SoundCast
Activity-Based Travel Forecasting Model for PSRC

Featuring ***DAYSIM***—the Person Day Activity and Travel Simulator

Model System Design

September 25, 2014

Prepared for

Puget Sound Regional Council

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Introduction and Model System Overview

Model system

SoundCast is a travel demand model system built for the Puget Sound Region, as shown in **Figure 1**. The model was built to depict diverse human travel behavior and include travel sensitivity to land use and the built environment. SoundCast outputs transportation network measures such as highway volumes in one hour periods in a future year or number of boardings on a transit line. It also outputs measures related to people like average distance to work by home county or the number of transit trips different types of people will take.

The three main components of SoundCast are:

- person trip demand in the **Daysim** activity-based model
- external, special generation, truck, and group quarters aggregate modeling
- assignment and skimming in **EMME**

DaySim is a modeling approach and software platform to ***simulate resident daily travel*** and activities on a typical weekday for the residents of a metropolitan region or state.

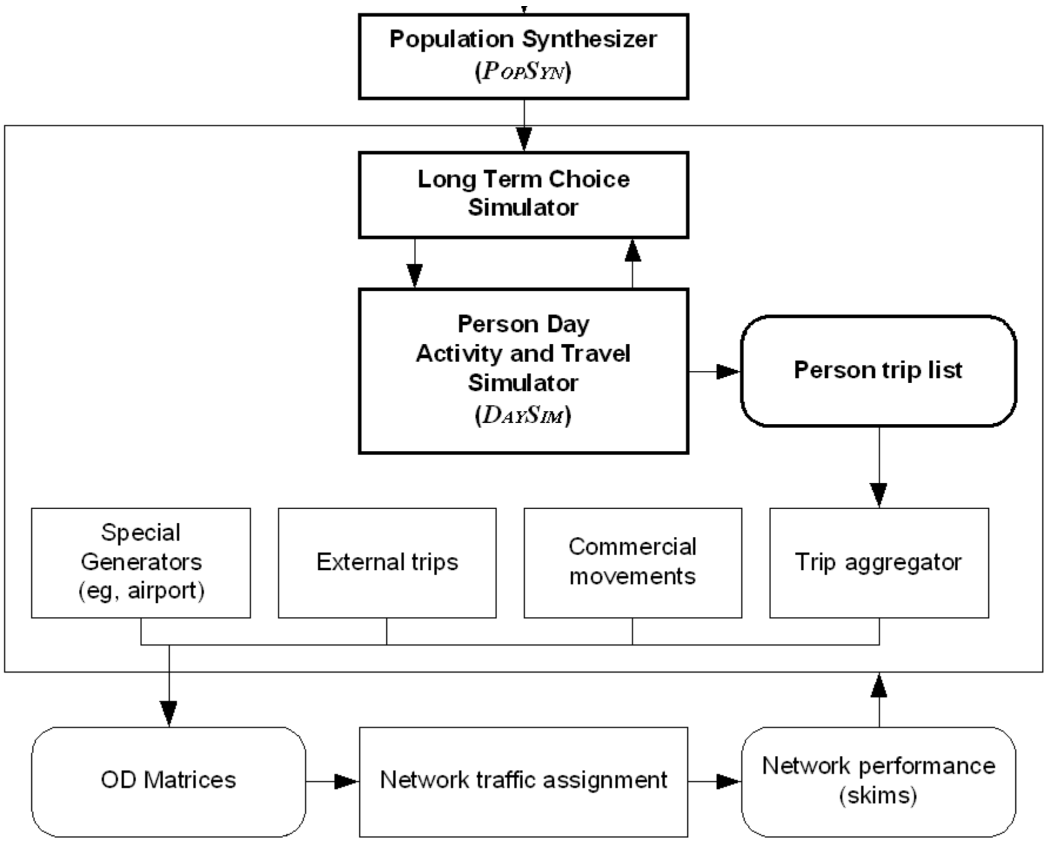
In essence, DaySim replaces the trip generation, trip distribution and mode choice steps of a 4-step model, while ***representing more aspects of travel behavior*** *(auto ownership, trip chaining, time of day scheduling, detailed market segmentation, etc.)*

Daysim ***integrates with EMME*** by generating resident trip matrices for assignment and uses the network skims from assignment for the next global iteration of DaySim.

The major inputs to SoundCast are transportation networks and modeled household and employment data from UrbanSim. In Daysim, The Population Synthesizer (PopSyn) creates a synthetic population, comprised of Census PUMS households, that is consistent with regional residential, employment and school enrollment forecasts. Long-term choices (work location, school location and auto ownership) are simulated for all members of the population. The Person Day Activity and Travel Simulator (DaySim) creates a one-day activity and travel schedule for each person in the population, including a list of their tours and the trips on each tour.

The trips predicted by DaySim are aggregated into EMME trip matrices and combined with predicted trips for special generators, external trips and commercial traffic into time- and mode-specific trip matrices. The EMME network traffic assignment models load the trips onto the network. Traffic assignment is iteratively equilibrated with the Long Term Choice Simulator, DaySim and the other demand models. The parcel level land use inputs come from UrbanSim.

Figure 1: New PSRC Regional Travel Forecasting Model System



Daysim

The following section describes the design features of PopSyn, the long term choices and DaySim. These include a description of each model component, definitions of the variables included in the simulated output, details about accessibility variables employed to help integrate the model system, and the sampling procedure used in the destination choice models. The sub-models in the system are:

1. Work Location
2. School Location
3. Pay to Park at Work
4. Transit Pass Ownership
5. Auto Ownership
6. Individual Person Day Pattern
7. Exact Number of Tours

8. Work Tour Destination
9. Other Tour Destination
10. Work-based subtour Generation
11. Work Tour Mode
12. Work Tour Time
13. School Tour Mode
14. School Tour Time
15. Escort Tour Mode
16. Escort Tour Time
17. Other Tour Mode
18. Other Tour Time
19. Work-Based Subtour Mode
20. Work-Based Subtour Time
21. Intermediate Stop Generation
22. Intermediate Stop Location
23. Trip Mode
24. Trip Time

Model variables

Table 1 lists the variables that will be produced by the Daysim models. The variables are at five different levels: household, person, person day, tour and trip. The table also lists the range of values that will be used for each output variable. **Table 1** contains only the most elemental variables. More output variables can be computed in combination with the network and/or zonal data, such as the VMT traveled by a person.

Table 1—Elemental variables produced by PopSyn and DaySim

Level VARIABLE ID	**Variable Description**	**Range of Values**
Household		
SAMPN	household ID number	
HHSIZE	# persons in HH	0-10
TOTVEH	# vehicles in HH	0-4+
INCOME	total household income	
HHPARCEL	household residence parcel	
Person		
PERNO	person ID number	
GEND	Gender	
AGE	Age	0-98+
WORKER	employment status	employed, not employed
STUDENT	student status	University student, grade school student, nonstudent
HRSWORK	# hours worked per week	
WPCL	usual work location parcel	
SUPARCEL	usual school location parcel	
Person Day		
Tour		
TOURNO	tour ID number (in simulation order)	
PDTYPE	primary destination purpose type	1-work 2-school 3-escort 4-per.bus 5-shopping 6-meal 7-social/rec 8-home
OPCL	Tour origin location parcel	Home parcel for home-based tours Work tour destination location for work-based tours
DPCL	Primary destination loc. parcel	
MMODE	tour main mode (may be an aggregated set of the 9 modes)	1 –walk 2 –bike 3 – sov 4 –hov2 5 –hov3+ 6 –walk-transit 7 –park and ride 8-school bus
Trip		
TOURHALF	Trip tour half	1st, 2nd
TRIPNO	Trip ID within tour half (outward from primary dest)	
SOTYPE	Trip origin purpose type	see tour primary destination purpose
SDTYPE	Trip destination purpose type	see tour primary destination purpose
SOPARCEL	Trip origin parcel	
SDPARCEL	Trip destination parcel	
SOTIME1	Trip origin arrival time	30-minute time periods
SOTIME2	Trip origin departure time	30 10-minute time periods
SDTIME1	Trip destination arrival time	30 10-minute time periods
SDTIME2	Trip destination departure time	30 10-minute time periods
SMODE	Trip mode	see tour main mode

Population Synthesizer

This model/procedure produces a list of household and person records from the PUMS microdata. Each household is defined in terms of income and household size, plus the age, gender, employment status and student status of all household members. Using CTPP and STF tables in the base year, appropriate numbers of each type of household are allocated to each TAZ. In forecast years, these numbers are adjusted according to demographic forecasts from the land use model and any additional sources. Parcel level inputs on residential land use are used to further allocate households to parcels.

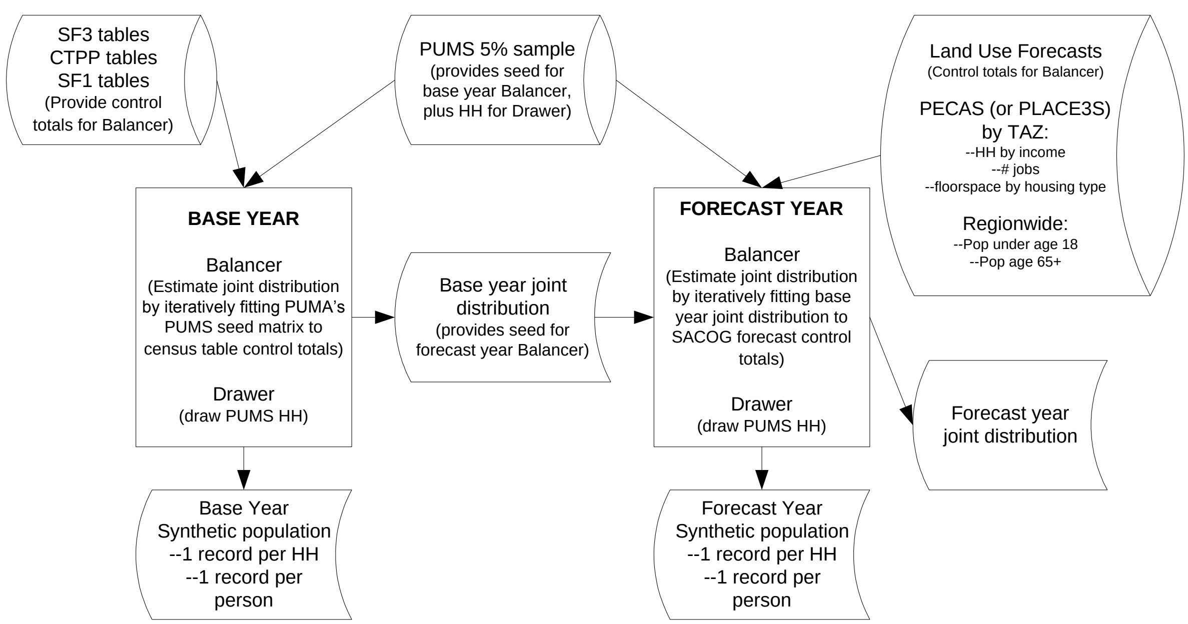
SoundCast uses the population synthesizer (PopSyn) also used by Atlanta Regional Commission. **Figure 2** provides a schematic of PopSyn, showing key inputs and outputs for the base year and a forecast year, and the procedures are described in the next two subsections.

Base year synthetic population

By far the best available detailed information about households comes from the US census. Therefore, the model system is set up to use a census year (2000) as the base year for model forecasts, and PopSyn is designed to extensively use census data to create the base year SynPop. Census SF1, SF3 and CTPP tables provide rich information about the distribution of various important household characteristics within each census block [SF1] or block group [SF3, CTPP]. Many of these tables are multidimensional; that is, the table provides information about the joint distribution of two or more important variables. PopSyn is set up so that it can synthesize a base year population that matches any number of desired multidimensional SF1, SF3 and CTPP distributions at the TAZ level of detail.

The distribution of households is synthesized through an iterative proportional fitting (IPF) procedure called ‘Balancer’ that is like a traditional Fratar procedure for balancing trip ends, except the ‘cells’ of the joint distribution are defined by household characteristics and the control values can apply to any designated subset of cells. For the base year, Balancer’s ‘seed’ distribution is the joint distribution observed in the census 5% Public Use Micro Sample (PUMS). The PUMS distribution is used because each PUMS household has enough data available to assign it precisely to one household demographic category (HHCat) defined jointly by several different variables. This allows us to define HHCats to take advantage of the SF1, SF3 and CTPP tables, and still have a reliable seed distribution. Since PUMS data is stripped of detailed geographic information, the seed distribution for each TAZ is the distribution of the PUMA to which it belongs.

Figure 2: Basic inputs, processes and outputs of population synthesizer (PopSyn)



Once Balancer determines the distribution of households by HHCat within TAZ, then the second major step in PopSyn—HHDrawer—creates the SynPop by drawing, for each TAZ, the correct number of households of each HHCat from the PUMS households with matching HHCat and

PUMA. Then, parcel level inputs on residential land use are used to further allocate households to parcels. Since the number of households determined by Balancer is fractional, HHDrawer is preceded by a procedure that 'integerizes' the IPF results, preserving the distribution as much as possible. Also, since the number of households within a particular HHCat for a given PUMA may be small, Drawer is set up to draw from similar PUMAs if the same household would otherwise be drawn more than a prescribed number of times. PUMA similarity and the maximum number of times that a household may be drawn is specified in the control file.

In summary, PopSyn creates the base year SynPop in two steps called Balancer and HHDrawer. Balancer is an iterative proportional fitting procedure that estimates the base year distribution of households by household demographic category (HHCat) for each TAZ. HHDrawer is a sampling procedure that populates each TAZ by drawing the correct number of households of each HHCat from census PUMS data. For the base year, PopSyn matches exactly the targets determined by census SF1, SF3 and CTPP tables at the TAZ level, while preserving to the extent possible the full multi-dimensional distribution observed in PUMS at the PUMA level.

Forecast year synthetic population

PopSyn uses the same two steps, Balancer and HHDrawer, to synthesize the population for a forecast year, but it uses regional forecasts from (PLACE3S or PECAS) as input instead of census data. Balancer creates a forecast population distribution that matches the following PSRC forecasts: (a) households by income category in each TAZ, (b) number of jobs held by employed persons living in each TAZ, (c) floorspace by housing type in each TAZ, (d) number of persons aged 65 and older in the region, and (e) number of persons aged 0-17 in the region. Like the base year, PopSyn's forecast inputs come from input parameters in its control file, so it would be possible, without software programming, to fairly quickly and inexpensively adjust PopSyn to match other regional forecasts.

Since the available forecast year information can be quite limited, and the distribution of household and personal characteristics change gradually over time, Balancer is set up to preserve the base year distribution as much as possible while matching the above-described forecast control totals. That is, Balancer uses the base year distribution created by PopSyn as its seed distribution for the forecast year. However, since the distribution at the TAZ level of geography may not be very stable over time, Balancer's seed distribution for each TAZ is a blend of the TAZ, census tract and PUMA base year distributions. The exact blend for each TAZ depends on the sizes of the TAZ and its tract, and is determined by easily changed parameters in the control file; the bigger the TAZ, the more heavily it weighs in the blend.

Long Term Choice Simulator and DaySim

Figure 3 presents the DaySim model hierarchy, embedded within the program looping structure in which the models will run. Program loops are bounded by lines starting with 'Begin' and 'End', and indentation indicates embedded sub-loops. The models themselves are numbered. For each household, the long term choice models (1.2-1.4) run first. Then, a loop runs for each person, in which their day pattern (models 2.1-2.2) is simulated. Within that loop, each tour of the pattern is simulated in turn (models 3.1-3.4), and each stop is simulated within each tour (models 4.1-4.4). Work-based tours are modeled as tours, but at the same level of priority as stops on the way to and from work.

The next subsections describe each of the model types. Additional details about each model can be found in tabular form in **Appendix 1**, including the model type, output variables, and important variables that it uses. **Appendix 2** provides a detailed list of variables produced by the DaySim models, including for each a reference to the model that produces it.

Figure 3—DaySim models (numbered) within the program looping structure

```
Begin
  {Read run controls, model coefficients, TAZ data, LOS matrices,
                    population controls, and Parcel data into memory}
  {Draw a synthetic household sample if specified}
  {Pre-calculate destination sampling probabilities}
  {Pre-calculate (or read in) TAZ aggregate accessibility arrays}
  {Open other input and output files}
  {Main loop on households}
    {Loop on persons in HH}
       {Apply model 1.1 Work Location for workers}
       {Apply model 1.2 School Location for students}
       {Apply model 1.1 Work Location for students}
    {End loop on persons in HH}
    {Apply model 1.3 Household Auto Availability }
    {Loop on all persons within HH}
        {Apply model 2.1 Activity Pattern (0/1+ tours and 0/1+ stops)
          and model 2.2 Exact Number of Tours for 7 purposes}
       {Count total home-based tours and assign purposes}
       {Initialize tour and stop counters and time window for the person-day before looping on tours}
       {If there are tours, loop on home-based tours within person in tour priority sequence,
              with tour priority determined by purpose and person type}
           {Increment number of home-based tours simulated for tour purpose (including current)}
           {Apply model 3.1 Tour destination}
           {If work tour, apply model 3.2 Number and purpose of work-based subtours}
           {Loop on predicted work-based sub tours and insert then tour array after current tour}
           {Apply model 3.3 Tour mode}
           {Apply model 3.4 Tour primary destination arrival and departure times}
           {Loop on tour halves (before and after primary activity)}
               {Apply model 4.1Half tour stop frequency and purpose}
               {Loop on trips within home-based half tour (in reverse temporal order for 1st tour half)}
                   {Increment number of stops simulated  for stop purpose (including current)}
                   {Apply model 4.2 Intermediate stop location}
                   {Apply model 4.3 Trip mode}
                   {Apply model 4.4 Intermediate stop departure time}
                   {Update the remaining time window}
               {End loop on trips within half tour}
           {End loop on tour halves}
        {End loop on tours within person}
        {Write output records for person-day and all tours and trips}
    {End loop on persons within household}
  {End loop on Households}
 {Close files}
 {Create usual work location flow validation statistics}
End.
```

Long term choice models

Work location (1.2) and School location (1.3)

These are essentially destination choice models, but they determine the longer term choice of usual work and school locations (parcel within TAZ). These, along with residence location, tend to structure a person's spatial activity patterns. The choice is primarily a function of travel accessibility across all modes and land use characteristics in and surrounding each possible TAZ and parcel. Key segmentation variables include income for workers and age group for students. In the model sequence, work location conditions the school location for most workers, but for university and young driving age students, school location conditions work location.

Auto availability (1.4)

This model is applied at the household level, and determines the number of vehicles available to the household drivers. Key variables are the numbers of working adults, non-working adults, students of driving age, children below driving age, income, auto and non-auto accessibilities to work and school locations, and more general pedestrian, transit and auto accessibility to retail and service locations.

Day level models

Day activity pattern (2.1-2.2)

This model is a variation on the Bowman and Ben-Akiva approach, jointly predicting the number of home-based tours a person undertakes during a day for seven purposes, and the occurrence of additional stops during the day for the same seven purposes. The seven purposes are work, school, escort, personal business, shopping, meal and social/recreational. The pattern choice is a function of many types of household and person characteristics, as well as land use and accessibility at the residence and, if relevant, the usual work location. The main pattern model (2.1) predicts the occurrence of tours (0 or 1+) and extra stops (0 or 1+) for each purpose, and a simpler conditional model (2.2) predicts the exact number of tours for each purpose.

Tour level models

Within each tour, three main models are used, to first simulate the tour's destination, then the beginning and ending period of the tour's primary activity, and finally the main mode used for the tour. For work tours, the number of work-based subtours is also modeled, after destination choice, and before timing and travel mode.

Destination choice (3.1)

Similar to the work and school location models, these models determine the primary destination TAZ and parcel for home-based tours and work-based subtours. For the primary tour destination, the logsum from the mode choice model across all modes is used as the main level of service variable.

The universal choice set of destinations is very large, including all parcels within the metropolitan area. In any given situation, some of the parcels will be infeasible, either because the location cannot be reached in the available time, or because the desired activity cannot be accomplished there. Also, for the sake of computational feasibility, the huge size of the choice set makes it necessary to sample alternatives when applying the destination choice models. A sampling procedure has been designed to deal with both of these issues. The available alternatives are sampled in a way that allows the probability of being drawn into the sample to be calculated for each drawn alternative. Statistical procedures are then used during model estimation and application to allow the sample to represent the entire set of available alternatives without biasing the results.

The chosen sampling procedure is called two-stage importance sampling with replacement. In the first stage, a TAZ is drawn with a known probability approximately equal to its chance of containing the chosen destination. Then, a parcel is drawn within that TAZ with a known probability approximately equal to its chance of being the chosen parcel within the TAZ. The two main criteria used in the design of the procedure are statistical soundness and computational efficiency. A later technical memo on the location choice models will document these procedures in detail.

Number and purpose of work-based tours (3.2)

For this model, the work tour destination is known, so variables measuring the number and accessibility of activity opportunities near the work site are expected to influence the number of work-based tours.

Tour main mode (3.3)

The tour mode choice model determines the main mode for each tour (a small percentage of tours are multi-modal), with the alternatives being drive to transit, walk to transit, school bus, car shared ride 3+, car shared ride 2, car drive alone, bike and walk.

Primary activity periods (3.4)

The dependent variables of this choice model are a pair of 30 minute time periods representing the times that the person arrives at and departs from the tour primary activity location. It therefore provides an approximation of both time-of-day and activity duration. Since entire tours, including stop outcomes are modeled one at a time, first for work and school tours and then for other tours, the periods away from home for each tour become unavailable for subsequently modeled tours. The time period of a work-based subtour is constrained to be within the time period of its parent tour.

Trip/stop level models

Although the presence of extra (intermediate) stops in the day pattern is determined in the pattern model, the exact number of stops for each purpose is a result of the stop level models. Within each tour, the stops are modeled one-by-one, first for stops before the tour destination, and then for stops after the tour destination. This is an iterative model structure, very similar to the one used in Model 3.2 for the number and purpose of work-based subtours.

Stops before the tour destination are modeled in reverse temporal sequence. First the possible participation in a stop is modeled simultaneously with the stop's purpose (4.1). If the stop occurs, then its location (4.2), and then its trip mode (4.3), and finally the 10-minute time period of the arrival at the tour destination (4.4) are modeled. These results also determine the time period in which the trip from the stop location begins, since the trip mode and travel level of service are known. If a stop occurs, then the possible participation and purpose of a prior stop are modeled, along with details of location, trip mode and timing. This continues, constructing the trip chain from the tour primary destination to the tour origin in reverse chronological sequence until the model predicts no more stops (at which point, the "final" trip between the "last" stop and the tour origin is modeled). The reason for modeling in reverse chronological sequence for the first half tour is the hypothesis that people aim to arrive at the primary destination at a particular time, and adjust their tour departure time so as to enable completion of the desired intermediate stops. After the trip chain for the first half-tour is modeled, the trip chain for the second half-tour back to the tour origin is similarly modeled, but this time in regular chronological order.

Number and purpose of intermediate stops (4.1)

Throughout the construction of the trip chains, the making of intermediate stops by purpose is accounted for, so that as stop purposes called for by the pattern model are accomplished, the likelihood of additional stops decreases.

Intermediate stop location (4.2)

For intermediate stop locations, the main mode used for the tour is already known, so the choice is primarily a tradeoff between the additional deviation and impedance of making another stop by that mode versus the accessibility to additional land use opportunities in alternative zones and parcels.

As with tour destinations, a sampling procedure is required for the stop location models, and a procedure has been designed that employs importance sampling with replacement. The exact procedure is different, however, because the sampling problem is more complex. For intermediate stops, the travel impedance affecting choice is a function of three locations instead of two: the intermediate stop location, as well as locations before it and after it in the half tour. This expands the number of relevant impedances geometrically. Therefore, a 3-stage importance sampling procedure has been designed. For each parcel to be drawn, first a stratum is drawn, then a TAZ within the stratum, and finally a parcel within the TAZ. A later technical memo on the location choice models will document these procedures in detail.

Trip mode (4.3)

The trip-level mode is conditional on the predicted tour mode, but now uses a specific OD pair and a time anchor, and also the trip mode for the adjacent, previously modeled trip in the chain. The trip mode alternatives are more precisely defined than the tour mode alternatives. The tour and trip level mode choice models are estimated simultaneously to ensure the most significant and consistent values for key travel time and cost coefficients.

Trip timing (4.4)

For intermediate stop locations, this model predicts either the departure time (for stops on the 2nd half tour) or the arrival time (for stops on the 1st half tour). The use of travel time variables in this model and model 3.4 allows us to capture peak spreading effects for car tours and trips.

Accessibility variables

Accessibility variables are discussed separately in this memo for two reasons. First, they are very important because they capture the sensitivity of activity and travel decisions to the utility of opportunities associated with conditional (and hence undetermined) model outcomes. For example, in a destination choice model, a logsum variable can capture the expected utility of the available travel mode alternatives. This is a very important aspect of model integration. Without it, the model system will not effectively capture sensitivity to travel conditions. Second, when there are very many alternatives (millions in the case of the entire day activity schedule model), the most preferred measure of accessibility, the expected utility logsum, requires an infeasibly large amount of computation.

So, this section describes a carefully designed approach for capturing the most important accessibility effects with a feasible amount of computation. The approach involves using two basic techniques to substitute for a pure logsum in cases where the logsum computation is very costly and a substitute can provide much of the benefit. First, in some cases, an approximate logsum is used. This is a variable that is calculated in the same basic way as a true logsum, by calculating the utility of multiple alternatives, and then taking expectation across the alternatives by calculating the log of the sum of the exponentiated utilities. However, the amount of computation is reduced, either by ignoring some differences among decisionmakers, or by calculating utility for a carefully chosen subset or aggregation of the available alternatives. Second, in some cases where the attractiveness of a location alternative may depend on the accessibility near the location for pursuing secondary activities, directly measurable attributes of the location are used instead of logsums for the potential secondary stops themselves. Such attributes include indicators of pedestrian friendliness and density of activity opportunities in the neighborhood.

The remainder of this section will discuss the accessibility variables used for each component of DaySim. However, one approximate logsum, which is pre-calculated and used by several of the model components, is explained first, and then referred to as needed in the subsequent discussion.

The approximate mode-destination choice logsum

This logsum is used in situations where information is needed about accessibility to activity opportunities in all surrounding locations by all available transport modes at all times of the day. Because of the large amount of computation required for calculating a true logsum for all feasible combinations in these three dimensions, an approximate logsum is used with several simplifications. First, it ignores socio-demographic characteristics, except sometimes it distinguishes between situations where a car is available and those where it isn't. Second, it uses aggregate distance bands for transit walk access. Third, sometimes it uses a logsum for a composite or most likely purpose instead of calculating it across a full set of specific purposes.

Finally, instead of basing the logsum on the exact available time window of the choice situation, and calculating it across all of the available time period combinations within the window, it either uses a particular available time window size and time period combination, or a weighted average of attributes for several time period combinations. With these simplifications, it is possible to pre-calculate 39 approximate logsums for each TAZ, and use them when needed at any point in the simulation of any person's day activity schedule. **Table 2** lists the models in which this approximate logsum is used, along with the variations required in each of the four dimensions discussed above.

Table 2: Models using approximate logsums, and their approximating categories

Model	Car availability	Walk dist to transit	Purposes	Time window	Time period combo
Work location School location Tourdestination	Available	Short (<¼ mi), Medium (¼-½ mi), Long (½+ mi)	Composite nonwork	½ hr	Weighted avg of attributes across five 1-period time combos (early-early, am-am, MD-MD, PM-PM, Night-Night)

Calculation of the approximate logsums and estimation of the parameters for the calculations

The set of 39 approximate logsums is calculated for each TAZ as follows:

Calculate aggregate size variables for a composite non-work purpose for three subgroups of parcels in each TAZ defined by three ranges of walk distance to transit (less than ¼ mile, ¼ to ½ mile and more than ½ mile). Estimate a non-work tour mode-destination choice model without socioeconomic explanatory variables, using destination zones defined by the distance-range categories, and using survey tours with short available time windows. Calculate 12 logsums from this model for different assumed combinations of walk distance to transit at origin (short, medium, long) and time period combo (weighted avg, MD-MD, PM-PM, and Night-Night). For the weighted average, use mode-dest choice attributes composed as a weighted average, where the weights are the relative frequencies of each 1-period time combination.

Similarly, calculate size variables and estimate a mode-destination choice model using all non-work survey tours, regardless of available time window size. Calculate 6 logsums from this model for different assumed combinations of auto availability (available, not available) and walk distance to transit at origin (short, medium, long), using a weighted average of attributes across 15 time period combinations.

Similarly, calculate size variables and estimate a mode-destination choice model with purpose-specific parameters, using all tours except those to usual work or school location. Calculate 21 logsums from this model for different assumed combinations of purpose (7 purposes) and walk distance to transit at origin (short, medium, long), using a purpose-specific weighted average of attributes across 15 time period combinations.

Accessibility variables used in DaySim model components

Work location, school location, and auto availability

The work location model uses the individual's tour mode choice logsum from the home parcel to each of the sampled parcel locations, using the urban and transportation system attributes for a work tour, and a sample-based time-of-day weighted average of mode choice utility attributes across the 15 feasible time period combinations. This approach is far less time consuming to calculate than a two-stage logsum that calculates time-of-day and mode utility for all possible combinations. The school location uses an analogous logsum for school tours.

In order to capture the effect of accessibility for work-based subtours and intermediate stops near the work location, these models also use the approximate mode-dest logsum for nonwork tours originating at the work (or school) location, as well as attributes of the work (or school location) indicating pedestrian friendliness and density of nearby activity opportunities.

The auto availability model uses logsum accessibility to the chosen work location and school locations of workers and students, calculated with and without an auto available. These logsums can be derived from the logsums calculated for the work location and school location models, as long as the with and without auto components of the logsums are kept separate. The auto availability model also uses the approximate logsums for nonwork tours originating at the home location, and directly measured attributes of the home location and the usual work and school locations.

Activity pattern

The activity pattern model uses the logsums previously calculated for the chosen work and/or school location, to capture the effect of accessibility on the probability of going to work or school on any given day. For other purposes (and for work or school when there is no usual work or school location) the pattern model uses the purpose-specific approximate mode-dest logsums. The model also uses attributes of the residential, usual work and usual school locations to capture the accessibility for short tours or intermediate stops near those key locations.

Tours

In the tour model hierarchy, destination choice conditions time-of-day choice, which conditions mode. The destination and time-of-day models incorporate time-of-day variations in mode accessibility. For the time-of-day choice, 15 mode choice logsums are calculated, one for each of 15 begin and end time period combinations, using five aggregate time categories: before AM peak, AM peak, Midday, PM peak, and evening. By assuming accessibility equivalence of the before AM and evening periods, the number of logsums would drop from 15 to 13. For the destination choice, the logsums use a sample-based weighted average of LOS attributes across all time period combinations.

Other attributes of the sampled destinations (such as distance to bus & LRT stops, and sidewalk density) are also used, to help capture the accessibility for short tours or intermediate stops in the neighborhood.

Stops

The measurement of accessibility at the stop level is fairly simple because it is at the lowest level of the model's conditional hierarchy. At this stage, the main destination, approximate time-of-day and mode of the tour are known, and the stop models determine the stop location, trip mode, and timing for each trip segment on both half-tours, from the tour destination back to the tour origin. So, the stop location model can use a direct measurement of travel times and costs for the tour's main mode to the sampled stop location. In addition it uses the approximate mode-dest logsum and other attributes to measure attractiveness of trips in the vicinity of the sampled stop.

The trip mode model uses direct measures of times and costs, and the timing model is essentially a stop duration model, not dependent on accessibility.

Recent Updates to Daysim

The parcel land use data

A number of improvements have been made to the preparation of the parcel data:

- The buffering of the number of transit stops and open space parcels, in addition to the variables that were buffered previously (households, jobs, student enrollment, paid parking, and intersections).
- Calculation of the distance to the nearest transit stops separately by submode (bus and light rail).
- The use of short-distance "circuity factors" in order to be able to use a better approximation of actual walk distance rather than using crow-fly distance in buffer calculations. (This adjustment is also used in estimating the distance to the nearest transit stop.)
- An option to use distance decay functions for weighting the contents of the buffer, instead of using the "typical" approach of weighing everything inside the buffer equally.

The latter two improvements are substantial, and deserve some further discussion. First, the process that goes into creating the circuity factors is as follows:

1. For each parcel in the region, create 24 synthetic points in 8 radial directions (E, NE, N, NW, W, SW, S, SE) at 3 distances (0.5, 1.0 and 1.5 miles).
2. For each parcel centroid or synthetic point, find the node on the all-streets network that is closest to that point.
3. Using a very efficient network path-finding program (DTA Lite), find the distance along the all-streets network between the two nodes assigned to each parcel/synthetic point pair.
4. Using a Delphi program, read in the results of steps 1-3 above, and create a record for each parcel that has a calculated "circuity ratio" from the parcel to each of the 24 synthetic points. This ratio is typically equal to the distance along the street network between the two nodes divided by the crow-fly distance between those same two nodes. The ratio is typically in the range 1.0-2.0, with a median value of about 1.4, but can be much greater for parcel/point pairs with obstacles or poor connectivity between them. Figure 3 below shows a frequency distribution across all parcels. The distribution is more "spread" to the right at the lowest distance, as one would expect because any detour will have a larger proportional effect with the smaller denominator.
5. The new parcel file with the 24 circuity factors is read into the new parcel buffering program, and interpolative averaging is used to approximate the street network distance to any other parcel within 2 miles. (This same logic is also used in DaySIM itself to adjust the network-based distance for short trips by auto, walk or bike.)

The new buffering program also has the option to use distance-decay functions (based on the circuity-adjusted distance) to weight the contents of the buffer. Figure 4 shows the quarter mile and half mile "flat" buffers used previously (FlatQ and FlatH) , along with the logistic decay buffers (1 and 2), as a function of distance from the origin parcel. These buffers were specified so that the area under the distance curve remains about the same as for the corresponding flat buffers, giving buffer values comparable to those used before. The advantage of decay-type buffers over flat buffers is that they correspond more closely to behavior and perceptions. They also minimize “edge effects”, whereby flat buffers can be very sensitive to the (somewhat arbitrary) distance used to define their edge.

Figure 2: Frequency distribution of circuity ratios, separately for 0.5, 1.0 and 1.5 mile distance

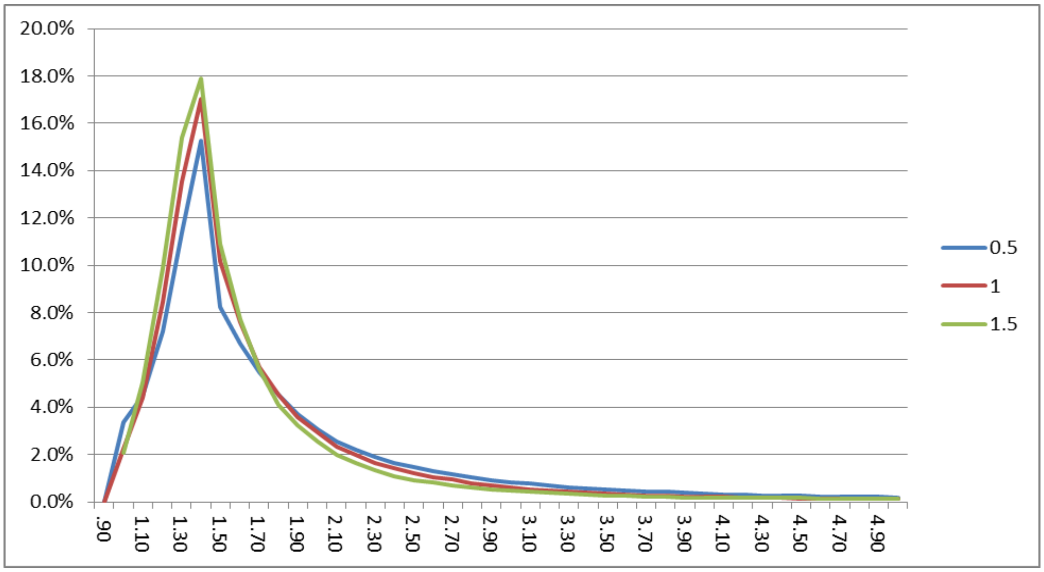
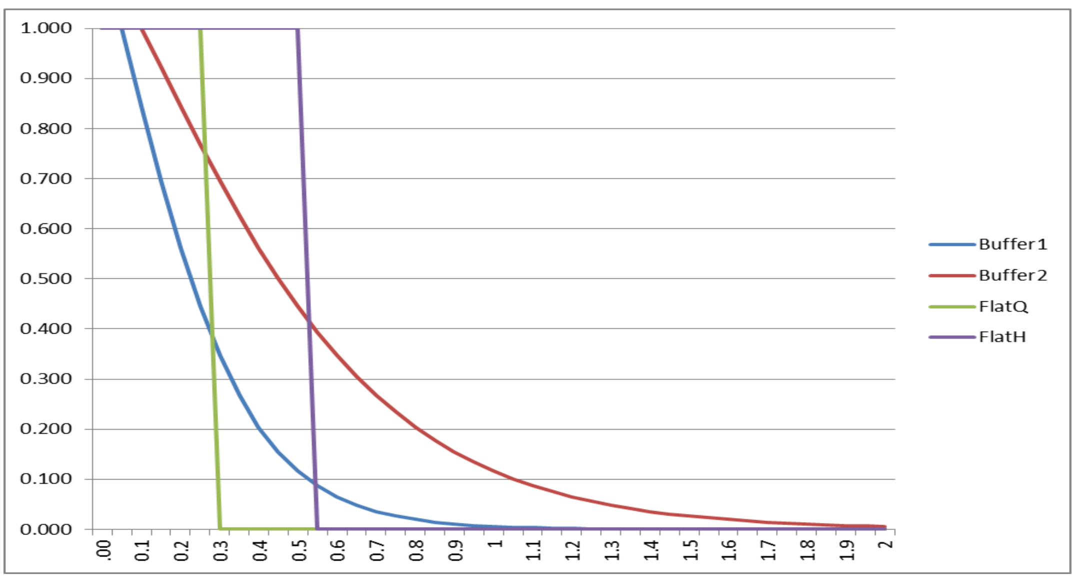


Figure 3: Distance decay weight functions used in buffering



Other DaySIM input files

In addition to the input files described above, other input data files required to run DaySIM (and shown in Figure 2) are:

- A zone index file, indicating which zones numbers relate to valid internal and external zones
- A park and ride node file, with location, capacity, and price data for park and ride lots
- Internal-external (IXXI) factors,

Changes to support the treatment of policy-based pricing

Before re-estimating the various DaySIM models, we added a number of new features to DaySIM to support the treatment of pricing effects in the models. Many of these were based on the research done as part of the SHRP 2 C04 project on model improvements to address pricing and congestion. These include:

Distributed value of time:

Each tour simulated in DaySIM can have its own time/cost tradeoff, with the functions used to set the cost coefficient (c[i]) and time coefficient (t[i]) shown in Figure 5 below. The cost coefficient is based on an inverse power function of income and car occupancy, with the power exponents differing for work and non-work tours. The time coefficient also has different functions for work and non-work tours, and uses a log-normal distribution (see Figure 6) to simulate random variation around the mean.

Note that this random variation in VOT is not used in model estimation, and can also be switched off by the user for model application, in which case the mean value is assumed. Also note that this value is for auto in-vehicle time. Relative values for other types of travel time can be specified by the user as part of the DaySIM configuration (as can all of the parameters used in Figure 5).

Functions from SHRP 2 C04 for Tour-Specific Value of Time

Work tours

c(i) = -0.15/$ / [((income(i) / 30,000) ^ 0.6) * (occupancy(i) ^ 0.8)]

t(i) = -0.030/min * draw from a log-normal distribution, with mean 1.0 and std. deviation 0.8

Non-work tours

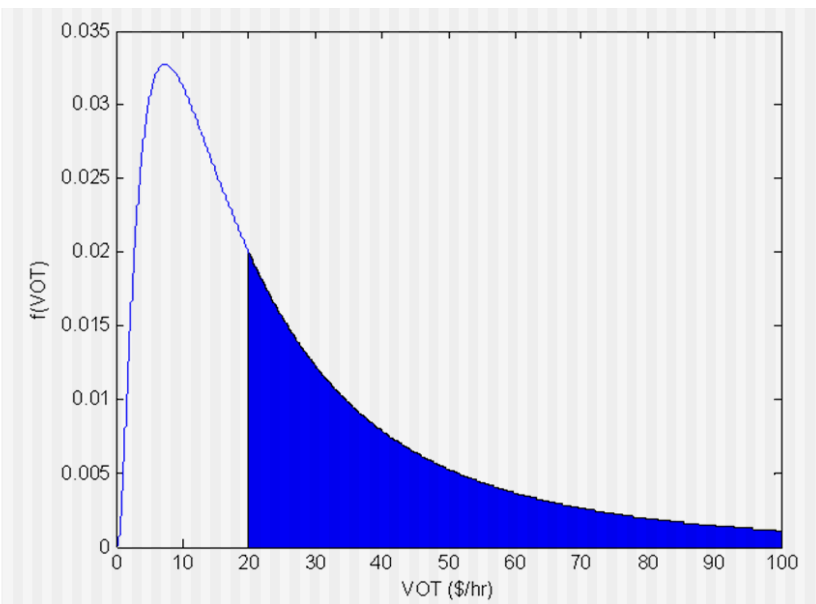
c(i) = -0.15/$ / [((income(i) / 30,000) ^ 0.5) * (occupancy(i) ^ 0.7)]

t(i) = -0.015/min * draw from a log-normal distribution, with mean 1.0 and std. deviation 1.0

Flexibility in using impedance matrices: Another new feature of DaySIM that supports pricing analysis is a great deal of flexibility in defining and using network impedance skim matrices. This flexibility includes:

- Matrices for a given mode can be specified for different path types. This can be used for auto (i.e. the full network versus a network that excluded tolls) and for transit (i.e. the local bus network versus a light rail network)
- Matrices for any mode can be defined to be for a specific range of VOT, allowing tours with different VOT to use different matrices reflecting differences in their "best" path.
- Matrices can be for any minute, hour or period of the day, and these periods do not need to correspond to any fixed time periods used elsewhere in DaySIM or in supporting trip-based models. This allows a great deal of flexibility to reflect time-of-day pricing policies.
- The same input matrix can be used to reflect multiple combinations of mode, path type, time period and VOT class, providing efficiency in memory usage and I/O.

Figure 4. Shape of the log-normal probability frequency distribution



Consideration of transit fare passes and discounts

Although the transit fare input through the transit impedance skims reflect the full fare, DaySIM no longer assumes that everyone pays that fare. Fare reduction is simulated in two ways:

- First, transit users can receive a percentage discount based on their age and student status. This is controlled via discount factors input by the user in the DaySIM configuration.
- Also, a new Transit Pass Ownership model has been added to DaySIM. This is a binary choice model predicting whether or not each person age 16+ owns a transit pass, as a function of person type, age, employment status, student status, and accessibility by transit from their home, workplace and/or school location. The user can also vary the price and price-sensitivity for transit passes via configuration inputs. If a person is

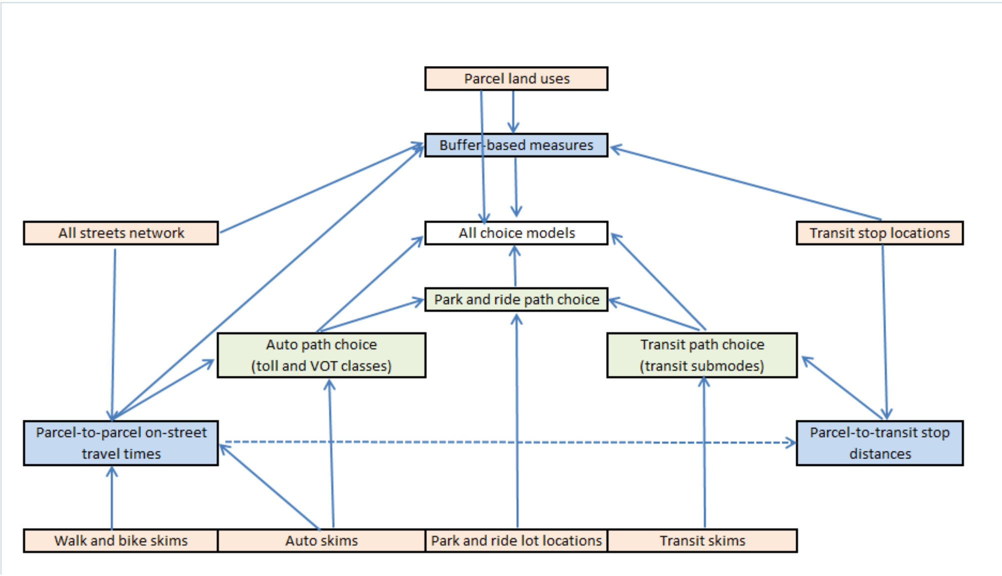
predicted to own a transit pass, then their marginal fare cost for transit is 0 (100% discount factor).

The use of path type choice models for all modes

This reflects a fundamental change to how DaySIM uses impedance information in the choice models. Figure 7 illustrates how all skim information works through the path type model, which performs the following functions in a consistent way:

- For a given mode/origin parcel/destination parcel/time of day, it determines if a valid path is available via one or more path types for that mode. ("Valid" meaning that there is a network path, and that the total travel time is less than a user-defined maximum.) The path can be one-way (for trip-level models) or round trip for two different times of day (for tour-level models)
- For each possible path type, a utility is determined, using the tour-specific time and cost coefficients (VOT) as well as additional time weights provided by the user.
- If one or more path types is available, a logsum across those path types is calculated and passed back for use in higher-level models such as mode choice or time of day choice.
- The travel time, cost, and distance via a chosen path type is also generated. For most uses, this is deterministic, via the path type with the best utility, although at the trip-level where the path type is predicted for the final simulated trips, a stochastic choice can be simulated instead.

Figure 5. Schematic of the use of path choice models to support other DaySIM choice models



A good deal of technical detail on the path type models is provided in the DaySIM Users Guide. Some highlights for specific modes include:

- For bicycle, the user can define additive weights for distance on specific types of links, to calibrate the usage of different facility types.
- For auto, the user can define different VOT ranges for the skim matrices, and also specify the size of a constant term to be used for toll routes to calibrate/reflect resistance to using tolled facilities.
- For walk, bicycle, and auto, the parcel-based circuity factors are applied to get a more accurate estimate of distance and travel time for short trips (particularly intra-zonal trips for which the network skims provide little useful information)
- For transit, the user can define additive in-vehicle time weights, as well as path type-specific constants, in order to calibrate the usage of different types of transit services (as well as vary their attractiveness in higher level models such as mode choice)
- For transit, access and egress walk distance are determined based on parcel-specific walk distances to the nearest stops, and the user can change parameters related to the maximum walk distance and the characteristics of walking to direct paths versus paths that involve transfers.
- For park and ride, the model is similar to the transit model, but substituting drive access time for walk access at the home end. (Park and ride is always evaluated round trip, assuming the same lot on both halves of a tour.)
- For park and ride, DaySIM will search across all park and ride lots and find the one that provides the best utility for the given O/D/mode/path type/times of day. Alternatively, the user can find the best park and ride lot node with other software outside of DaySIM and provide a matrix of the best park and ride lot for each O/D pair.

A few more features of the path type models:

- Even if the user does not define different path types for a mode, the path type model will be used for the single, default path type in order to calculate the generalize time utility for that alternative. This ensures that the calculations are done consistently whether or not there are multiple path types available. For example, only the "full network" path type is currently available for the walk and bike modes, and that is why no "walk/bike path choice" is shown in Figure 7, even though those modes are also evaluated via the path type model. Furthermore, DaySIM could be used to evaluate multiple path types even for those modes—an example would be to use completely separate bike skims for path types with and without Class 1 or 2 bike lines.
- As shown in Figure 7, the use of the path type model means that all DaySIM models access and use the skim information consistently via path type choices and logsums. This also extends to the accessibility logsums used by the upper level DaySIM models.
- The ability to do park and ride lot choice within DaySIM is new, and more advantage of this could be taken in the future. For example, lot capacity constraint is not currently included and has to be done outside of DaySIM (as with the previous SacSIM). In future versions of DaySIM, it will be possible to incorporate capacity constraint via a time of day-specific shadow-price mechanism.

Changes to specific DaySIM choice models

All models were re-estimated using the new DaySIM estimation capabilities and the new parcel data and skim data. The new model coefficients are given and annotated in the DaySIM Users Guide. This section provides some key points for each model, starting from the "bottom" up:

Mode choice models

Mode choice models at the tour and trip levels were estimated using the logsum from the path type model for each mode as a key input. (Note: Upon first pass, this approach appears to be predicting too many long trips for walk, bike and transit, so the models will be estimated using different weights on the time component for those modes.) The use of the new parcel buffer variables also improved the land use effects on mode choice somewhat.

Time of day models

These models were also estimated (and applied) using the generalized logsums from the path type model for each time of day, rather than simply the travel time, enhancing the response to time-of-day pricing. Also, the use of time window variables and availability constraints in these models was improved to ensure that more realistic schedules are simulated.

Location choice models

The new parcel buffer variables were useful in re-estimating neighborhood effects, in combination with the size variable effects. Time window effects and availability constraints were also enhanced. Distance functions were consolidated and simplified somewhat, as recommended by the peer review panel.

Day pattern models

These include the main person-day pattern model, as well as models of the exact numbers of tours, work-based subtour generation, and intermediate stop generation. These models were re-estimated to include enhanced accessibility logsum effects via the disaggregate and aggregate logsums. Other minor changes to the specifications were carried out as well.

Vehicle availability model

The auto ownership model was re-estimated, taking advantage of new accessibility logsum variables, but otherwise the specification was not changed.

Transit pass ownership model

This is a newly-added binary choice model predicting whether or not each person age 16+ owns a transit pass, as a function of person type, age, employment status, student status, and accessibility by transit from their home, workplace and/or school location.

Pay to park at workplace model

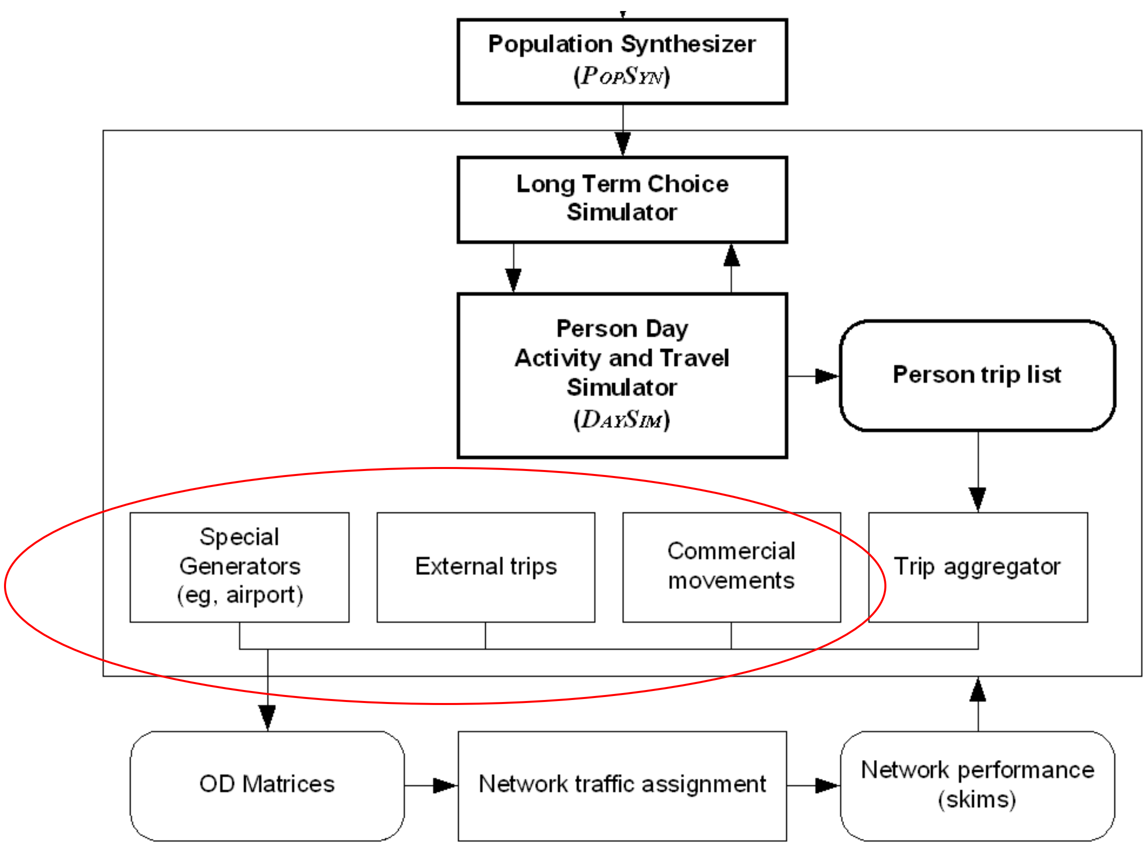
For each worker, this model predicts whether or not the person has to pay to park at/near their workplace—i.e. that they do not receive free or totally subsidized parking. It is a binary model, mainly a function of income, employment status, and the land use and parking supply around the workplace. If the model predicts that a worker does have to pay, then the parking cost at their workplace is determined by the average daily price for paid off-street parking in the (smaller) buffer around the work parcel. Otherwise, the parking cost is set at 0 (free). This model was estimated on SACOG 2000 survey data.

Supplemental Trip Modeling: External, Trucks, Special Generation, and Group Quarters

The following section depicts the supplemental trips that are added to the Daysim internal regular travel demand to build a full set of trips in assignment. The four types of trips, external, trucks, special generation, and group quarters are aggregated at the end of their processes, and then combined with Daysim trips. Cambridge Systematics designed PSRC's external trip modeling processes.

Each of the special model types have their own trip generation and trip distribution processes as traditionally performed in a four-step model. Then finally, they are factored by mode and time of day to match into the SoundCast assignment periods.

Figure 6. Supplemental Trips



External Modeling

External trips can be defined as three types of trips: 1) internal-external; 2) external-internal; and 3) external-external. Of these three types, the trip generation model estimates only the internal-external and external-internal trips

The external-external trip table is estimated from a separate source and added to the trip tables prior to trip assignment.

External trips were originally derived from an external survey conducted in 1970 that covered King, Pierce, and Snohomish county borders. These external trip tables have been updated over time, based on current traffic counts and cross-sound data.

Table 4. Internal-External and External-Internal Trips by Purpose

Trip Purpose	Trips
Home-Based Work	73,252
Home-Based College	4,137
Home-Based School	5,266
Home-Based Shop	37,760
Home-Based Other	103,678
Non-Home-Based (Total)	22,916
Total	**247,009**

External trips involve classifying external trips into three types of trips and two vehicle types, as follows:
- Internal-external trips by auto (I-E auto);
- External-internal trips by auto (E-I auto);
- External-external trips by auto (E-E auto);
- Internal-external trips by truck (I-E truck);
- External-internal trips by truck (E-I truck); and
- External-external trips by truck (E-E truck).

These classifications are made based on the origin and destination of trips traveling through external stations around the four-county region. Origins and destinations are defined based on whether they are inside or outside the region.

There are 18 external stations in the Puget Sound region. Through trips (classified as E-E trips) are those trips that begin and end outsid ethe region, but travel through the region at some point. These trips were originally created from an origin-destination survey conducted in 1961, and then updated in 1971 during a model update process. Since that time, the external trips have remained relatively constant, while the overall traffic at external stations has grown to match external station counts.

A through trip table is used to represent external-to-external trip interchange. Passenger through trips are those trips that begin and end outside the region, but travel through the region at some point. These trips were originally created from an origin-destination survey conducted in 1961, and then updated in 1971 during a model update process. Since that time, the external trips have remained relatively constant, while the overall traffic at external stations has grown.

Special Generators

The use of special generators allows for the inclusion of trip activities that are difficult to replicate using general cross-classification or linear regression equations. The trips associated with these generators are established outside the four-step modeling process, but were evaluated using the *ITE Trip Generation*

Manual. The PSRC model traditionally has included four special generators(Seattle Center, SoDo Sports Complex, SeaTac Airport, and Tacoma Dome). In addition, the FASTruck model generators for each of the major ports in the region (the Port of Seattle and the Port of Tacoma) and warehouse and distribution centers in the SR 167 corridor.

Table 5. Special Generators

Generator	Special Generation Trips	Daysim Regular Trips
Seattle Center	14,013	3,145
Exhibition Center	7,567	8,145
SeaTac Airport	101,838	15,941
Tacoma Dome	1,682	1,309

Group Quarters

Trip rates per student in college housing are derived from a university trip model developed for the University of Michigan. This is one of the few university trip models that are developed from household survey data, including students. The results of this model indicate thatthere are 1.18 university trips per student on a daily basis. It is assumed that there is no work or school trips made by university trip students. Other trip purposes are assumed to be proportional to the regional average, but adjusted so that the total of non-university trip purposes matches the ITE trip generation rate for University Housing (ITE Code 550). The ITE total vehicle trip rate is 2.38 trips per student per day,converted to 3.14 person trips per student per day, using average regional auto occupancy of 1.32 persons per vehicle. The home-based college trips are held constant at 1.18 trips per student, so the total trip rate per person in college housing is 3.82 trips per person, compared to the regional average of 3.48 trips per person.

Proposed trip rates per person in military housing are derived from a special generator model developed for the MacDill Air Force Base inTampa Bay (Florida), and controlled to Institute of Transportation Engineers (ITE) trip generation rates for military housing (ITE Code 501). Tampa Bay is one of the few military trip models that are developed by trip purpose. The ITE total vehicle trip rate is 1.78 trips per employee per day, converted to 2.35 person trips per employee per day, using average regional auto occupancy of 1.32 persons per vehicle. This is further converted to 2.97 person trips per unit per day, using a conversion factor of 1.27 employees to population rate in Fort Lewis. The results of this model indicate that there are 2.97 trips per person from military housing on a daily basis, compared to the regional average of 3.48 trips per person.

Trip rates per person in retirement homes are derived from a retired person's model developed in Tucson (Arizona) and controlled to ITE trip generation rates for retirement homes (averaging ITE codes 250 through 253). Tucson is one of the few models that have retired persons trip rates developed by trip purpose from household survey data. The ITE average vehicle trip rate is 2.55 trips per unit per day, converted to 3.37 person trips per unit per day, using average regional auto occupancy of 1.32 persons per vehicle. This is further converted to 3.37 person trips per person per day, using a conversion factor of 1.0 person to unit rate. The results of this model indicate that there are 3.37 trips per person from retirement housing on a daily basis, compared to the regional average of3.48 trips per person.

Table 6. Group Quarters Trip Generation Rates

Trip Purpose	College Dormitories	Military Quarters	Retirement Homes	PSRC Regional Average for Household
Home-Based Work	-	0.37	0.10	0.60
Home-Based College	1.18	-	-	0.08
Home-Based School	-	-	0.03	0.29
Home-Based Shop	0.40	0.74	0.70	0.40
Home-Based Other	1.24	1.09	1.49	1.09
Non-Home-Based	1.00	0.76	1.04	1.03
Total	3.82	2.97	3.37	3.48

Table 7. Group Quarters Trips

County	College Dormitories	Military Quarters	Retirement Homes	Total
King	42,516	689	46,211	89,416
Snohomish	-	8,557	1,714	10,270
Pierce	10,537	19,657	13,850	44,044
Kitsap	267	6,423	11,423	18,113
Total	**53,321**	**35,324**	**73,198**	**161,843**
Percent of Total Regional Trips	0.5%	0.3%	0.6%	1.4%
Percent of Total Regional Population	0.4%	0.4%	0.7%	1.5%
Difference	0.1%	-0.1%	-0.1%	-0.1%

Truck Model

The PSRC truck model was derived from the *FASTrucks Forecasting Model*, developed in 2000 for the WSDOT. The truck model uses more disaggregateemployment categories than the passenger model. The outputs of the truck model are truck trip tables for heavy-, medium-, and light-weight trucks. The light trucks are commercial vehicles that include light trucks and other nonpersonal-use vehicles.

Cambridge Systematics developed the FASTruck model23 for the WSDOT Office of Urban Mobility as part of a larger study for FAST Freight Mobility (Phase II) led by TranSystems. The FASTruck model was fully integrated with the PSRC regional travel model using the following techniques:
 Commercial vehicles in the PSRC model were deleted and replaced with light, medium, and heavy trucks estimated by the FASTruck model.
 Trip generation and distribution models were applied to estimate light ,medium, and heavy trucks. Trip rates were based on 10 categories ofemployment, which required stratification of existing employment into these
categories.
 These truck trips were then converted to Passenger Car Equivalents (PCE) and assigned in a multi-class assignment with the drive alone and HOV trips in the PSRC passenger demand model.

The development of the truck model was based on using different forecasting methods for internal and external truck trips, because the factors that influence these truck trips are very different. In the case of the external trips, defined asthose truck trips that begin and end outside the region, truck trips are affected by economic factors beyond the region borders. In the case of the internal trips, defined as those truck trips that begin and end within the region, truck trips are affected by economic factors within the region borders. Truck trips that have either an origin or destination outside the region and a destination or origin inside the region are affected by both external and internal factors. These three types of truck trips are, therefore, estimated separately using unique methods for each type.

The truck model was developed using a base year of 1998 and a forecast year of 2020. These were updated to represent the base year of 2000. The truck model was integrated with the passenger model by using the same socioeconomic and network input data and by integrating EMME/2 macros for implementation.

Truck Types

The truck model defines a truck based on relative weight classes and separates light, medium, and heavy trucks for analysis purposes. Medium and heavy trucks are defined to match the definitions used for collecting truck counts by the
WSDOT. While these definitions rely primarily on weight, these categories also are loosely correlated to other defining characteristics of trucks for other purposes. The following general categories of trucks are used:

- Light trucks are defined as four or more tires, two axles, and less than 16,000 lbs. gross vehicle weight (this also includes non-personal use of carsand vans);
- Medium trucks are defined as single unit, six or more tires, two to four axles

and 16,000 to 52,000 lbs. gross vehicle weight; and

- Heavy trucks are defined as double or triple unit, combinations, five or moreaxles, and greater than 52,000 lbs. gross vehicle weight.

In these definitions, the medium trucks are directly correlated to single-unit trucks collected in the WSDOT truck counts, and heavy trucks are directly correlated to double- and triple-unit trucks in the counts. The truck counts do not separate light trucks from passenger cars, so there is no truck count data available for validating the light trucks in this model.24 Light trucks have been included in this analysis primarily, so that all vehicles are represented in the traffic assignments. Light trucks are intended to include all commercial vehiclesthat are not included in the medium- and heavy-truck categories. Commercial vehicles are not included in the non-home-based trip purpose model as theserepresent only noncommercial vehicles

The socioeconomic data used in the truck model are consistent with those data used in the passenger model, except that the employment data are stratified intomore employment categories. This process provides more accuracy for truck travel and allows for a direct relationship between the commodities being estimated in the external trip model and the allocation of these commodities toTAZs within the region.

The stratification of employment data was provided by PSRC for the base year. The development of these data is not entirely consistent with socioeconomic data used in the passenger model, because there are confidentiality issues; and these data have not been cleaned to the same extent as the existing regional data. The confidentiality issues caused the two-digit SIC code employment data to generally underestimate the total employment, because some employment is not reported using this method. This comparison also demonstrates that there are certain kinds of manufacturing that are not included in the PSRC land use model; these are primarily construction and resources employment.

Table 8. Truck Employment data categories.

	Model Categories		SIC Codes	SIC Codes That Are Empty
	Truck	Passenger		
1	Agriculture/Forestry/ Fishing	Manufacturing	1-2,7-9	3, 4, 5, 6
2	Mining	Manufacturing	10,12-14	11
3	Construction	WTCU	15-17	18, 19
4	Manufacturing – Products	Manufacturing	20-29	
5	Manufacturing – Equipment	Manufacturing	30-39	
6	Transportation/ Communication/ Utilities (TCU)	WTCU	40-42, 44-49	
7	Wholesale	WTCU	50-51	
8	Retail Trade	Retail Trade	52-59	
9	FIRES	FIRES	60-67, 70, 72-73, 75-76, 78-81, 83-84, 86-89	68, 69, 71, 74, 77, 85
10	Education/Government	Education and Government	43, 82, 90-97	98, 99

Employment data in the current truck model excludes employment categories, where the employment location is different than the employer location, such as agriculture, mining, and construction. These categories were included in the development of employment data for the original truck model because they are important to the development of total truck trips. Full-time college employment was not included in the employment data for the FASTruck model, but was included in the PSRC and Seattle models.

In order to provide consistency and forecasting capabilities, a set of adjustment factors were developed that converts the passenger model employment datasetinto the truck model employment dataset.

Truck Model Parameters

The development of the truck model parameters and the data sources used are contained in the FASTruck model documentation. Relevant model parameters and assumptions used in the integration of the truck model with the passenger model are provided herein for reference.

Truck Trip Generation

Truck trip production rates for internal truck travel were developed separately for the three different truck types: light, medium, and heavy.

Table 9. Truck Generation Rates by Employment Category

Employment Category	Truck Type		
	Heavy	Medium	Light
Agriculture/Forestry/Fishing	0.1057	0.1457	1.2311
Mining	5.4488	7.6182	44.8093
Construction	0.0311	0.0451	0.2418
Manufacturing – Products and Equipment	0.0223	0.0277	0.2414
TCU	0.0404	0.0513	0.4754
Wholesale	0.0094	0.0181	0.1369
Retail Trade	0.0034	0.0063	0.0469
FIRES	0.0095	0.0193	0.1488
Education and Government	0.0078	0.0083	0.0903
Households	0.0076	0.0198	0.1620

Truck Special Generator Trips

Special generator trips were developed for the following three generators:
1. Port of Seattle;
2. Port of Tacoma; and
3. Warehouses and distribution centers in the SR 167 corridor.

In the case of the two ports, the port activities are included in several TAZs. All special generator truck trips from the ports are heavy trucks. Port truck trips were estimated by subtracting the truck traffic generated by existing employment in the zone from the total truck traffic expected in each TAZ. Warehouse and distribution centers in the SR 167 corridor were estimated from a truck survey conducted in February 2006.

Truck External Trips

There are three primary types of external trips represented in the truck model: 1) trips that begin in Puget Sound region and leave the region; 2) trips that begin outside the region and are destined to someplace within Puget Sound region; and 3) trips traveling through the region. The primary source of data for these trips is the TRANSEARCH commodity flow data for the year 1997, which is converted to truck trips. The Strategic Freight Transportation Analysis (SFTA)collected origin-destination data on commodity flow in 2001-2003 (same locations for each of four seasons) were used to update the TRANSEARCH data.
The TRANSEARCH data were converted from annual truck trips to daily truck trips by dividing by 264 days of operation per year. Since the TRANSEARCH data did not include all of the data needed to develop comprehensive truck trip tables, some adjustments were made to these sources to fill in the gaps in the data source.

Table 10. Truck External Trips

External Stations	TAZ	Total Trucks	Total External Volumes	Percent trucks
I-5 to Olympia	939	7,385	76,194	9.7%
SR 507 to Yelm	940	-	10,168	-
SR 7 to Morton	941	-	2,492	-
SR 706 to Longmire	942	-	2,408	-
SR 123 S of Cayuse Pass	943	-	1,157	-
SR 410 E of Chinook Pass	944	-	997	-
I-90 to Snoqualmie Pass	945	4,165	12,304	33.9%
SR 2 to Stevens Pass	946	427	3,008	14.2%
SR 92 to Monte Cristo	947	-	2,060	-
SR 530 N of Darrington	948	-	3,678	-
SR 9 N of Arlington	949	-	1,263	-
I-5 to Mount Vernon	950	4,253	48,966	8.7%
SR 530 N of Stanwood	951	-	4,346	-
SR 532 to Camano Island	952	28	20,058	0.1%
Mukilteo Ferry to Whidbey Island	953	20	7,682	0.3%
Hood Canal Bridge	954	114	17,033	0.7%
SR 3 to Belfair	955	15	12,809	0.1%
SR 302 to Shelton	956	149	3,369	4.4%
Total		**16,555**	**229,993**	**7.2%**

Truck Trip Distribution

The light, medium, and heavy trucks are distributed from origins to destinations using the gravity model technique. This is the same distribution method used in the auto passenger model. The friction factor curves were derived from the *Quick Response Freight Manual*[26] originally, and adjusted to provide the best fit with the average trip lengths from the origin-destination survey of trucks.[27] The re-calibration of the truck trip distribution model involved adjusting the truck trip friction factors to better match observed trip lengths identified in the SFTA.

These friction factors were developed using the following gamma functions:

- Light Trucks, Short Trips = {EXP(3.75-0.08 * “daily travel time“). max. 1};
- Medium Trucks, Short Trips = {EXP(4.75-0.05 * “daily travel time“). max. 1};
- Light Trucks, Long Trips = {EXP(2.1-0.005 * “daily travel time“). max. 1};
- Medium Trucks, Long Trips = {EXP(4.2-0.003 * “daily travel time“). max. 1};
- Light Trucks, Kitsap Pen. = {EXP(4.0-0.05 * “daily travel time“). max. 1};
- Medium Trucks, Kitsap Pen. = {EXP(5.0-0.10 * “daily travel time“). max. 1};
- Heavy Trucks, All Trips = {EXP(4.0-0.10 * “daily travel time“). max. 1};

Truck Time of Day

Truck trip tables by type (light, medium, and heavy) are converted to truck trip tables by the five time periods using time period factors developed from the PSRC screenline counts for trucks.

Table 11. Truck Time-of-Day Factors

	Truck Type		
Time Period	**Light**	**Medium**	**Heavy**
A.M. Peak	19.4%	20.8%	20.9%
Midday	34.6%	41.7%	46.8%
P.M. Peak	24.0%	20.4%	18.9%
Evening	12.6%	9.5%	7.1%
Night	9.4%	7.6%	6.3%
Total	**100.0%**	**100.0%**	**100.0%**

Truck Trip Assignment

Multi-Class Assignments

Trip assignment of the truck trips was completed using an equilibrium highway assignment. Truck trips were assigned simultaneously with the passenger model, because congestion has a significant impact on travel times experienced by trucks. Truck trips are assigned separately by type using the multi-class assignment technique for five vehicle types:

1. Single-occupant passenger vehicles;
2. High-occupant passenger vehicles;
3. Light trucks;
4. Medium trucks; and
5. Heavy trucks.

During model calibration of truck trip assignments, it became clear that trucks were not operating at the same speeds as autos and that this fact caused an overestimation of trucks on freeways, compared to arterials. As a result, a 25 percent factor on travel time for trucks traveling on freeways was included in the multi-class assignments of trucks.

Passenger Car Equivalents

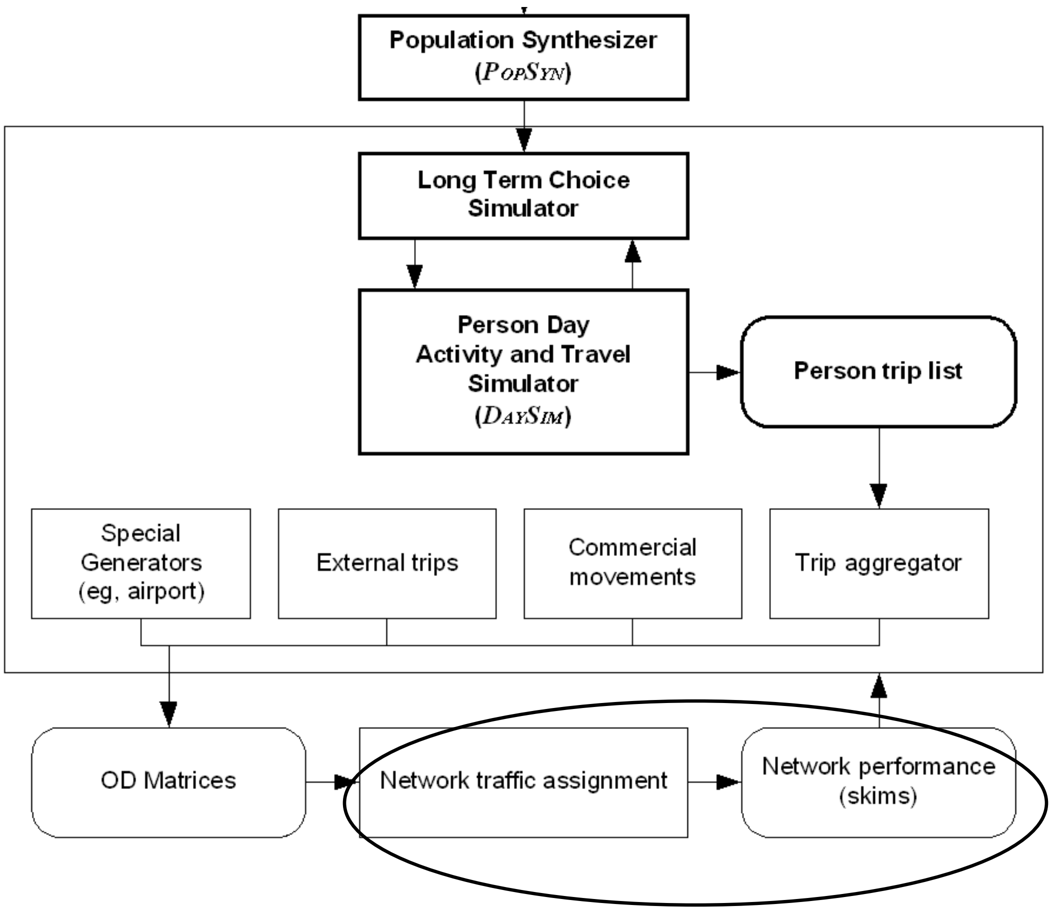
This truck model was developed using a conversion of truck volumes to passenger car equivalents (PCE) for assignment purposes. This factor provides ameans to account for the fact that larger trucks take up more capacity on the roads than passenger cars. This model is important to determine the effects on capacity and congestion for assignment of both trucks and passenger cars. The following assumptions were used:

- Light trucks are 1.0 PCE;
- Medium trucks are 1.5 PCEs; and
- Heavy trucks are 2.0 PCEs.

Network Assignment and Skimming

After all the daily trips for the region have been generated, SoundCast assign the trips to the network. The assignment results in a set of travel impedances which are skimmed from the network.

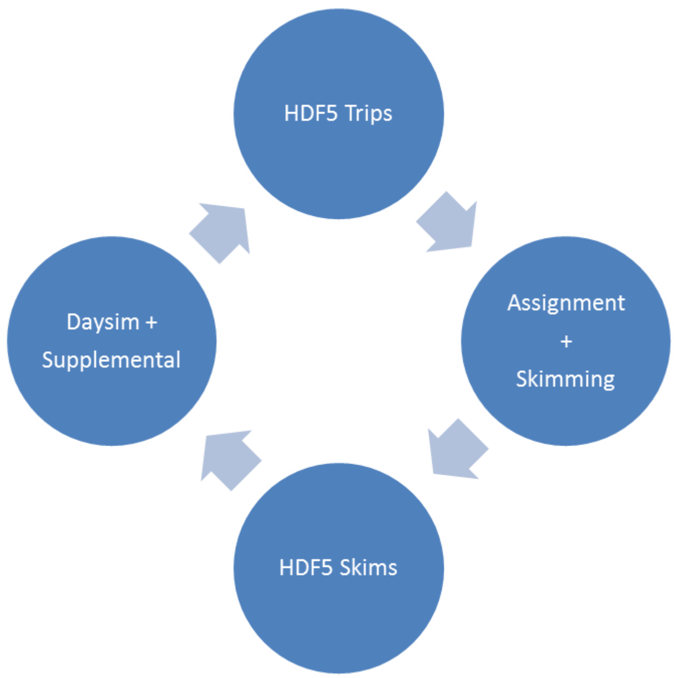
Figure 4. SoundCast Design



Skim and Trip Data Exchange

The skims are sent from the skimming process in EMME into Daysim; and the supplemental trips and the Daysim trips must be sent into the assignment, as shown in the figure below.

Figure 5. Data Exchanges



DaySim is configured to read skims that are stored in HDF5. The disaggregate trip-list based estimates of passenger travel demand produced by DaySim, as well estimates of demand produces by auxiliary models such as trucks and special generators, are inputs to EMME 's network assignment. In order to assign the demand generated by DaySim, the trip-list based demand are aggregated into matrices identified by time period, TAZ, mode and market segment.

Skims

Skims of network performance are produced by EMME, and are characterized by the time period, mode, and market segment. The skims are used to represent travel impedance when generating travel demand.

Table 12. Time Period Definitions

Mode	Time Period Name	Time Period Definition
Roadway	Early AM	5:00 am - 6:00 am
	AM Peak Hour 1	6:00 am - 7:00 am
	AM Peak Hour 2	7:00 am - 8:00 am
	AM Peak Hour 3	8:00 am - 9:00 am
	AM Peak Hour 4	9:00 am - 10:00 am

	Midday	10:00 am - 2:00 pm
	PM Peak Hour 1	2:00 pm - 3:00 pm
	PM Peak Hour 2	3:00 pm - 4:00 pm
	PM Peak Hour 3	4:00 pm - 5:00 pm
	PM Peak Hour 4	5:00 pm - 6:00 pm
	Evening	6:00 pm – 8:00 pm
	Overnight	8:00 pm - 5:00 am
Transit	AM	6:00 am - 9:00 am
	Midday	9:00 am - 3:00 pm
	PM	3:00 pm - 6:00 pm
	Evening	6:00 pm - 8:00 pm
	Night	8:00 pm - 6:00 am
Walk	Allday	6:00 am - 6:00 am
Bike	Allday	6:00 am - 6:00 am

Skim Attributes

For each of the time periods described in the preceding section, a set of modal-specific skim attributes is developed. As shown in the table below, twenty-one roadway attributes are skimmed. These are derived from the combinations of three primary attributes (time, distance, and cost) and market segments.

For the roadway modes, the basic time, distance and cost measures are skimmed for SOV, HOV 2 and HOV 3+. DaySim incorporates a nest under each auto occupancy mode of toll/no toll choices, and as a result it is necessary to develop separate skims that reflect the availability (or unavailability) of tolled facilities. This skimming approach does not include a distinction between so-called “value tolls” and other tolls that may be unavoidable.

In addition, DaySim has been enhanced to use distributed values of time rather than a single average value. In order to support these enhanced capabilities, the skims should reflect this VOT segmentation, a set of truck trip skims reflect different values of time assumptions for commercial vehicle travel .

Table13. PSRC Model Skim Attributes

Mode	Segment	Skims
Roadway (x12 time periods)	General Purpose/SOV, No Toll, VOT 1	Time, distance & cost

	General Purpose/SOV, No Toll, VOT 2	Time, distance & cost
	General Purpose/SOV, No Toll, VOT 3	Time, distance & cost
	General Purpose/SOV, Toll, VOT 1	Time, distance & cost
	General Purpose/SOV, Toll, VOT 2	Time, distance & cost
	General Purpose/SOV, Toll, VOT 3	Time, distance & cost
	HOV 2, No Toll, VOT 1	Time, distance & cost
	HOV 2, No Toll, VOT 2	Time, distance & cost
	HOV 2, No Toll, VOT 3	Time, distance & cost
	HOV 2, Toll, VOT 1	Time, distance & cost
	HOV 2, Toll, VOT 2	Time, distance & cost
	HOV 2, Toll, VOT 3	Time, distance & cost
	HOV 3+, No Toll, VOT 1	Time, distance & cost
	HOV 3+, No Toll, VOT 2	Time, distance & cost
	HOV 3+, No Toll, VOT 3	Time, distance & cost
	HOV 3+, Toll, VOT 1	Time, distance & cost
	HOV 3+, Toll, VOT 2	Time, distance & cost
	HOV 3+, Toll, VOT 3	Time, distance & cost
	Light Truck	Time, distance & cost
	Medium Truck	Time, distance & cost
	Heavy Truck	Time, distance & cost
Transit (x5 time periods)	Generalized Transit	Transit in-vehicle time
	Generalized Transit	Initial wait time
	Generalized Transit	Total transfer time
	Generalized Transit	Average number of boardings
	Generalized Transit	Transit fare

	Generalized Transit	In-vehicle time on local bus
	Generalized Transit	In-vehicle time on premium bus
	Generalized Transit	In-vehicle time on commuter rail
	Generalized Transit	In-vehicle time on light rail
	Generalized Transit	In-vehicle time on ferry
Walk (x1 time period)	Walk	Walk distance
	Walk	Walk time
Bike (x1 time period)	Bike	Bike onroad distance
	Bike	Bike offroad distance
	Bike	Bike time

Daysim Trips to EMME

Demand is assigned using the same time periods and market segments described in the earlier discussion of skimming. For roadways, it is proposed that for each time period a total of 21 classes will be assigned.

Transit assignment uses a single transit mode, with the DaySim determining whether transit is accessed by driving, and the EMME pathbuilder determining the specific modes and routes to which transit demand is assigned.

Table 14. PSRC Model Assignment Segments

Mode	Segment
Roadway (x12 time periods)	General Purpose/SOV, No Toll, VOT 1
	General Purpose/SOV, No Toll, VOT 2
	General Purpose/SOV, No Toll, VOT 3
	General Purpose/SOV, Toll, VOT 1
	General Purpose/SOV, Toll, VOT 2
	General Purpose/SOV, Toll, VOT 3
	HOV 2, No Toll, VOT 1
	HOV 2, No Toll, VOT 2

	HOV 2, No Toll, VOT 3
	HOV 2, Toll, VOT 1
	HOV 2, Toll, VOT 2
	HOV 2, Toll, VOT 3
	HOV 3+, No Toll, VOT 1
	HOV 3+, No Toll, VOT 2
	HOV 3+, No Toll, VOT 3
	HOV 3+, Toll, VOT 1
	HOV 3+, Toll, VOT 2
	HOV 3+, Toll, VOT 3
	Light Truck
	Medium Truck
	Heavy Truck
Transit (x5 time periods)	Generalized Transit

Appendix 1—DaySim Model Features

This appendix consists of a table listing all the basic models in DaySim. For each model it gives the model type, the dependent variables predicted by the model, and important other variables used in the model, especially spatial, temporal, and accessibility variables.

	Model	Model Type	Dependent Variables	Additional Variables Used in Model
1.1	Population synthesizer	Iterative Proportional Fitting IPF)	**Household variables** Household ID Household size # in HH by Person type Number in HH employed Number in HH students Family/nonfamily code HH annual income Res location **Person variables** household ID Person ID Age Sex Person type Employment status Usual hrs worked per week Student status	TAZ-level marginals Parcel "sizes" based on dwelling types
1.2	Work location	Multinomial logit (MNL)	Work location (Parcel, TAZ)	Sample of valid parcel locations Worker's work mode choice logsums from home parcel to sampled parcel locations, using weighted avg attributes across all time periods Non-work tour mode/dest. approximate logsum for sampled location (pre-calculated, generic nonwork purpose, for 1 of 2 transit accessibility levels within O parcel's TAZ, 1/2 hr time window, using weighted avg attributes across 5 one-period time windows) Size variables and other sampled parcel attributes, including..... for student over 15 or college student, school location conditions work location
1.3	School location	MNL	School location (Parcel, TAZ)	Analog of 1.2 For other than student over 15 or college student, work location conditions school location
1.4	Household vehicles available	(MNL: 0, 1, 2, 3 or 4+ vehicles)	Number of vehicles available (0-4+)	Workers' (all ftw & ptw) tour mode choice logsum to usual workplace with, and without, auto-based alts available, using weighted avg attributes across time periods Worker's (all ftw & ptw) parking price and walk accessibility [f(nodes w 4+ links,service+retail employment)]at usual workplace Student's (all uni & das) tour mode choice logsum to usual schoolplace with, and without, auto-based alts available, using weighted avg attributes across time periods Worker's (all uni and das) parking price and walk accessibility [f(nodes w 4+ links,service+retail employment)]at usual school loc Non-work tour mode/dest. approximate logsum for home (pre-calculated, generic nonwork purpose, for 1 of 2 transit accessibility levels within O parcel's TAZ, 2+ hr time window, with and without auto-based alts available, use weighted avg attributes across time periods) Residence parking price and walk accessibility [f(nodes w 4+ links,service+retail employment)]

	Model	Model Type	Dependent Variables	Additional Variables Used in Model
2.1	Activity pattern	MNL	0/1+ tours and 0/1+ stops by 7 purposes	Residence parcel attributes (walkability, densities, etc.) Usual work and/or school location parcel attributes (walkability, densities, etc.) Worker's work mode choice logsum from home parcel to usual work location, using weighted avg attributes across all time periods Student's school mode choice logsum from home parcel to usual school location, using weighted avg attributes across time periods Purpose-specific mode/dest. approximate logsums for home location (pre-calculated, 7 purposes, for 1 of 2 transit accessibility levels within O parcel's TAZ, 2+ hour time window, purpose-specific weighted avg attributes across time periods)
2.2	Exact number of tours for 7 tour purposes	MNL	Number of tours for 7 tour purposes	Minimum # tours assigned to pattern so far, by purpose Residence parcel attributes (walkability, densities, etc.) Usual work and/or school location parcel attributes (walkability, densities, etc.) Worker's work mode choice logsum from home parcel to usual work location, using weighted avg attributes across all time periods Student's school mode choice logsum from home parcel to usual school location, using weighted avg attributes across time periods Purpose-specific mode/dest. approximate logsums for home location (pre-calculated, 7 purposes, for 1 of 2 transit accessibility levels within O parcel's TAZ, 2+ hour time window, purpose-specific weighted avg attributes across time periods)
3.1	Tour destination	MNL	Tour destination (Parcel, TAZ)	Longest available contiguous time window. Sample of valid parcel locations Non-work tour mode/dest. approximate logsum for sampled location (pre-calculated, generic nonwork purpose, for 1 of 2 transit accessibility levels within O parcel's TAZ, 1/2 hr time window, using weighted avg attributes across 5 one-period time windows) Size variables of sampled parcels and corresponding size of 1/2 mile buffers Sampled parcel attributes: distance to bus & LRT stop, ped environment variables Purpose-specific mode choice logsums from home to sampled locations, using purpose-specific weighted avg attributes across time periods
3.2	Number and purpose of work-based subtours	Recursive MNL [no more subtours or one more subtour with purpose p]	Tour participation (yes or no). Tour purpose (if yes). Tour ID (if yes)	Longest available contiguous time window for parent tour Non-work tour mode/dest. approximate logsum for tour destination (pre-calculated, generic nonwork purpose, for 1 of 2 transit accessibility levels within D parcel's TAZ, 1/2 hr time window using weighted avg attributes across 5 one-period time windows) Size variables of D parcel and corresponding size of 1/2 mile buffers D parcel attributes
3.3	Tour main mode	NL	Tour mode	For work tours: Number of work-based subtours TAZ-to-TAZ car, transit and walk/bike skim variables O and D parcel transit accessibility, pedestrian measures, etc. D parcel parking costs For WB tours, tour mode of parent tour
3.4	Primary activity start and end periods	MNL	Arrival period at primary activity location (to within 30 minutes) Departure period from primary activity location (to within 30 minutes)	For work tours: number of work-based subtours Availability array of all 30 minute time periods across the day Travel time to and from tour dest by mode / time of day For WB tours, arrival and departure hour at tour destination

	Model	Model Type	Dependent Variables	Additional Variables Used in Model
4.1	Stop participation and purpose	Recursive MNL [no more stops or one more stop with purpose p]	Stop participation (yes or no). If yes, then stop's purpose. Stop ID	Allocation deficit/surplus of stop purposes on pattern (conditioned by prior modeled tours and stops) Number of stops already assigned to pattern Stops by purpose already assigned to each segment of tour (before dest, work subtour, after dest) Accessibility around tour origin and adjacent prior modeled stop Tour/stop purpose interactions Tour mode Tour destination begin and end time periods Stop departure time (10 min) from adjacent prior modeled location [if any] Available time window for tour segment between this stop and tour origin
4.2	Stop location	MNL	Stop location (Parcel, TAZ) [if not last modeled trip in half-tour]	Sample of valid parcel locations Tour mode-specific LOS between adjacent prior modeled stop and tour origin (in direction of movement and through sampled location) Non-work tour mode/dest. approximate logsum for sampled locations (pre-calculated, generic nonwork purpose, for 1 of 2 transit accessibility levels within O parcel's TAZ, 1/2 hr time window in the time period determined by actual available time window, with auto-based alts available) Size variables of sampled parcels and corresponding size of 1/2 mile buffers Sampled parcel attributes: distance to bus & LRT stop, ped env vars Trip mode of adjacent prior modeled trip
4.3	Trip mode	MNL or NL	Trip mode	TAZ-to-TAZ car, transit and walk/bike skim variables O and D parcel transit accessibility, pedestrian measures, etc. D parcel parking costs Tour mode Mode used for trip from adjacent prior modeled location. Trip modes used for already modeled stops on tour (12 0/1 flags)
4.4	Inter-mediate stop arrival time	MNL or NL	Trip departure time (arrival time for 1st half-tour) Trip travel time and arrival (departure) time [determined by trip mode and departure time]	Availability array of all 30 minute time periods across the day Tour destination begin and end time periods (60 minute) Arrival time of adjacent prior modeled trip [if any] (departure time for 1st half-tour) Trip mode-specific travel times for different time periods (peak spreading model)

Appendix 2—DaySim Variables

This appendix contains a table with the current complete list of DaySim variables, with the names as included in the estimation data files from the household survey. It includes the elemental variables and derived variables that will be output from DaySim application runs.

Household Variables

Variable	Definition	Type
HHNO	Household id	ID
Fraction_with_jobs_outside	Residence zone worker IX fraction	Continuous
HHSIZE	Household size	Count
HHVEHS	Vehicles available	Count
HHWKRS	Household workers	Count
HHFTW	HH full time workers (type 1)	Count
HHPTW	HH part time workers (type 2)	Count
HHRET	HH retired adults (type 3)	Count
HHOAD	HH other adults (type 4)	Count
HHUNI	HH college students (type 5)	Count
HHHSC	HH high school students (type 6)	Count
HH515	HH kids age 5-15 (type 7)	Count
HHCU5	HH kids age 0-4 (type 8)	Count
HHINCOME	Household income ($)	Continous
HOWNRENT	Household own or rent	Categorical
HRESTYPE	Household residence type	Categorical
HHPARCEL	Residence parcel id	ID
ZONE_ID	Internal id based on parcel id	ID
HHTAZ	Based on parcel id	ID
HHEXPFAC	HH expansion factor	Continuous
SAMPTYPE	Sample type	Categorical

Key	
	Basic ID and expansion variables
	Exogenous inputs
	Inputs for model estimation only
	Predicted by choice models
	Reserved for new choice models in future
	New fields added by Daysim upon import
	Computed by Daysim upon import

PersonVariables

Variable	Definition	Type
ID	internal daysim record ID	ID
HHNO	hh id	ID
PNO	person seq no on file	ID
PPTYP	person type	Categorical
PAGEY	age in years	Continuous
PGEND	gender	Categorical
PWTYP	worker type	Categorical
PWPCL	usual work parcel id	ID
PWTAZ	usual work TAZ	ID
PWAUTIME	auto time to usual work	Continuous
PWAUDIST	auto distance to usual work	Continuous
PSTYP	student type	Categorical
PSPCL	usual school parcel id	ID
PSTAZ	usual school TAZ	ID
PSAUTIME	auto time to usual work	Continuous
PSAUDIST	auto distance to usual work	Continuous
PUWMODE	usual mode to work	Categorical
PUWARRP	Usual arrival period to work	Categorical
PUWDEPP	Usual depart period from work	Categorical
PTPASS	transit pass?	0 / 1
PPAIDPRK	paid parking at workplace?	0 / 1
PDIARY	Person used paper diary?	0 / 1
PPROXY	proxy response?	Categorical
PSEXPFAC	Person expansion factor	Continuous

Key	Basic ID and expansion variables
	Exogenous inputs
	Inputs for model estimation only
	Predicted by choice models
	Reserved for new choice models in future
	New fields added by Daysim

Person Day File

Variable	Definition	Type
ID	internal daysim record ID	ID
PERSON_ID	internal daysim record ID	ID
Household_day_ID	internal daysim record ID	ID
HBTOURS	home based tours in day	Count
WBTOURS	work based tours in day	Count

UWTOURS	tours to usual workplace in day	Count
WKTOURS	work tours	Count
SCTOURS	school tours	Count
ESTOURS	escort tours	Count
PBTOURS	pers.bus. Tours	Count
SHTOURS	shopping tours	Count
MLTOURS	meal tours	Count
SOTOURS	social tours	Count
RETOURS	recreation tours	Count
METOURS	medical tours	Count
WKSTOPS	work stops in day (?)	Count
SCSTOPS	school stops in day (?)	Count
ESSTOPS	escort stops in day (?)	Count
PBSTOPS	pers.bus stops in day (?)	Count
SHSTOPS	shopping stops in day (?)	Count
MLSTOPS	meal stops in day (?)	Count
SOSTOPS	social stops in day (?)	Count
RESTOPS	recreation stops in day (?)	Count
MESTOPS	medical stops in day (?)	Count
WKATHOME	Minutes worked at home in day	Continuous
PDEXPFAC	Person-day expansion factor	Continuous

Key	Basic ID and expansion variables
	Exogenous inputs
	Inputs for model estimation only
	Predicted by choice models
	Reserved for new choice models in future
	New fields added by Daysim

Tour Variables

Variable	**Definition**	**Type**
ID	internal daysim record ID	ID
PERSON_ID	internal daysim record ID	ID
Person_day_ID	internal daysim record ID	ID
JTINDEX	hh joint tour index	ID
PARENT	parent tour id	ID
SUBTRS	number of subtours	Count
PDPURP	prim.dest.purpose	Categorical
TLVORIG	time leave tour origin	0000-2359
TARDEST	time larrive tour dest	0000-2359
TLVDEST	time leave tour dest	0000-2359
TARORIG	time arrive tour origin	0000-2359
TOADTYP	tour origin address type	Categorical
TDADTYP	tour destination address type	Categorical
TOPCL	tour origin parcel	ID
TOTAZ	tour origin TAZ	ID
TDPCL	tour dest parcel	ID
TDTAZ	tour destination TAZ	ID
TMODETP	tour main mode type	Categorical
TPATHTP	tour main mode path type	Categorical
TAUTOTIME	tour 1-way auto time	Continuous
TAUTOCOST	tour 1-way auto distance	Continuous
TAUTODIST	tour 1-way auto cost	Continuous
TRIPSH1	1st half tour # of trips	Count
TRIPSH2	2nd half tour # of trips	Count
TOEXPFAC	trip expansion factor	Continuous

Key	Basic ID and expansion variables
	Exogenous inputs
	Inputs for model estimation only
	Predicted by choice models
	New fields added by Daysim

Trip Variables

Variable	Definition	Type
ID	internal daysim record ID	ID
TOUR_ID	internal daysim record ID	ID
HHNO	Household id	ID
PNO	person seq no on file	ID
DAY	Diary / simulation day ID	ID
TOUR	tour id	ID
HALF	tour half	ID
TSEG	trip seqgment no within half tour	ID
TSVID	original survey trip id no.	ID
OPURP	trip origin purpose	Categorical
DPURP	trip dest purpose	Categorical
OADTYP	trip origin address type	Categorical
DADTYP	trip destination address type	Categorical
OPCL	trip origin parcel	ID
OTAZ	trip origin zone	ID
DPCL	trip dests parcel	ID
DTAZ	trip dest zone	ID
MODE	trip mode	Categorical
PATHTYPE	transit submode	Categorical
DORP	trip driver or passenger	Categorical
DEPTM	trip departute time (min after 3 am)	0000-2359
ARRTM	trip arrival time (min after 3 am)	0000-2359
ENDACTTM	trip dest activity end time	0000-2359
TRAVTIME	network travel time, min (by sov)	Continuous
TRAVCOST	network travel time, min (by sov)	Continuous
TRAVDIST	network travel distance, miles (by sov)	Continuous
VOT	trip value of time (cents/minute)	Continuous
TREXPFAC	trip expansion factor	Continuous

** recompute in Application mode using samp
rate

Key	Basic ID and expansion variables
	Exogenous inputs
	Inputs for model estimation only
	Predicted by choice models
	Reserved for new choice models in future
	New fields added by Daysim

Appendix 3 : DaySIM Software and Other Detailed Improvements

The new software improvements have been referred to several times in the preceding sections. This final section provides a concise overview of the key improvements.

- The new code is written in C#, which is a standard language now used by software engineers for creating professional software. It is programmed in the Microsoft Visual C# integrated development environment (IDE), using 64-bit code.
- The new code was co-designed and created by RSG's top software engineers (Bryce Lovell and Leo Duran), and is maintained using state-of-the practice software subversion control (Tortoise SVN) and project management tools (Redmine). Each revision of the code is reviewed to maintain professional standards of code legibility, efficiency, and manageability.
- The code is fully object-oriented, enhancing legibility and adaptability.
- The code uses multi-threading (parallel processing) wherever it is most efficient, making optimal use of hardware.
- The code uses advanced memory handling features, allowing most regional model systems to be run with less than 8 GB of RAM (depending mainly on the number of zones used for network skims)
- Most of the constants and parameters in the code are user-configurable, enhancing legibility of the code and avoiding the need for revising and re-compiling.
- The formats for the input and output files are now consistent, enhancing the capability to do partial runs.
- DaySIM now includes a model estimation capability that produces data and control files that can be used "as is" to immediately estimate models using the ALOGIT software. This has multiple advantages:
    - Ensures consistency between model estimation and application, avoiding a major source of potential bugs
    - Makes it very quick and efficient to re-estimate the models when new data becomes available or when minor changes are desired.
    - Ensures consistency across the different choice models and the way they are coded, making it easier for new users to understand different models.
- The new "skim roster" capability makes it possible (and fairly easy) to change many aspects of how the network skims are used (adding or subtracting submodes and path types, use of different VOT classes, changes in time period definitions, etc.) without needing to change or recompile the DaySIM code.
- In addition to the above features, the new DaySIM has maintained key distinctive features that were present in the old version:
    - The ability to work with parcel-level spatial alternatives. This is now configurable, also allowing inputs at the zone, or micro-zone (e.g. block) level.
    - A facility for synchronizing random seeds, reducing differences between runs/scenarios that is due solely to random simulation error.
    - Shadow pricing to maintain supply/demand consistency for choices of work and school locations.

Traveler- & tour-specific model coefficients

Work tours

c(i) = -0.15/$ / [((income(i) / 30,000) ^ 0.6) * (occupancy(i) ^ 0.8)]

b(i) = -0.030/min * draw from a log-normal distribution, with mean 1.0 and coef. of variation 0.8

a(i) = -1.00

s = 1.5

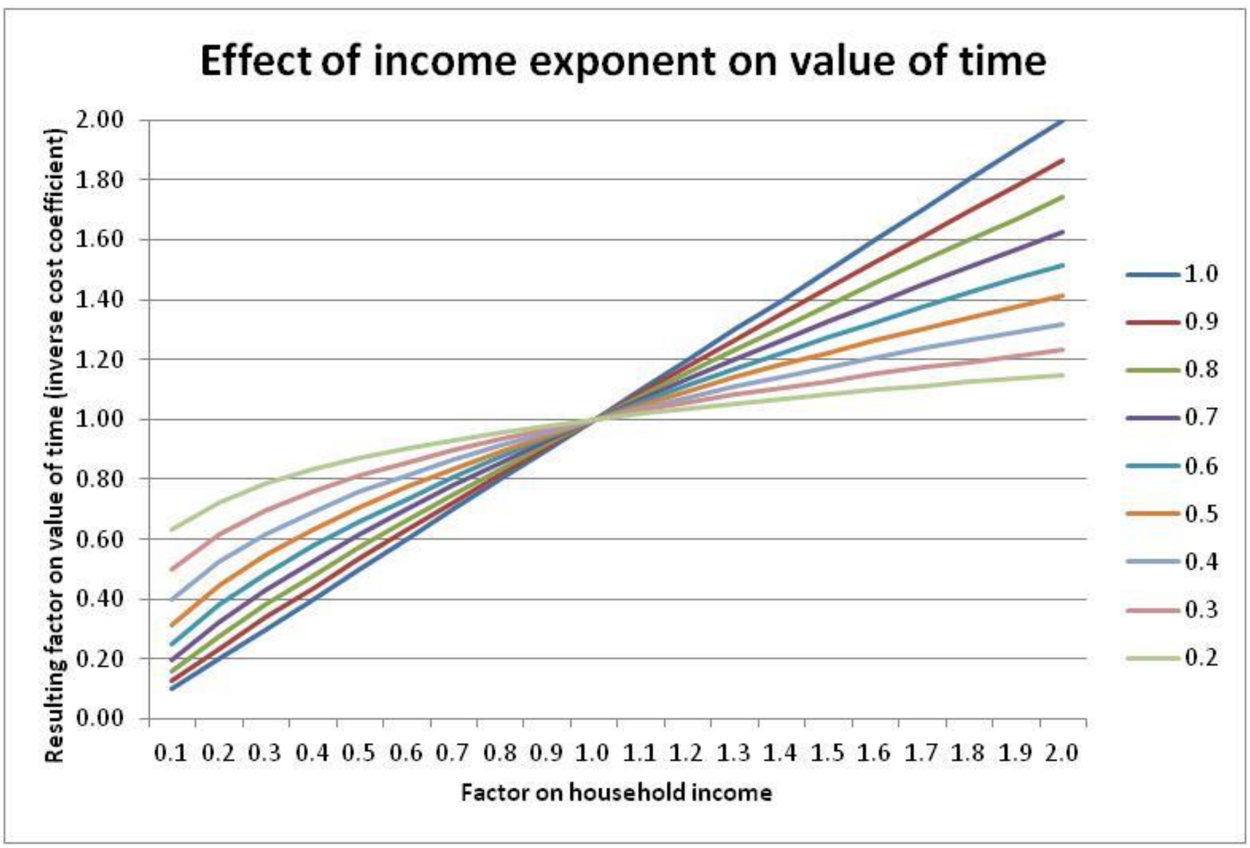
Non-work tours

c(i) = -0.15/$ / [((income(i) / 30,000) ^ 0.5) * (occupancy(i) ^ 0.7)]

b(i) = -0.015/min * draw from a log-normal distribution, with mean 1.0 and coef. of variation 1.0

a(i) = -1.00

s = 1.5



Use EMME to generate time, distance, toll matrices for each combination of :

<u>Time period</u>: In the range of 4 to 12 different skim periods

<u>Path type</u>: (1) full network, (2) network excluding tolled links

<u>VOT threshold</u>: A user-defined number of different values, V(1), V(2), … V(N)

<u>Occupancy</u>: (1) SOV, (2) HOV 2 (3) HOV 3+ (if necessary)

2. Use DaySim to simulate toll/no toll choice for a given trip, depending on the VOT for that specific person/tour/trip…

    - If VOT < V(1), use V(1) skims
    - If V(1) < VOT < V(2), use V(2) skims, etc.
    - If V(N-1) < VOT, use V(N) skims

3. Every auto trip predicted by Daysim has a VOT and path choice (full network or non-toll network)
4. Aggregate trips into vehicle matrices by time period x path type x VOT group for multi-class assignment.

Park and ride path type and lot choice model

- Applied at the tour level, and park and ride tours are constrained to stop at the same park and ride lot on both half tours.
- Uses data on available park and ride lots: location, price, capacity
- Applied "on the fly", like the other path type models. For each transit path type, find the best combined auto/transit path via all possible park and ride lots.
- Can be applied with "shadow pricing" across global iterations…. Lot / time of day combinations where simulated occupancy exceeds capacity are given an artificially higher price during those periods.
- Currently used only for home-based-work tours
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Treatment of transit pricing

- Transit skims assume full fare.
- User can define fare discount fractions depending on person type.

Example of assumptions

- Child under age 5 80% discount
- Child age 5-15 50% discount
- Grade school student age 16+ 50% discount
- University student 50% discount
- Adult age 65+ 35% discount
- The transit pass ownership model overrides the discount factors – transit pass owners are assumed to face 0 fare for an individual trip

Pay to park at workplace model - estimation

- Estimated on data from the 2000 SACOG Household Travel Survey

Key variables (+ means higher prob. of paying to park at work):

- Part-time worker (+)
- Higher income (--)
- Log of total employment in the work parcel buffer (+)
- Log of paid parking spaces per employees in the work parcel buffer (+)
- Frac. Government employment in the work parcel buffer (+)
- Frac. Education employment in the work parcel buffer (-)
- Workers who are predicted to have to pay to park at the workplace face the average daily price for paid parking spaces in the usual work parcel buffer.
- Otherwise, parking at work is assumed to be free in the work tour and trip level models.
- In the future, a capacity-constrained model for choice of a CBD paid parking lot/garage could be implemented, similar to the model for park and ride lot choice

DaySim Software and Hardware

- **Software**
    - Programmed in C#, Visual Studio, Microsoft .Net platform

- Optimized memory and data handling
- Two levels of distributed processing for faster runs
  - Distribution of households across different processors on a single machine.
  - Higher level distribution of households to different physical or virtual machines.
  - On a standard PC, simulates about 1 million persons per hour. Less if distributed across multiple machines. (Significantly faster than quoted for other AB model software)
- Client project is customized
- Inputs and outputs are integrated with any travel modeling package
- Same code used for model estimation and application

- **Hardware**
  - Runs on 64-bit Windows systems
  - Expected minimum configuration:
    - Single box with 4+ processing cores (more cores will reduce run times)
    - 8 GB RAM (16 GB if using more than 1,500 zones)