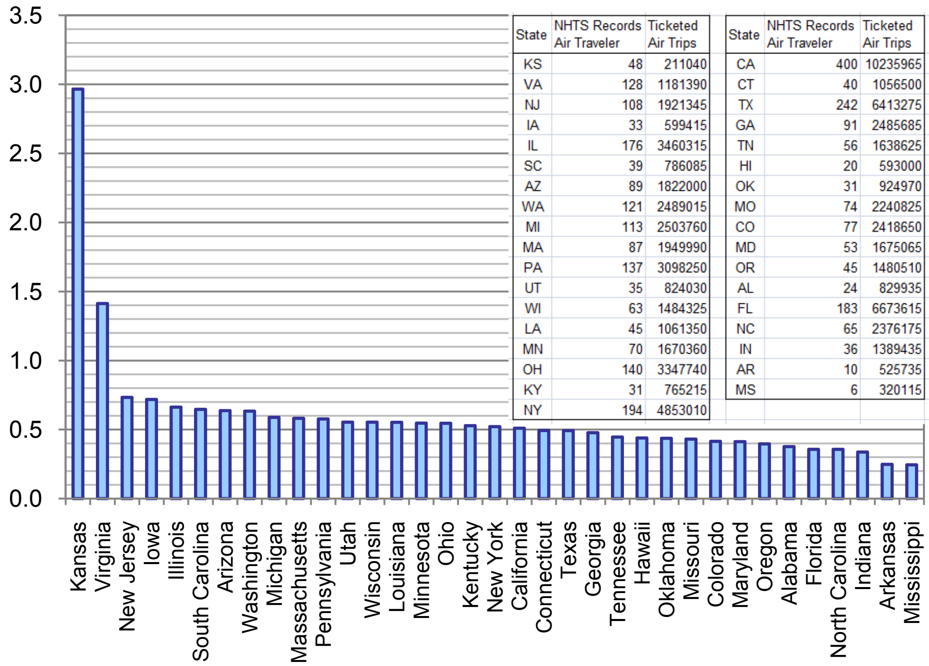
$$2 \text{ trips} / 28 \text{ days} \times 365 \text{ days} = 26 \text{ trips per year} \tag{1}$$

cannot be carried out with high confidence. This person may have done far fewer trips greater than 50 miles in this year. Because long-distance trips are relatively rare, a simple expansion produces statistically non-robust results.

The total number of long distance trips had to be derived for a current year from other data sources. From the NHTS data, all records were counted that had the main mode air travel and for which a home state was reported, providing a total of 3,110 data records. For ticketed air passengers, data from the Bureau of Transportation Statistics (BTS) website were summarized. Round trips were counted by the state the trip started in. One-way trips, for which it could not be identified whether the this leg is the outbound trip or the return trip, were counted half. As respondents of the NHTS were asked about their travel in the last 28 days, the yearly BTS air travel data was multiplied by 28 days and divided 365 days to compare the same time periods.

Figure 3 shows the ratio of NHTS air travel records and ticketed passengers by home state. While most states have between 0.25 and 0.75 NHTS records per 1,000 ticketed passengers, a outliers were found for Kansas and Virginia. Studying the geography of Kansas suggests that the most likely reason for this exception is that the largest airport for Kansas is located in Kansas City, Missouri. While the NHTS data reports the home state (in this case Kansas), the BTS air travel data report the airport where the passenger boarded an airplane (in this case Kansas City International Airport in Missouri). The seemingly oversampling of Kansas appears to be due to the fact that no major airport is located within Kansas. Consultation with the NHTS support team could not clarify why Virginia showed more NHTS records per 1,000 ticketed passenger than other states.

Because of the relatively small sample sizes, the NHTS support team recommended not to use the NHTS air travel data for analysis at the state level. These data shall only be used as a national average. As a consequence, the total number of passengers could only be estimated at the national level. Assuming that the NHTS is representative across modes, it is assumed that the nationwide average number of approximately 0.5 air travel NTHS records per 1,000 ticketed passengers may be applied to expand all modes.



State	NHTS Records Air Traveler	Ticketed Air Trips
KS	48	211040
VA	128	1181390
NJ	108	1921345
IA	33	599415
IL	176	3460315
SC	39	786085
AZ	89	1822000
WA	121	2489015
MI	113	2503760
MA	87	1949990
PA	137	3098250
UT	35	824030
WI	63	1484325
LA	45	1061350
MN	70	1670360
OH	140	3347740
KY	31	765215
NY	194	4853010

State	NHTS Records Air Traveler	Ticketed Air Trips
CA	400	10235965
CT	40	1056500
TX	242	6413275
GA	91	2485685
TN	56	1638625
HI	20	593000
OK	31	924970
MO	74	2240825
CO	77	2418650
MD	53	1675065
OR	45	1480510
AL	24	829935
FL	183	6673615
NC	65	2376175
IN	36	1389435
AR	10	525735
MS	6	320115

Figure 3: NHTS air travel records per 1,000 ticketed trips

Table 4 shows the expanded number of long-distance travelers on an average day in the U.S. After synthesizing NHTS records for missing states (Table 3), a total of 3,343 air travel records is available. Given the number of air passengers according to BTS database, an expansion factor of 25,318.793 was calculated, which led to a yearly number of travelers for all modes. According to these data, the average American resident traveled 4.15 long-distance trips within one year. It should be noted that the survey period covered the 9/11 attack, which may have led to fewer than usual long-distance trips, particularly by air.

Table 4: Expanded number of long-distance travelers in the U.S.

	Auto	Air	Bus	Train	Ship	Other
NHTS Records	36,790	3,110	833	370	36	70
Synthesized records	5,687	233	102			
Total number of records	42,477	3,343	935	370	36	70
BTS air statistics		84,640,725				
Expansion factor	25318.793					
Number of yearly travelers	1,075,466,370	84,640,725	23,673,071	9,367,953	911,477	1,772,316
Number of daily travelers	2,946,483	231,892	64,858	25,666	2,497	4,856

The yearly number was converted into average weekday travelers by dividing by 365. In urban travel demand models, it is common to use a smaller number than 365 to convert yearly in daily traffic volumes, as it is assumed that weekday traffic carries more trips than weekend traffic. For long-distance travel, however, weekends carry at least a similar number of trips as weekdays, particularly for personal trips. For lack of better information -the NHTS records do not report the weekday- yearly data was divided by 365 to derive travel on an average day.

It should be noted that Table 4 shows how many long-distance trips are started on a given day. Each record, however, describes a journey including both the outbound trip and the return trip. In the expansion process, NHTS records are duplicated until the number of air travelers matches the observed total of 231,892 trips.

DIRECTION OF TRAVEL

The NHTS data records describe complete trips, including outbound trip, stay at the destination and return trip. For each long-distance traveler, the number of nights stayed away from home is provided by NHTS. As an average day shall be simulated, both the outbound and the inbound trip shall be represented. If someone is staying away from home for 0 nights, it is assumed that this person travels the outbound trip and the return trip on the same day, thus the trip of this person is added to the trip table twice: from home state to destination state and from destination state to home state. Travelers who stay one night are assigned with half a trip from their home state to the destination state and another half trip from the destination state back to their home state. For travelers staying two nights, 1/3 outbound and 1/3 inbound trips are simulated, etc. Currently, it is disregarded that a few travelers might travel over night and spend part of their traveling on a different day.

In addition, the number of trips is influenced by the distance traveled, at least for auto trips. Someone traveling from San Francisco to Chicago has to drive approximately a day and half. Even if there were several drivers allowing the vehicle to travel without overnight stays, traffic would be overestimated if the entire trip from San Francisco to Chicago was assigned to the network as traveled on the single day simulated. The assumption was made that the average traveler would drive for a maximum of 750 miles per day, and then rest for an overnight stay. Trips below 750 miles are not adjusted, but trips longer than this threshold are reduced proportionally to the distance traveled.

$$trips_{state_a,state_b} = longtrips_{state_a,state_b} \cdot \frac{\sigma}{\max\left(\sigma, dist_{state_a,state_b}\right)} \tag{2}$$

where $trips_{state_a,state_b}$ is the number of average daily trips from $state_a$ to $state_b$

$longtrips_{state_a,state_b}$ is the number of trips from from $state_a$ to $state_b$ reported by NHTS

σ is a threshold the average traveler is assumed to be able to travel per day, for auto travel it is set to 750 miles

$dist_{state_a,state_b}$ is the travel distance from $state_a$ to $state_b$

This way, long-distance trips of more than 750 miles are scaled down to account for the fact that it is impossible to drive from coast to coast in a single day. A trip from San Francisco to Chicago (2,133 miles) would be assigned as 0.47 trips.

DISAGGREGATION

The NHTS reports trip origins and destinations by state. Urban travel demand models work at a geography that is much smaller than states. To make these long-distance trips usable for local models, trip origins and destinations are disaggregated to the county level. This disaggregation is done based on population and employment. Counties with more population and employment are expected to generate and to attract more long-distance trips than less populated counties. Furthermore, the larger the distance between two counties, the smaller is the attraction between them. This reasoning follows common gravity theory. The following equation is applied to disaggregate trips between states to trips between counties

$$trips_{county_i, county_j} = trips_{state_a, state_b} \cdot \frac{weight_{county_i, county_j}}{\sum_{county_k \in State_a} \left(\sum_{county_l \in State_b} weight_{county_k, county_l} \right)} \tag{3}$$

where $county_i$ is located in $state_a$
$county_j$ is located in $state_b$
$county_k$ are all counties located in $state_a$
$county_l$ are all counties located in $state_b$

The weights for disaggregation are calculated by

$$weight_{county_i, county_j} = (\lambda \cdot p_i + (1-\lambda) \cdot e_i) \cdot (\mu \cdot p_j + (1-\mu) \cdot e_j) \cdot \exp(\beta \cdot d_{i,j}) \tag{4}$$

where p_i is population in county i
e_i is employment in county i
λ is a parameter to weigh population and employment as a trip generator
μ is a parameter to weigh population and employment as a trip attractor
β is a parameter calibrated by origin state (average across all states is -0.014)
$d_{i,j}$ is the travel distance from county i to county j

The parameter β was calibrated by origin state to match the average long-distance trip length by car. Across all states, an average trip length by auto of 216 miles is simulated. The parameters λ and μ were set to reflect impact of population and employment by trip purpose. For personal trips, population is given a bigger weight, while for business trips employment by county is more significant. For commute trips, population is used to disaggregate the origin of the trip, and employment is used to disaggregate the destination of the trip.

This calculation disaggregates travel between the 48 continuous states to travel between 3,109 counties. As the NHTS covers only trips of 50 miles or more, county pairs with a distance of less than 50 miles were excluded.

LONG-DISTANCE TRAVEL ASSIGNMENT

If a local travel model covered Washington D.C., a long distance trip from Philadelphia to Miami could either go through the D.C. study area or avoid the city on the beltway. The route choice decision is simulated by a traffic assignment model, using similar methods as commonly used in urban travel modeling.

Only long distance trips are assigned to the network. Short distance trips of less than 50 miles are added as background volume to reflect congestion faced by all travelers, particularly in urban areas. In rural areas, a Level of Service (LOS) C is assumed, with a corresponding volume-to-capacity (V/C) ratio of 0.6 filled by short distance trips. In other words, if the total capacity of a highway link is assumed to be 1,700 vehicles per hour per lane (vphpl), local auto flows fill 60 percent of this capacity. In urban areas, highways are assumed to be more congested and to operate between LOS D and E, such that the background volume of short-distance trips corresponds to a V/C ratio of 0.9. If applied for a specific local travel model, volumes of internal trips simulated by the local travel model should be used as background volumes instead.

Figure 4 shows the assignment of long-distance travelers to the U.S. network. The Texas triangle between Houston, Dallas/Fort Worth and San Antonio is pronounced, as well as trips in the northeast focused on New York. Chicago appears like a major hub, and trips across Ohio between the three Cs (Cleveland, Columbus and Cincinnati) are notable. The largest volumes of long-distance trips can be found in California along Interstate 5 between the two massive urban agglomerations Bay Area and the Greater Los Angeles Region. Lacking a good alternative like hourly train connections between major cities in the Northeast, travelers between these Californian regions are fairly dependent on either flying or driving. For any given local study area, E-I, I-E and E-E trips can be extracted in a subarea analysis and used as external volumes for the local study area.

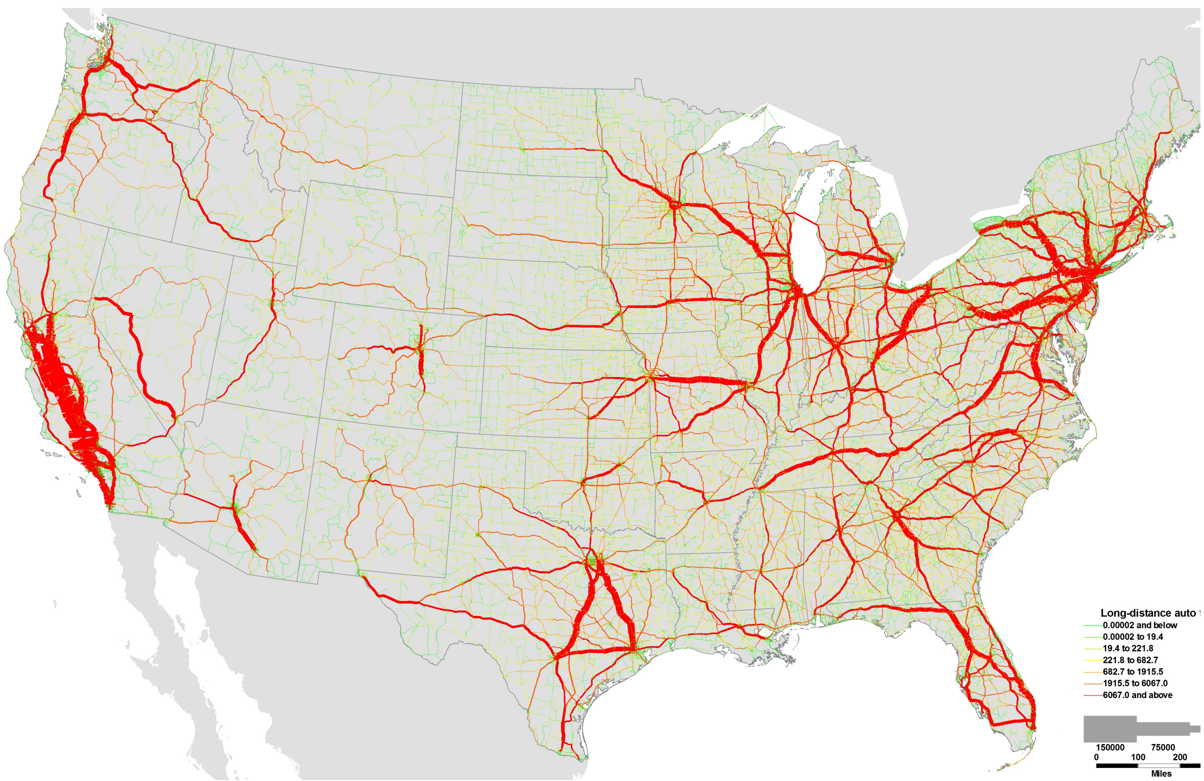


Figure 4: Assignment of long-distance travelers

EXTRACT DATA FOR LOCAL STUDY AREA

A local travel demand model may have more external stations than simulated in NELDT. Such local roads may need to be added on a case-to-case basis if they are assumed to have a particular relevance for local traffic flows. In most cases, however, the national network is expected to carry the vast majority of all external trips. Furthermore, all long distance travelers destined to the local study area at hand may be added to the local population to add local trips while they are visiting the study area. In the opposite direction, long distance travelers that leave the local study area should be subtracted from local travelers, as they cannot make local trips while they are outside the study area. Keeping track of who actually is traveling in the study area may be of interest to account for the different travel behavior between residents, tourists or business travelers.

A practical application of NELDT has been implemented for the Arizona Statewide Travel Demand Model (AZTDM2), sponsored by the Arizona Department of Transportation. The long-distance model has been validated at the state border, aggregating flows into the four neighboring states and Mexico. Since the NHTS data covers exclusively U.S. residents, trips across the border with Mexico had to be scaled up to account for Mexicans visiting the U.S. Table 5 shows that the model validated reasonably well.

Table 5: Validation of NELDT application in Arizona

Direction	Count	Model	Difference	% Difference
California State Line	55,968	43,714	-12,254	-22%
Nevada State Line	60,266	53,185	-7,081	-12%
Utah State Line	26,944	32,242	5,298	20%
New Mexico State Line	34,802	31,259	-3,543	-10%
Mexico Border	51,548	48,950	-2,598	-5%
Total State Cordon	229,528	209,349	-20,179	-9%

CONCLUDING REMARKS

The main motivation for this research was to develop the ability of estimating external trips for local travel demand models. The tool is flexible enough to estimate traffic flows for local study areas anywhere within the lower 48 states or Hawaii. Besides serving local travel demand models, this research is also intended to serve studies on long-distance travel. The American Recovery and Reinvestment Act aims at investing in transportation infrastructure, among others in high-speed rail. Many state DOTs are under pressure to estimate the likely impact on traffic flows if high-speed rail was implemented in their particular state. To address such questions, it is planned to extend NELDT by a mode choice model.

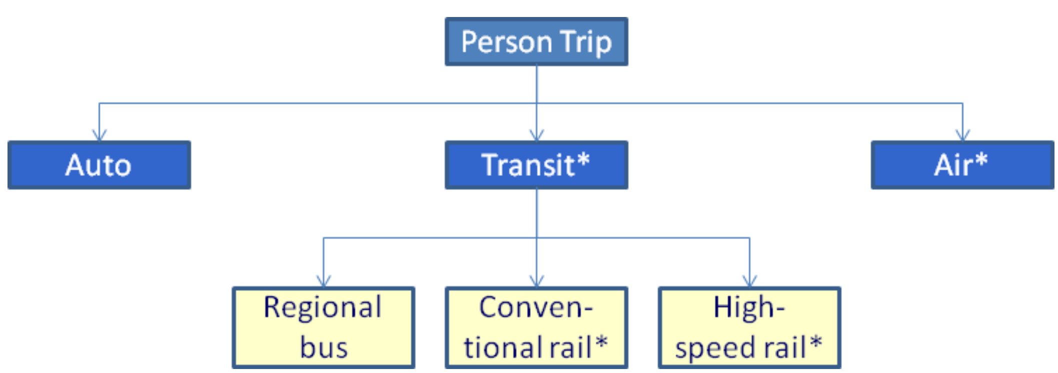


Figure 5: Structure of Mode Choice Model

Figure 5 shows the structure of the envisioned mode choice model. Choice options marked with an asterisk (*) carry a mode-specific constant calibrated to observed travel behavior. The utility of each mode will be calculated with a multiple regression function using travel time and travel costs for all modes, party size, and in addition for air and transit number of transfers, access time, wait time and egress time. For air, the time required for check-in and security check will be included as well. While most urban mode choice models distinguish drive-alone and shared-ride for the auto mode, the party size is given by the NHTS, which defines the auto occupancy in trip generation. De Lapparent et al. (2009) have estimated a mode choice model based on stated-preference survey from three European countries to simulate the choice between auto, train, bus and air. The estimated parameters could be used as a starting point in lack of comparable data for the U.S. Eventually, a one single mode choice model for short-distance and long-distance should be implemented in a given study area to avoid an artificial change in mode options for trips over 50 miles.

For future long-distance travel flows, external trips are commonly either assumed to be constant or growth assumptions are made. Obviously, this involves uncertainty, including but not limited to long-term trends in gasoline prices, economic growth, and individual travel behavior. Traditionally, long-distance travel rose with economic growth.

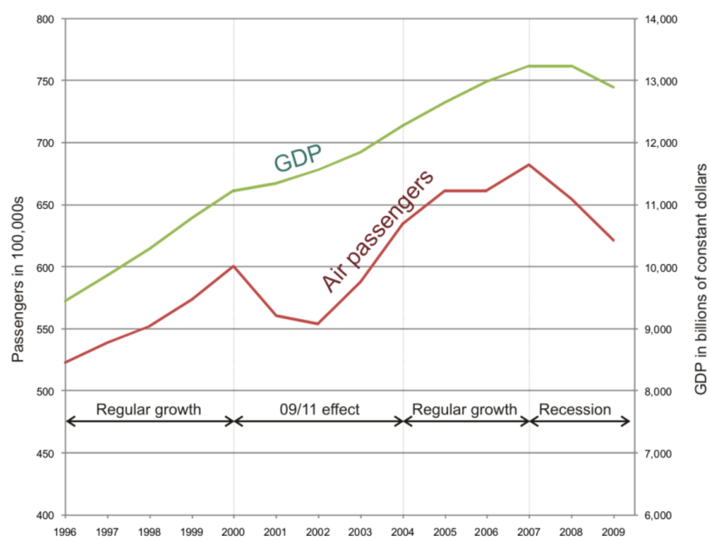


Figure 6: Yearly air passengers and GDP in the U.S.

Figure 6 reveals this relationship for the years 1996 to 2009. In more regular years, the number of yearly passengers grew in parallel to GDP growth. Exceptions were the years 2001 through 2004, which has a lower number of air passengers due to the events on September 11th, 2001. The recession that started in 2007 resulted in less air travel as well. Outside these unusual time periods, the number of passengers grew at a similar rate the GDP did, with the number of passengers slightly lagging behind the economic growth rate (Table 6). If the economy is expected to grow further, long-distance travel will be an even bigger factor for congestion. On the other hand, if energy prices are growing as forecasted by many experts, long-distance travel will be cut back as some of these

Table 6: Growth of air passengers and GDP

	1996-2000	2004-2007
Air passenger growth	14.8%	7.4%
GDP growth	19.0%	7.9%

trips are discretionary. The growth of long-distance travel in travel demand models will vastly depend on expert judgment and exogenous assumptions.

Even though the number of long-distance trips is much smaller than the number of short-distance trips, their impact on vehicle miles traveled is remarkable and deserves particular attention.

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