THE SACRAMENTO ACTIVITY-BASED TRAVEL DEMAND MODEL: ESTIMATION AND VALIDATION RESULTS

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1. INTRODUCTION AND MODEL SYSTEM OVERVIEW

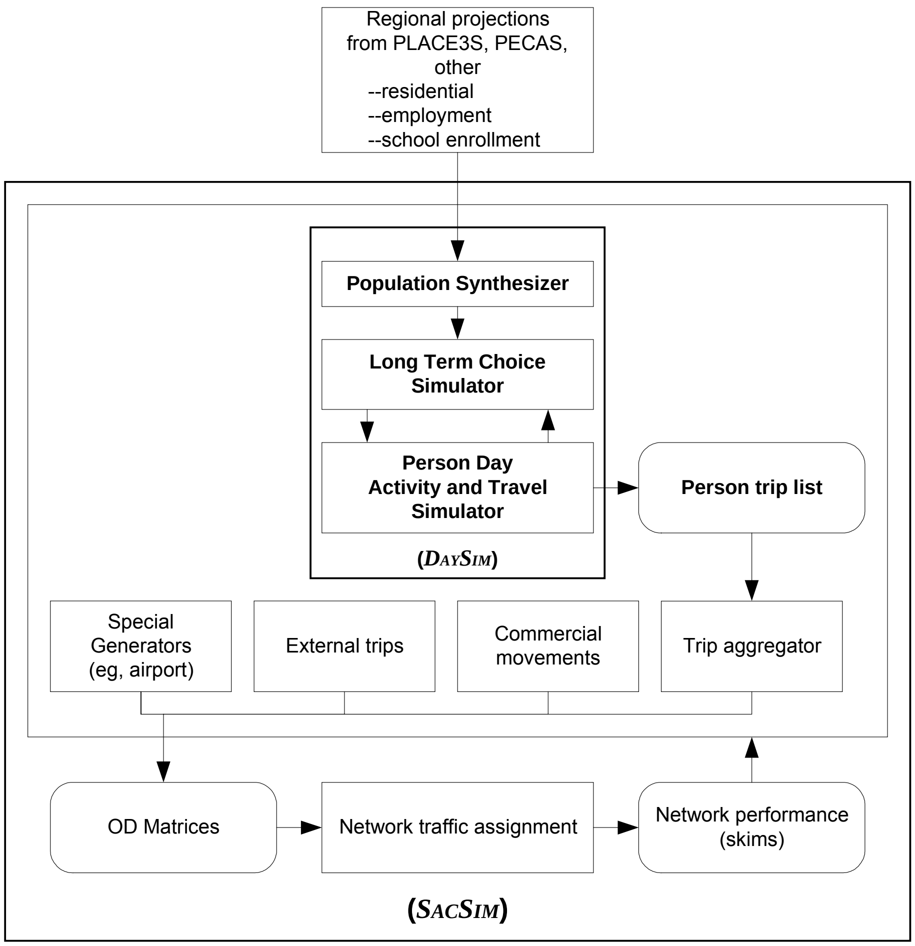
This paper presents a regional travel forecasting model system called SacSim, developed in 2005 and being implemented in 2006 for the Sacramento (California) Area Council of Governments (SACOG). The system includes an integrated econometric microsimulation of personal activities and travel (DaySim) with a highly disaggregate treatment of the purpose, time of day and location dimensions of the modeled outcomes. SacSim will be used for transportation and land development planning, and air quality analysis. At the time of the 2006 European Transport Conference (ETC) SacSim was fully implemented and forecasts for 2032 had been generated. Work was ongoing to calibrate the base year (2000), validate a 2005 forecast, conduct sensitivity tests, and tune the demand-assignment equilibration procedure.

A 2005 ETC paper (Bowman and Bradley, 2005) described the SacSim design, data, and partial estimation results of the DaySim component, emphasizing the techniques employed for effectively disaggregating the treatment of purpose, time and space. This paper focuses on several aspects in which progress has been made since then, including the time-of-day models, equilibration of demand and assignment, base year calibration, and sensitivity tests.

Figure 1 shows the major SacSim components. The Population Synthesizer creates a synthetic population, comprised of households drawn from the region's U.S. Census Public Use Microdata Sample (PUMS) and allocated to parcels. 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 then 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. These components, comprising DaySim and implemented jointly in a single software program, consist of a hierarchy of multinomial logit and nested logit models. The models within DaySim are connected by adherence to an assumed conditional hierarchy, and by the use of accessibility logsums. The trips predicted by

DaySim are aggregated into trip matrices and combined with predicted trips for special generators, external trips and commercial traffic into time- and mode-specific trip matrices. The network traffic assignment models load the trips onto the network. Traffic assignment is iteratively equilibrated with DaySim and the other demand models. As shown here, the regional forecasts are treated as exogenous. In subsequent implementations, it is anticipated that SacSim will be embedded in PECAS, Sacramento's new land use model (Abraham, Garry and Hunt, 2004), so that the long range PECAS forecasts will depend on the activity-based travel forecast of DaySim.

Figure 1: SACOG Regional Travel Forecasting Model System



2. DAYSIM OVERVIEW

DaySim follows the day activity schedule approach developed by Bowman and Ben-Akiva (2001). Its features include the following:

1 The model uses a microsimulation structure, predicting outcomes for each household and person in order to produce activity/trip records comparable to those from a household survey (Bradley, et al, 1999).

2 The model works at four integrated levels—longer term person and household choices, single day-long activity pattern choices, tour-level choices, and trip-level choices, yielding households with the following variables at five levels:

- household: income, family status, residence location
- person: gender, age, employment and student status, hrs worked per week, work location, school location
- person day: time availability for 48 half hour time periods
- tour: priority, purpose, origin, destination, main travel mode
- trip: half-tour; sequence in half-tour; location, arrival time and departure time at trip origin and destination; trip mode.

3 The upper level models of longer term decisions and activity/tour generation are sensitive to network accessibility and a variety of land use variables.

4 The model uses 7 purposes for both tours and intermediate stops (work, school, escort, shop, personal business, meal, social/recreation).

5 The model allows the specific work tour destination for the day to differ from the person's usual work and school location.

6 The model predicts locations down to the single parcel level.

7 The model predicts the time that each trip and activity starts and ends to the nearest 30 minutes, using an internally consistent scheduling structure that is also sensitive to differences in travel times across the day (Vovsha and Bradley, 2004).

8 The model is highly integrated, including the use of mode choice logsums and approximate logsums in the upper level models, encapsulating differences across different modes, destinations and times of day for different types of person.

9 Time and space constraints are used extensively in destination, mode and time-of-day choices to enhance realistic model behavior.

Features four through nine are key enhancements relative to its primary precursor, the model currently in active use by the San Francisco County Transportation Authority (SFCTA). See Bradley, et al. (2001) and Jonnalagadda, et al. (2001) for details of the SFCTA model.

Figure 2 presents DaySim's conditional heirarchy in outline form, identifying the program looping structure in which the models run. The hierarchy embodies assumptions about the relationships among simultaneous real world outcomes. In particular, outcomes higher in the hierarchy are treated as known in lower level models. It places at a higher level those outcomes that are thought to be higher priority to the decisionmaker. The model structure also embodies priority assumptions that are hidden in the hierarchy, namely the relative priority of outcomes on a given level of the hierarchy. The most notable of these are the relative priority of tours in a pattern, and the relative priority of stops on a tour. The formal hierarchical structure provides what has been referred to by Vovsha, Bradley and Bowman (2004) as downward vertical integrity.

Figure 2—DaySim models within the program looping structure

{Draw a synthetic household sample if specified}
{Loop on households}
 {Loop on persons in HH}
  {Apply model 1.1 Usual Work Location and model 1.2 School Location}
 {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}
  {Loop on home-based tours within person in tour priority sequence,
   {Apply model 3.1 Tour Destination}
   {If work tour, apply model 3.2 Number and Purpose of Work-Based Subtours,
    and insert work based tours after the work tour}
   {Apply model 3.3 Tour Mode and 3.4 Tour Destination Arrival and Departure Times}
   {Loop on tour halves (before and after primary activity)}
    {Apply model 4.1 Half Tour Stop Frequency and Purpose}
    {Loop on trips within home-based half tour (in reverse temporal order for 1st tour half)}
     {Apply model 4.2 Intermediate Stop Location}
     {Apply model 4.3 Trip Mode}
     {Apply model 4.4 Intermediate Stop Departure Time}

Just as important as downward integration is the upward vertical integration that is achieved by the use of composite accessibility variables to explain upper level outcomes. Done properly, this makes the upper level models sensitive to important attributes that are measured directly only at the lower levels of the model, most notably travel times and costs. It also captures non-uniform cross-elasticities caused by shared unobserved attributes among groups of lower level alternatives sharing the same upper level outcome.

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, in this project approaches have been developed to capture the most important accessibility effects with a feasible amount of computation. One approach involves using logsums that approximate the expected utility logsum. They are calculated in the same basic way, by summing the exponentiated utilities of multiple alternatives. 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. The approximate logsum is pre-calculated and used by several of the model components, and can be re-used for many persons. Two kinds of approximate logsums are used, an approximate tour mode-destination choice logsum and an approximate intermediate stop location choice logsum. The approximate tour mode-destination choice 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 day. The approximate intermediate stop location choice logsum is used in the activity pattern models, where accessibility for making intermediate stops affects whether the pattern will include intermediate stops on tours, and how many.

The other simplifying approach involves simulating a conditional outcome. For example, in the tour destination choice model, where time-of-day is not yet known, a mode choice logsum is calculated based on an assumed time of day, where the assumed time of day is determined by a probability-weighted Monte Carlo draw. In this way, the distribution of potential times of day is captured across the population rather than for each person, and the destination choice is sensitive to time-of-day changes in travel level of service.

In many other cases within the model system, true expected utility logsums are used. For example, tour mode choice logsums are used in the tour time of day models. Table 1 lists the DaySim model components and the accessibility measures providing upward vertical integrity.

Table 1: DaySim accessibility measures

	Model	Tour mode choice logsum	Simulated conditional outcomes	Aggregate tour mode-destination choice logsum	Aggregate intermediate stop location choice logsum
1.1	Usual Work Location	Yes.		At destination.	
1.2	School Location	Yes.		At destination.	
1.3	HH Auto Availability	To work. To school.		At home.	
2.1	Day Activity Pattern	For work & school.		At home.	Yes.
2.2	Number of Tours (by purpose)	For work and school tours.		At home.	
3.1	Tour Destination	Yes.	Primary activity periods	At destination.	
3.2	Number & Purpose of Work-Based Subtours				
3.3	Tour Mode		Primary activity periods		
3.4	Tour Destination Arrival and Departure Times				
4.1	Half-Tour Stop Frequency & Purpose				For auto-based tour modes.
4.2	Intermediate Stop Location				
4.3	Trip Mode				
4.4	Intermediate Stop Departure Time				

3. TIME OF DAY MODELS

3.1. Introduction

DaySim employs a method of modeling time of day developed by Vovsha and Bradley (2004). The time of day models explicitly model the 30 minute time periods of arrival and departure at all activity locations, and hence for all trips between those locations. It thereby also provides an approximate duration of the activity at each activity location. The model uses 48 half-hour periods in the day—3:00-3:29 AM, 3:30-3:59 AM, …, 2:30 AM-2:59 AM. Given the way that the activity diary data was collected, no tour begins before 3:00 AM or ends after 2:59 AM. DaySim includes two types of time-of-day models:

Tour primary destination arrival and departure time: For each home-based or work-based tour, the model predicts the time that the person arrives at the tour primary destination, and the time that the person leaves that destination to begin the return half-tour. The tour model includes as alternatives every possible combination of the 48 alternatives, or 48 x 49 / 2 = 1,716 possible alternatives. The model is applied after the tour primary destination and main mode have already been predicted. 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.

Intermediate stop arrival or departure time: For each intermediate stop made on any tour, this model predicts either the time that the person arrives at the stop location (on the first half tour), or else the time that the person departs from the stop location (on the second half tour). On the second (return) half tour, we know the time that the person departs from the tour primary destination, and, because the model is applied after the stop location and trip mode have been predicted, we also know the travel time from the primary destination to the first intermediate stop. As a result, we know the arrival time at the first intermediate stop, so the model only needs to predict the departure time from among a maximum of 48 alternatives (the same 30 minute periods that are used in the tour models). This procedure is repeated for each intermediate stop on the half tour. On the first (outbound) half tour, the stops are simulated in reverse order from the primary destination back to the tour origin, so we know the departure time from each stop and only need to predict the arrival time. As stops within a tour are modeled, the periods occupied by each modeled stop become unavailable for subsequently modeled stops and tours.

Time windows. A time window is a set of contiguous time periods that are available for scheduling tours and stops. When a tour or stop is scheduled, the portion of the window that it does not fill is left as two separate and smaller time windows. The time periods at either end of a scheduled sequence of activities on a tour are only partially filled, but the time periods in between are completely filled. It is possible to arrive at a tour or stop destination in a given time period if another tour ended in that period, and possible to leave a tour or stop destination if another tour began in that period, but it is not possible to arrive or depart in a time period that is already completely filled.

Shift variables. A shift variable is a dummy variable interacted with the arrival time or the duration of an alternative. If an arrival shift coefficient is negative, it means that activities tend to be made earlier (because the shift coefficient causes later arrival time alternatives to have lower utility), and if it is positive, it means that activities tend to be made later. If a duration shift coefficient is negative, it means that activities tend to be shorter (because the shift coefficient causes longer duration time alternatives to have lower utility), and if it is positive, activities tend to be longer. No departure shift coefficient is estimated because the departure shift is simply the sum of the arrival shift and the duration shift (e.g. if the arrival shift is an hour earlier and the duration shift is an hour longer, the departure shift is 0). For that reason, if either the arrival or duration shift is significant, both variables have been retained in the model. (This is not true for the intermediate stop model, where in most cases only the duration shift is relevant.) In the model, shift variables interact extensively with other characteristics of the person, day activity pattern and tour, as well as time-dependent attributes of the network, such as travel times and measures of congestion, to effectively represent their influence on time-of-day choice.

3.2. Estimation results

Table 2 below shows the number of tours and intermediate stops in the survey data by purpose. These observations were used to estimate 5 separate models:

1 Home-based work tours
2 Home-based school tours
3 Home-based other tours (escort, shopping, personal business, meal, and social/recreation)
4 Work-based subtours
5 All intermediate stops

Table 2: Sample sizes for time of day models

Purpose	Work	School	Escort	Shop	Pers. Bus	Meal	Soc-Recr	Work-Based	TOTAL
Tours	3,532	1,562	958	1,862	1,569	457	1,235	695	11,870
Intermediate Stops	522	116	1,997	2,145	2,117	880	974	NA	8,751

Detailed estimation results are available in a technical memorandum on the first author's website (Bowman and Bradley, 2005b). Below is a description of the key results, listed by variable type:

Constants. Each alternative in the models is characterized by three separate dimensions: arrival time, departure time, and duration of stay. Any one of these is defined by the other two—for example, the departure time equals the arrival time plus the duration of stay. In all of the models, we use 10 period-specific constants, spanning 24 hours, for each of the three dimensions. One of the 10 constants is constrained to 0, and the other 9 are estimated relative to the constrained one. It would be possible to estimate many more constants (the tour models have 1716 alternatives, so could support 1715 constants), but it is best to use constants only for the key periods, and let the rest of the variables explain the time periods as much as possible.

In the intermediate stop model, the departure time is fixed for stops on the outbound half tour, so those observations only contribute to the constants for arrival time and duration, and the arrival time is fixed for stops on the return half tour, so those observations only contribute to the constants for departure time and duration.

Person type variables. People with different roles in the household may tend to schedule their activities differently. This is captured in the models mainly through the use of shift variables. Findings for the person type variables are:

- Work: Part-time workers, university students, K-12 students age 16+, and other adults tend to all begin work later than full-time workers. Part-time workers and other adults also tend to work for the shortest duration. A dummy variable was added to capture the fact that full time workers rarely have work duration of less than 9 hours.
- School: K-12 students age 16+ tend to arrive at school earlier and stay longer than K-12 students age 5-15. All other person types tend to arrive at school later. University students stay at school for a somewhat shorter duration, while preschool children stay for a longer duration—presumably for as long as their parents stay at work.
- Other tours: University and K-12 students tend to begin their non-mandatory tours somewhat later in the day, while retired persons age 65+ tend to begin their non-mandatory tours earlier in the day, even after taking into account previously scheduled tours. Non-working adults, both over and under age 65, tend to make shorter non-mandatory tours.
- Work-based subtours: Part-time workers make subtours of slightly longer duration, although this coefficient may be offsetting availability effects (part-time workers have a shorter available time window).
- Intermediate stops: University students and children tend to make longer duration stops than adults do.

Income variables. Income-related variables were only significant for work tours. The findings are:

- Low income workers tend to work slightly shorter duration, while high income workers tend to work somewhat longer duration.
- High income workers are less likely to have extreme hours: they are less likely to arrive at work before 6 AM or depart after 10 PM.

Purpose variables. Other than the work and school tour models, each model was estimated for several purposes jointly, so activity purpose variables are very important for determining scheduling:

- Other tours: Relative to personal-business activities, people tend to arrive earlier for escort activities and later for shopping, meal and social/recreation activities. Escort and shopping activities also tend to be much shorter in duration, while social/recreation activities are much longer.
- In addition to the shift variables, some dummy variables are also significant: Escort and shopping activities are likely to last less than an hour, and

shopping and meal activities are likely to last 1-2 hours. Shopping activities are unlikely to begin before 7 AM or end after 9 PM. Meal activities are also unlikely to end after 9 PM. Escort activities are relatively likely to end after 9 PM.

- Work-based subtours: Relative to work-related activities on subtours, escort, meal and shopping activities tend to start later and be of shorter duration. Social/recreation activities also tend to start later, while personal business activities are also of shorter duration.
- Intermediate stops: Compared to work-related activities, stops for escort, shopping, meal, and personal business activities all tend to be of shorter duration. Escort, shopping, social/recreation and personal business stops also tend to be somewhat later in the day. These results are very similar to those in the work-based subtour model.

Presence of stops and subtours. Activities may be scheduled differently depending on the complexity of the tour and how many stops need to be scheduled. The tour time of day models are applied before the exact number and purpose of stops for a tour are determined. So, all we know at this stage is the number of purposes for which 1+ intermediate stops must be made, as well as the number of tours to be made.

- Work tours: The more purposes for which intermediate stops must be made, the shorter the duration at the primary destination. This effect is stronger when the work tour is the only tour of the day, in which case all stops must be part of that work tour. When the person makes 1+ escort stops in the day, the work activity tends to be both earlier and longer, presumably staying at work longer to coordinate schedules with a passenger. (The escort stop is not always part of the work tour, but it is in most cases.) The more work-based subtours that are part of the tour, the longer the total duration of the work activity (including the subtour). There is also a slight shift to later arrival times for tours with subtours, indicating that those people tend to depart later from work.
- School tours: The results are generally the same as for work tours, except that the influence of escort stops on duration is not as large.
- Other tours: These same variables for other non-mandatory tours have much less significant effects, with only the positive effect of escort stops on activity duration significant. Even if the tour is the only tour of the day, the duration of stay at the primary destination is not affected by the number of intermediate stops.
- Intermediate stops: Compared to stops made on the outbound half of a non-work tour, stops made on the return half of a non-work tour or on either half of a work-based subtour tend to be shorter. On the other hand, stops made as part of work tours tend to last longer.

Position of the tour in simulation priority order: Due to the rules for ordering tours by purpose and duration, there are some systematic effects on scheduling related to the simulation order:

- Work tours: If there are 2+ work tours made during the day, the lower priority one(s) tend to happen later and last longer than would be expected based on the available time window alone. In such cases, all work tours are more likely to last less than 8 hours, particularly the lower priority one(s). If the work tour is complemented by one or more tours of different purposes, then it is somewhat less likely to last less than 8 hours. (This effect probably offsets schedule pressure effects described below.)
- Other tours: If there are 2+ tours in the day for the same purpose, the highest priority one tends to be of longer duration, and the lower priority one(s) tend to be both shorter and earlier, compared to cases with just 1 tour. If there are 2+ tours in the day for different purposes, the lower priority one(s) tend to be both shorter and earlier than otherwise, and also tend to be of less than 4 hours duration. These latter effects are in addition to the availability effects of "shrinking" the available time window by the time spent in the higher priority tour(s).

Periods partially used. In the simulation, it is possible to arrive at the primary destination if another tour ended in that period, and possible to leave a primary destination if another tour began in that period. Such cases should be less likely, however, because part of the period is already "used up". These variables have negative and significant coefficients in all 5 models.

Schedule pressure effects. For each time period, six variables are used to calculate time pressure effects:

- Duration of adjacent empty window before period starts
- Duration of maximum consecutive empty window before period starts
- Total duration of all empty windows in the day before period starts
- Duration of the adjacent empty window after period ends
- Duration of the maximum consecutive empty window after period ends
- Total duration of all empty windows in the day after period ends

These variables, along with the remaining number of tours to be scheduled in the day after scheduling the current tour, are used to calculate several other variables:

- Work tours: The overall scheduling pressure is given by the number of tours remaining to be scheduled divided by the total empty window that would remain if an alternative is chosen. The negative effect indicates that people are less likely to choose schedule alternatives that would leave them with much time to schedule and little time to schedule it in. A similar variable is the number of tours remaining divided by the maximum consecutive time window. This is also negative, meaning that people with more tours to schedule will tend to try to leave a large consecutive block of time rather than two or more smaller blocks. In other words, they will tend to "crowd" the work tour and any other tours together rather than spacing them evenly across the day. As an offsetting effect, they will tend to avoid leaving small blocks of time immediately before the work activity.

- School tours: The estimated effects are very similar to those found for work tours.
- Other tours: Again, the effects are similar to those found for work and school tours. The main difference is that the overall time pressure effect is stronger, but the other effects are weaker, and there is evidence that people will try to space tours more evenly in the day.
- Work-based subtours: People try to leave consecutive windows both before and after the tour, meaning a tendency to "center" the subtour during the duration of the work activity.
- Intermediate stops: Stops will tend to be shorter when there are more tours to be scheduled in the day, and also when there more stops to scheduled on the half tour.

Travel time. The travel time for the period is based on the network travel times for the 4 periods of the day – AM peak, midday, PM peak, and off-peak. The variable is applied for both the outbound half tour (tour origin to tour destination) and the return half (tour destination to tour origin). For auto, the time is just the in-vehicle time, while transit time is in-vehicle time plus first wait time, transfer time, and drive access time. Walk access/egress time is not included, as that does not vary by time period. These variables are not applied for walk, bike or school bus tours.

- Work tours: For both auto and transit tours, both outbound and return half tours, the travel time coefficient is marginally significant at about -0.04 to -0.05. (One coefficient was constrained to have a value similar to the unconstrained ones.) If there is no network transit path in the period, that has a significant negative effect for transit tours (equivalent to about 70 minutes travel time). Note that not every trip in a transit tour has to be by transit, so it would be possible for somebody making a transit tour to arrive or depart work during a period when transit is not available.
- School tours: No significant travel time effects were found for school tours.
- Other tours: Large and significant negative travel time effects were found for auto tours, but not for transit tours. (There are relatively few transit tours for these purposes.)
- Work-based subtours: No significant travel time effects were found for subtours.
- Intermediate stops: The results are very similar to those for non-mandatory tours, with significant effects for auto time and for transit path not available.

Auto congestion effects. There may also be effects for time shifts **within** the AM peak and PM periods. For this purpose, the variable used was the extra time spent on links where the congested time is over 20% higher than the free flow time. This extra congested time was converted to shift variables by multiplying by the time difference between the period and the "peak of the peak":

1. AM shift earlier: If the period is 6 AM to 8 AM, multiply by (8 AM – time)
2. AM shift later: If the period is 8 AM to 10 AM, multiply by (time – 8 AM)
3. PM shift earlier: If the period is 3 PM to 5 PM, multiply by (5 PM – time)

4. PM shift later: If the period is 5 PM to 7 PM, multiply by (time – 5 PM)

With this formulation, the more positive the coefficient and the larger the congested time, the more that the peak demand is spread away from the peak of the peak.

- Work tours: For both AM and PM, the tendency is to move the work activity earlier as the time in very congested conditions increases.
- School tours and work-based subtours: No significant congestion effects were estimated.
- Other tours: The PM peak was found to shift both earlier and later with high congestion. No effects were found for the AM peak, where there are fewer such tours.
- Intermediate stops: Small positive effects were found for the AM peak shifting both earlier and later and the PM peak shifting earlier. Although these effects are not significant, they are of the correct sign, so were retained.

4. SACSIM EQUILIBRATION

4.1. Concepts

In the overall system design of SacSim, Figure 1 shows a cyclical relationship between network performance and trips: DaySim and the auxiliary trip models use network performance measures to model person-trips, which are then loaded to the network, determining congestion and network performance for the next iteration. The model system is in equilibrium when the network performance used as input to DaySim and the other trip models matches the network performance resulting from assignment of the resulting trips. Network performance for this purpose is times, distances, and costs measured zone-to-zone along the paths of least generalized cost.

Trip-based model systems with this same requirement have existed for at least thirty years (Evans, 1976), and the theory of system equilibrium for them is well developed now. Almost all convergent trip-based models, at some stage in an iteration process, use the method of convex combinations. This is to update the current best solution of flows (zone-to-zone matrices and/or link volumes) with a weighted average of the previous best solution of those flows ($\mathbf{x}_{n-1}$), and an alternative set of flows calculated by the new iteration ($\mathbf{x}_i$): $\mathbf{x}_n = (1-\lambda)\mathbf{x}_{n-1} + \lambda\mathbf{x}_i$, where the step size λ must satisfy $0 < \lambda \le 1$.

Within this category, the classic approach is the Method of Successive Averages (MSA). This method chooses $\lambda = 1/n$, so that, in effect, after any iteration n, the solution approximation is the average of all the iteration-result vectors computed so far: $\mathbf{x}_n = \dfrac{\mathbf{x}_{i(1)} + \mathbf{x}_{i(2)} + \ldots + \mathbf{x}_{i(n)}}{n}$. Some trip-based models converge reliably and more efficiently with a fixed step size (Bar Gera and Boyce, 2006), though care must be taken in the choice of that step size, which depends on the problem.

Equilibrium theory of trip-based models has unfortunately not been extended into activity-based models. However, trips from DaySim can be subjected to convex combination methods such as the method of successive averages, or with fixed step sizes.

With the unit of analysis being households instead of origin-destination pairs, come options not normally available to trip-based models. DaySim need not simulate the entire synthetic population in an iteration; it is able to run a selected sample of the population. Since its runtimes are long but proportional to the number of households modeled, early system-iterations can be sped up by simulating small samples.

4.2. Equilibrium solution procedure

The equilibration procedure employs equilibrium assignment iteration loops (a-iterations) nested within iterations between the demand and assignment models (da-iterations). This is similar to the nested iteration in many trip-based model systems.

Assignment is run for four time periods, and each one employs multi-class equilibrium assignment, with classes composed of SOV, HOVs not using median HOV lanes, and HOVs using them. A convex combinations algorithm is used, with the step size α determined automatically by the TP+ software, and closure criteria determined by the user: maximum number of a-iterations (N_i), and relative gap as defined by TP+ (g_i), where i indexes the da-iteration within which assignment is being run. Within the i-th da-iteration, the a-iterations stop when one of the closure criteria is satisfied.

In the *i-th* da-iteration, DaySim is run on a subset of the synthetic population, consisting of the fraction $1/s_i$ (i.e. $100/s_i$ percent) of the households, starting with the m_i-th household and proceeding uniformly every s_i households. The user determines s_i and m_i. DaySim scales up the synthesized trips by the factor s_i before they are combined with the estimated external, airport and commercial trips in mode-specific OD matrices for the four assignment time periods. During the *n-th* a-iteration within the *i-th* da-iteration, link volumes are estimated for the iteration *i* OD matrices, and combined in a convex combination with link volumes from the prior da-iteration, using a user-specified combination factor (or step-size) λ_i. This is the pre-loading method intended to prevent link volume oscillation between da-iterations. The resulting estimated volumes are then combined with link volumes from the prior a-iteration using the TP+-determined step size α as described in the previous paragraph. This is intended to prevent link volume oscillation between a-iterations.

The above description corresponds with the following algorithm:

0. Initialize i:=0, the index of the current da-iteration. Set starting link times $\{t_a^i\}$ using free flow times. Set i:=i+1.
1. Calculate shortest paths and skim OD matrices C, with elements $C_{krs}^i(\{t_a^{(i-1)}\})$, where k indexes skim variables, and r and s index origin and destination zones.
2. Run DaySim and trip-based demand models, generating OD flow matrices f, with elements $f_{rs}^i(\{C_{krs}^i\})$.
3. Run multi-class user equilibrium assignment:
3.0. Set n:=0, the index of the current a iteration. Set d-a iteration starting link times $t_a^{in} := t_a^{(i-1)}$ for all a, the final link time from iteration i-1 (freeflow if i=1), where t_a^{in} is the link time of a-iteration n within da-iteration i. Set n:=n+1.
3.1. Perform all or nothing assignment based on the current link travel times, yielding this a-iteration's shortest-path link volumes $\tilde{y}_a^{in}(\{t_a^{i(n-1)}\},\{f_{rs}^i\})$ for all links a.
3.2. Adjust this a-iteration's new link volumes by blending with link volumes from the previous da-iteration, $y_a^{in} = \lambda_i \tilde{y}_a^{in} + (1-\lambda_i)x_a^{(i-1)}$ for all a. (Notes: This step is intended to prevent link flow oscillation between da-iterations. λ_1 must be set to 1 if there are no previous da-iteration link volumes.)
3.3. Solve for α for which $\sum_a t_a((1-\alpha)x_a^{i(n-1)} + \alpha y_a^{in})(y_a^{in} - x_a^{i(n-1)}) \approx 0$. ($\alpha$ = 1 in a-iteration 1.) Set new a-iteration's link volumes by blending this a-iteration's new link volumes with the a-iteration's link volumes: $x_a^{in} = (1-\alpha)x_a^{i(n-1)} + \alpha y_a^{in}$ for all a. Compute new link times from those volumes, $t_a^{in}(x_a^{in})$. (This step is intended to prevent link flow oscillation between a-iterations.)
3.4. Check that the closure test statistic, "relative gap" , $\dfrac{\sum_a (t_a^{i(n-1)}x_a^{i(n-1)} - t_a^{i(n-1)}y_a^{in})}{\sum_a t_a^{i(n-1)}x_a^{i(n-1)}}$, is less than a user-specified tolerance criterion.

    IF fail, THEN increment n and go to step 3.1
    ELSE Set $t_a^i := t_a^{in}$ and $x_a^i := x_a^{in}$ for all a.
    IF i<I THEN increment i and go to step 1
    ELSE DONE and final values of link volume, link time, zone-to-zone travel costs, and zone-to-zone flow are $\{x_a^i\},\{t_a^i(\{x_a^i\}\},\{C_{krs}^i(\{t_a^{(i-1)}\})\},\{f_{rs}^i(\{C_{krs}^i\})\}$.
    (Note: final link volumes and times come from the final d-a iteration's assignment, but final OD flows come from the prior iteration's link times.)

As defined here, the equilibration procedure runs for a user-determined number (I) of da-iterations. Within each iteration, the user controls the synthetic population subset used by DaySim (via s_i and m_i), the weight (λ_i) given during assignment to the link volumes associated with this iteration's simulated trips, and the assignment closure criteria (N_i and g_i).

Note that, with the above algorithm, although a specified level of convergence (relative gap) is automatically met for assignment within each da-iteration, there is no assurance that a corresponding level of convergence will be met across the da-iterations (da-convergence). Indeed, the algorithm does not yet specify a formal measure for testing the level of da-convergence that has been achieved when it terminates. Work is ongoing to define such a measure and to also identify appropriate parameter settings to hasten da-convergence. The next section discusses parameter schedules that have been considered, and it is followed by a section of experimental findings related to parameter settings and da-convergence.

4.3. Selections for iteration parameters

The iteration parameters specifying the household sampling for DaySim (s_i and m_i), and the da-iteration step size λ_i are specified in advance of a SacSim run, due to the lack of a reliable basis on which to choose these automatically while a run progresses. Experimental runs have provided experience from which to choose these parameters, as is discussed below.

Basic MSA with I iterations is specified using $s_i \equiv I$, $m_i = i$, and $\lambda_i = 1/i$. This method samples an equal number (within 1) of households in each iteration, and when complete, each household has been simulated exactly once, and each household's trips contribute equally to the overall demand. A problem with this is that households in the early iterations incur significantly different travel costs than the converged costs, and make their choices based on these.

A variation is "staged MSA." This starts over the MSA procedure at some iteration; this iteration keeps the latest skims but does not average in the old trips and volumes. Staging is specified with $\lambda_i=1$ for a start-over iteration, then choosing s_i, m_i, and λ_i afterwards as if the start-over iteration is iteration 1. An empirical test-run series is described below using only the first four iterations of a 30-iteration MSA schedule, then starting over with a complete 8-iteration MSA schedule, then one final pass through the complete population specified with all three parameters = 1. Table 4 (below in Experimental Study) details the specifics of a family of test models with the staged MSA design. The final pass through the entire population assures that all persons' schedules are simulated in light of the same most recently assigned travel times and costs.

An iteration schedule with a constant step size of one-half was also tested. Experience with this constant step size has been generally favorable with trip-based models. A parameter schedule for a pass through the population in *I* iterations is as shown in Table 3:

Table 3: Constant Step Size Iteration Schedule, General Form for *I* Iterations

i	s_i	m_i	λ_i
1	2^{I-1}	2^{I-1}	1
2	2^{I-1}	2^{I-2}	0.5
3	2^{I-2}	2^{I-3}	0.5
4	2^{I-3}	2^{I-4}	0.5
…	…	…	…
I	2	1	0.5

This iteration schedule provides that the sampling rates double with each iteration (except the first and second are equal), and that, when complete, each household will have been simulated exactly once, and each household's trips contribute equally to the overall demand. A final pass through the complete population may be specified afterwards, to give a complete, consistent simulation database. Some potential advantages of this method over regular MSA is that early iterations are sped through at low sample rates, their residual results comprise a small fraction of the final results, and experience indicates it converges in fewer iterations than MSA.

Either of these iteration parameter schedules is predetermined. The test applications discussed in this report examine approximations to system equilibrium that can be achieved using these schedules with one simulation per household (or slightly more). If, for a given application, a higher precision in zone-to-zone times or other system output is needed, an enhanced schedule can be implemented. Several options exist for improving convergence precision and/or reducing variation caused by Monte Carlo simulation. These include the following, alone or in combination:

1 tightening the assignment's relative gap closure criterion, especially in later system iterations

2 adding more system iterations with smaller step sizes and/or smaller first sample

3 adding more system iterations that simulate schedules for the entire synthetic population

4 running the entire model system multiple times and averaging the results

5 coordinating random number seeds across policy scenarios and measuring differences (see section 6 of this paper)

6 running the model system with a synthetic sample significantly larger than the actual population, and rescaling each iteration's resultant trip matrices accordingly before assignment

Options 1-3 adjust the iteration schedule to improve convergence, but cannot reduce or eliminate the effects of random simulation error. Options 4 and 5 reduce the effects of random simulation error but do not affect convergence of a single run. Option 6 does both. Further experimental and theoretical study is needed to determine the interactions of equilibrium precision and trip demand precision. That is, what kind and amount of equilibrium tolerance must be achieved to ensure a trip demand quantity's random error is sufficiently close to what is expected at its sampling rate? This experimental study should fit into the beginning, not the end, of efforts to answer these questions.

4.4. Experimental study

After a variety of early experiments to test and refine various details of the model system, an MSA schedule in two stages was coded and run several times, identically except for the random-number seed in DaySim. (To reduce randomness, the same synthetic population was used throughout these tests, rather than regenerated as in the standard procedure.) This schedule is the staged-MSA example described above. This staging was devised to (1) eliminate residual effects of the first iterations, when the times and volumes fluctuate the most, faster than MSA alone will, and (2) accomplish these early iterations with a lower sampling rate, reducing run times. A final stage passes through all the households, to generate a complete, consistent database of a simulation for post-hoc analysis. Table 4 lists these iteration parameters.

Table 4: Experimental Staged MSA Iteration Schedule

i	s_i	m_i	λ_i	households sampled (index)
1	30	1	1.0000	1, 31, 61…
2	30	2	0.5000	2, 32, 62…
3	30	3	0.3333	3, 33, 63…
4	30	4	0.2500	4, 34, 64…
5	8	1	1.0000	1, 9, 17… (start over)
6	8	2	0.5000	2, 10, 18…
7	8	3	0.3333	3, 11, 19…
8	8	4	0.2500	4, 12, 20…
9	8	5	0.2000	5, 13, 21…
10	8	6	0.1667	6, 14, 22…
11	8	7	0.1429	7, 15, 23…
12	8	8	0.1250	8, 16, 24… (completes all HH)
13	1	1	1.0000	1, 2, 3, 4… (final full pass)

The SacSim model thus specified was run with year 2000 existing conditions demographic, employment, and network data, using a fairly complete DaySim, but not the final coefficients. Figure 3 shows convergence of vehicle-hours traveled (VHT) for the four time periods of the day, in one typical run.

The peak period vehicle-hours drop rapidly from the first to the second iteration, because the demand in iteration 1 is based on free-flow conditions, while the demand from iteration 2 is the average of the iteration 1 demand and the first estimate of congested conditions. Some of this is due to demand shifting from peak to off-peak time periods, some is due to shortening of trip length, and some might be from changes in the number of trips. Vehicle-hours change more slowly afterwards, partly due to convergence of demand, and partly due to the decreasing step size dampening the fluctuations in the system. Iteration 5 is a start-over, so it is not dampened by step size averaging. That Iteration 5's results are closer to the final values than iteration 4 is evidence that the MSA step sizes get too small too soon. But this also shows that a few iterations across a small sample are sufficient to reach the neighborhood of a converged solution, and serve as a good starting point for a group of iterations that collectively process the whole population. Some random movement is expected for iteration 13, since it starts over with a new simulation and does not average it with the previous. (In early runs with a lax and improperly specified assignment closure criterion, iteration 13's VHTs usually jumped up a small but significant amount compared to late-iteration fluctuations.)

Figure 3--Convergence of Vehicle-Hours Traveled in a Staged-MSA Model

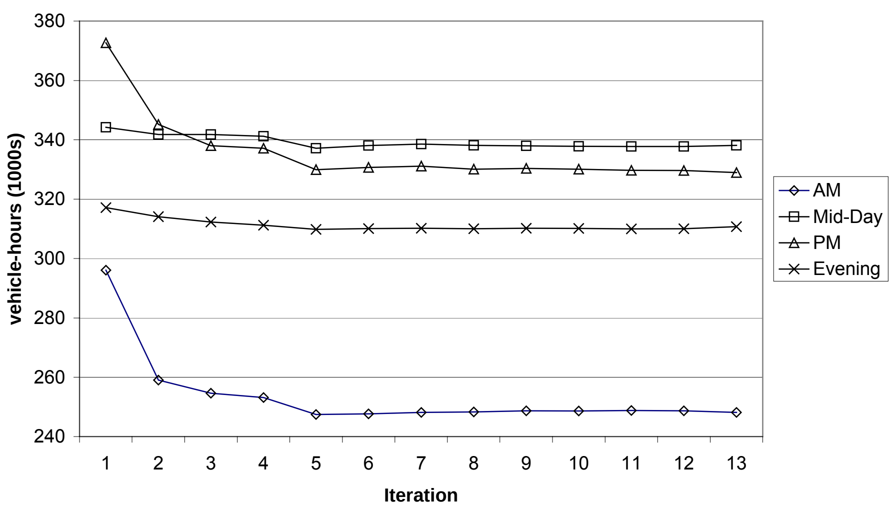
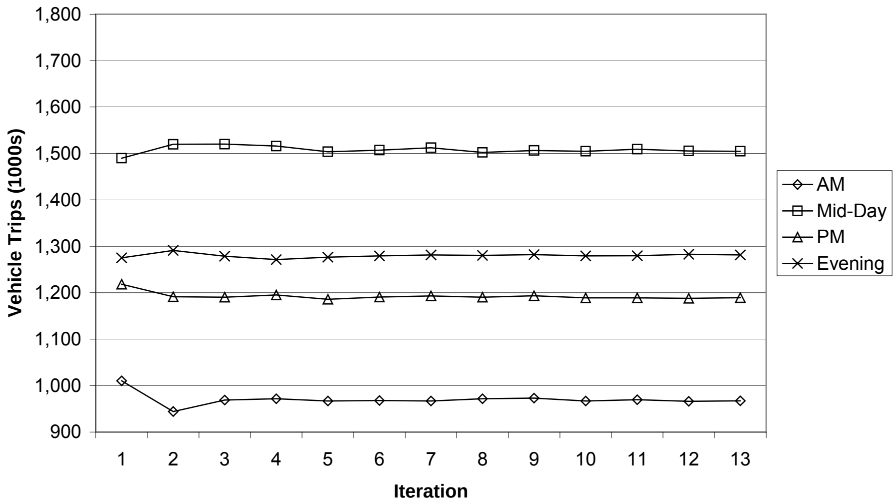


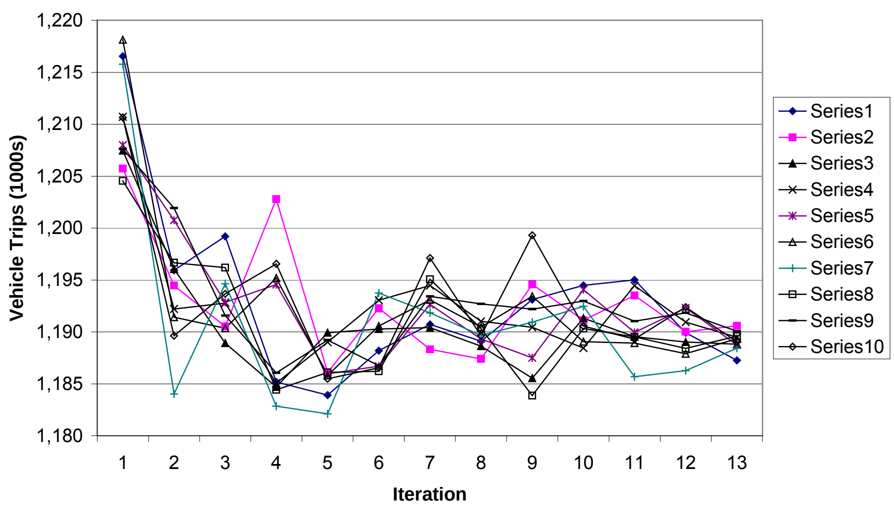
Figure 4 tracks the number of vehicle trips produced by the demand models during each iteration, in the same model run as above. Note these are not successively averaged. (The link volumes are.) It appears the first iterations show a shift from peak to off-peak time-of-day choice, more than a reduction in total vehicle trips, due to congestion. Random fluctuation is evident, but this is expected due to the Monte Carlo process.

Figure 4--Iteration Progress of Iteration Vehicle-Trips in a Staged MSA Model



To examine random fluctuations, Figure 5 shows the PM iteration vehicle trips for ten runs of this model, each identical in inputs except for the random number seed for DaySim. The widest random fluctuation is seen in the first four iterations, as would be expected.

Figure 5--Progress of PM Iteration Vehicle Trips in 10 Staged-MSA Runs



Some measures of convergence were examined that summarize changes in zone-to-zone travel time during each iteration, from the skimming before the demand models, to the skimming after assignment. The first measure is the largest absolute change in skimmed travel time for O-D pairs having at least one trip; the second is the root-mean-square (RMS) average travel time change across all O-D pairs, weighted by the number of trips. Figure 6 summarizes the absolute change statistics for one of these staged-MSA runs. The most varying period, the PM peak, fluctuates within around ±2 minutes in its extreme O-D change; that is, between the next to last and last iteration, the O-D pair with the biggest change in auto travel time saw a change of about 2 minutes. The RMS average travel time change for the PM period is below 0.2 minutes in the later iterations, and is less for the other time periods.

Figure 6--Largest Change in O-D Travel Time Occuring in Each Iteration, Staged MSA

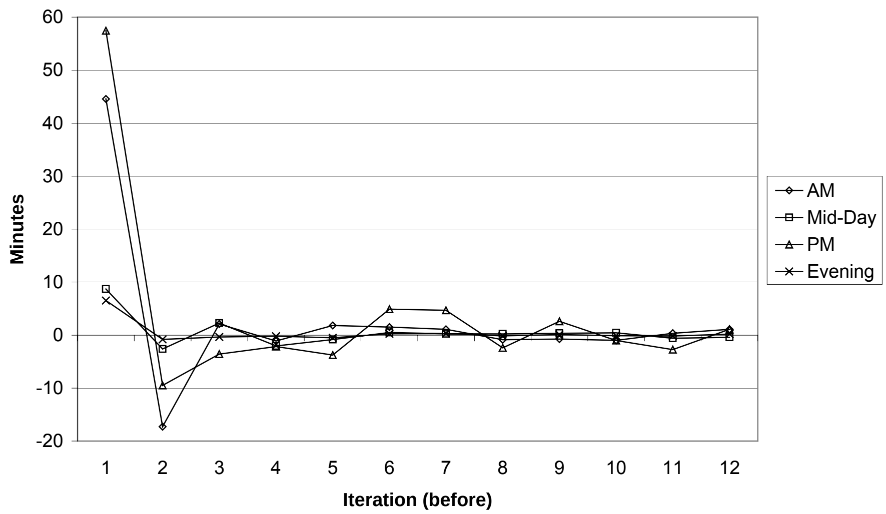


Table 5 shows an iteration schedule used in a series of experimental constant step-size runs. This particular sampling scheme can be easily adapted to different numbers of iterations, but not to a different constant step size.

Table 5: Experimental Constant Step Size Iteration Schedule

i	s_i	m_i	λ_i	**Series of households sampled**
1	128	128	1	128, 256, 384, 512...
2	128	64	0.5	64, 192, 320, 448...
3	64	32	0.5	32, 96, 160, 224...
4	32	16	0.5	16, 48, 80, 112...
5	16	8	0.5	8, 24, 40, 56...
6	8	4	0.5	4, 12, 20, 28...
7	4	2	0.5	2, 6, 10, 14...
8	2	1	0.5	1, 3, 5, 7... (completes all HH)
9	1	1	0.5	1, 2, 3, 4... (final full pass)

Figures 7-9 show comparable iteration convergence statistics for these runs.

Figure 7--Iteration Progress of VHT, Constant Step Size

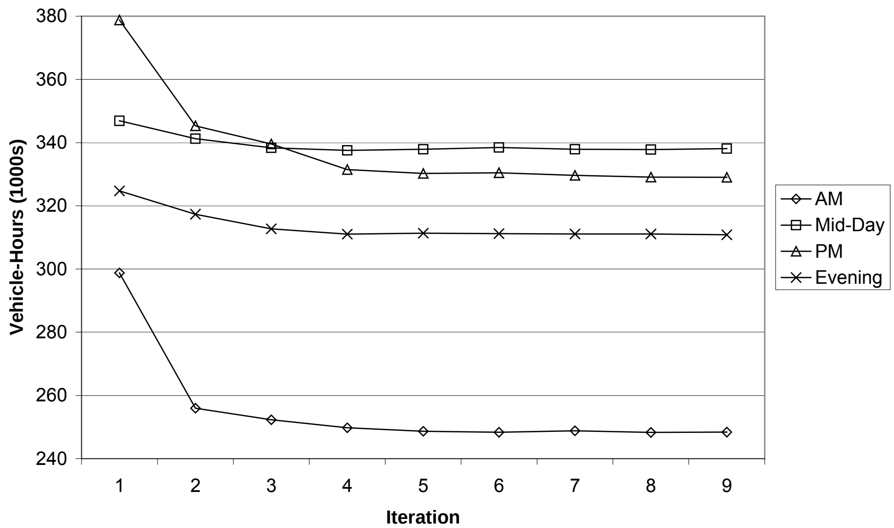
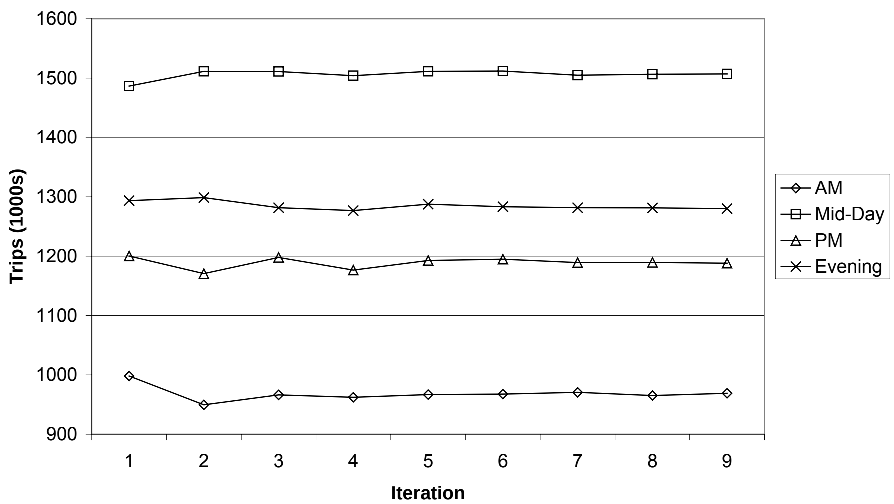


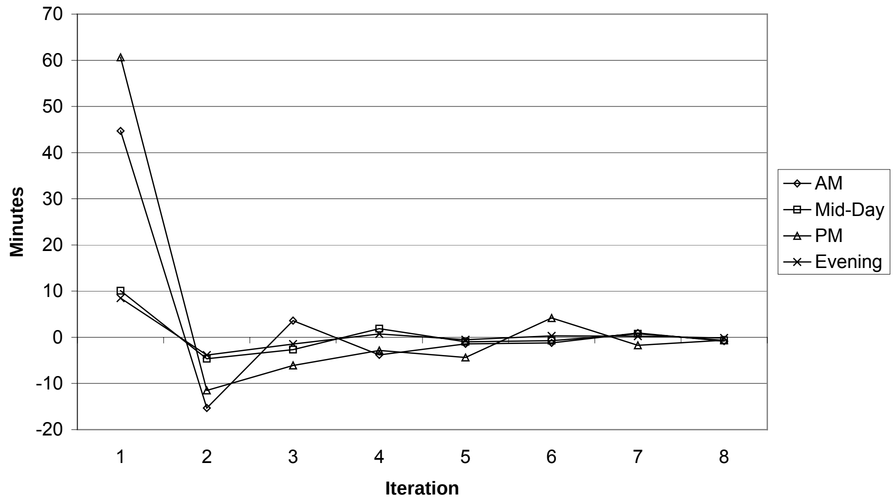
Figure 8--Iteration Progress of Iteration Vehicle Trips
Constant Step-Size



Both of the example procedures steadily progress toward equilibrium, reaching a fair approximation in equilibrium travel times with a fraction of the population actually simulated, and zone-to-zone travel demand dominated by “noise” from the Monte Carlo simulation process. One pass through the population (across 8 to 12 iterations) achieves a precision of around 0.15 minutes in PM zone-to-zone travel time, and better for other time periods. This demonstrates the compensatory nature of equilibrium trip assignment upon volumes and zone-to-zone travel times: random perturbations in trip demand are smoothed out in assignments into comparatively small perturbations in the resulting travel times.

Individual travel demand matrix elements can have standard deviations comparable to their own values, yet after assigning those trips, the corresponding elements in travel time matrices can be precise to the minute.

Figure 9--Largest Change in O-D Travel Time Occuring in Each Iteration, Constant Step Size



Although the closure criteria were not exactly the same in the two example procedures, the constant step size example achieved comparable levels of equilibrium precision with fewer iterations (9 vs 13), slightly less DaySim simulation (2 passes through the population instead of 2.13) and approximately two thirds the total run time (20hrs. 45min. vs 30hrs. 45min.) running under Windows XP on a PC with 2 GB RAM and dual 3GHz Pentium D processors. (The entire SacSim run is singlethreaded; while SacSim ran, the machine was used for relatively low intensity office applications.) While DaySim's computation time is dominated by the number of household simulations, other aspects of simulation are not, so reducing the number of DaySim simulations and the number of da-iterations both reduce total run time. Further application and development of SacSim will probably focus on the constant step size method, with the MSA method retained as a "fall-back" for applications with convergence difficulty.

5. CALIBRATION AND VALIDATION

SacSim calibration and validation work is proceeding in three steps: preliminary validation, base year calibration, and prediction validation.

5.1. Preliminary validation

Preliminary validation involves comparing model estimation and software application results to the household survey sample. It occurred during DaySim model estimation and software development, and is substantially complete. After each model was estimated, it was applied to the survey data. Aggregate results for various subpopulations were checked, as were model sensitivities, to detect deficiencies in the model specifications, so they could be corrected. After each model was implemented in the application software, it was again compared to the survey sample to find software bugs.

5.2. Calibration

A base year validation run consists of running a base year 2000 scenario of the entire model system to an equilibrated state, and comparing aggregate results to the best available external information about the actual base year characteristics on a typical weekday. This information comes from census data, transit on-board surveys, and screenline and other counts. Calibration then involves iteratively adjusting parameters and repeating validation runs until the base year prediction adequately matches the external information. Although all model calibration adjustments have a simultaneous impact on the model predictions, it is natural to calibrate sequentially from the top to the bottom of the DaySim model hierarchy, because adjustments to upper level models will tend to impact lower level model predictions more than vice versa.

Table 6 summarizes the validation checks and actions that have occurred for the long term model components, and that are planned for the day activity and travel models. Table 7 provides validation statistics for the uncalibrated and calibrated versions of the long term models. The tables refer to PUMA, RAD and TAZ, which are three levels of aggregation of the region's parcels (14 PUMAs (subregions), 72 RADs (communities) and 1279 TAZs (traffic analysis zones).

Usual work location. Without calibration, some RADs are far more attractive than their employment levels can support, and vice versa. Therefore we implemented a partial constraint feature into the application software that prevents a TAZ from being designated as usual location for more workers than 110% of the assumed employment. This approach fails to adequately increase the prediction of commutes to remote locations with large available employment. A better approach might be to add a utility term to all locations that, after each equilibration iteration, automatically adjusts the attractiveness of all locations according to the degree of over or under prediction in the previous iteration. In addition, the uncalibrated model predicts more at-home workers and shorter work commutes than the available census data indicate, so the at-home constant and piecewise linear distance coefficients were adjusted accordingly. However, the at-home constant was not fully calibrated to achieve a perfect match because the uncalibrated model predicts much lower incidence of within-TAZ commutes than the census data, and we suspect that the census data incorrectly assigns some at-home workers to the within-TAZ category.

Auto availability. The uncalibrated auto availability model overpredicts car ownership levels, especially in rural areas, arising from an apparent bias in the household sample used for model estimation. To get a reasonablly accurate joint distribution of households by auto ownership level and number of drivers in household we used a calibration constant for each combination. The resulting model overpredicted 0-auto households in the most urban areas, so we reduced the sensitivity to accessibility of the 0-car alternative in urban parcels by 10%, and made separate 0-car constant adjustments for urban and rural parcels, which substantially improves the calibration.

Table 6: SacSim Validation Checks and Calibration Actions

Model level	**Status**
Validation check	Calibration action
Long term models	**Substantially complete**
Workers by work location TAZ Number who work at home Work distance distribution Workers by HH income by residence PUMA RAD-to-RAD work flows	Adjusted usual work location model: 1. Partially constrain in application 2. Reduce at-home constant 3. Adjust two piecewise linear auto distance coefficients
Students by school end RAD by primary & other	None
HH by #vehicles avail by # drivers by RAD	Adjusted auto availability model: 1. Adjust constant for each combinaion of # vehicles and # drivers 2. Decrease sensitivity of 0-car alternative to accessibility variables (urban RADs only) 3. Increase two 0-car constants (rural and urban)
Person-day activity and travel models	**Incomplete**
vehicles crossing screenline by time period	Expected adjustments: Adjust constants in the pattern model and/or stop frequency model to increase the incidence of trips in patterns, compensating for survey underreporting. Uneven spatial or temporal distribution of discrepancies may require re-estimation of destination or time-of-day models to capture subregional idiosyncrasies
transit trip Os by RAD, submode & purp transit trip Ds by RAD, submode & purp transit OD matrix by purp & time of day	Expected adjustments: Adjust mode choice constants to compensate for survey under- or over-reporting of transit trips relative to auto trips. Submode-specific discrepancies may require re-estimation of mode choice models with submode- specific parameters. Subregional discrepancies may require re-estimation of mode choice models with subregion-specific variables, or the use of subregion-specific calibration constants.
transit boardings by station or TAZ or RAD	See notes above for transit on-board survey.
O-D flows for specific high bicycle traffic facilities, and OD pairs (data unavailable for this)	None
O-D flows for specific high pedestrian traffic facilities and OD pairs (data unavailable for this)	None

Day activity and travel simulator. This calibration, which has not been completed, involves comparisons based on screenline counts, transit boarding counts, and transit trip estimates from the on-board transit survey. Comparisons will also be made between SacSim and SACOG's current trip-based model system. It is expected that some substantial discrepancies will surface. In particular, we expect underprediction of screenline counts arising from trip under-reporting in the travel survey used for model estimation. Transit counts or expanded onboard survey results will be used to identify mode share discrepancies resulting from limited volumes of transit in the estimation data set. Estimates of bicycle and walk OD flows or screenline counts are not available, so it will not be possible to calibrate them. Other discrepancies may also surface, such as time-of-day results between the counts and the model outputs.

Table 7: Statistics for uncalibrated and calibrated long term models

	Uncalibrated	Calibrated
Usual work location		
work at home (model/census)	2.26	1.39
less than 3 mi (model/census)	0.91	0.85
3-10 mi (model/census)	1.02	1.01
over 10 mi (model/census)	0.90	1.02
average distance (model/census)	0.85	0.99
Auto availability		
HH with 0 vehicles (model/census)	0.66	1.00
HH with 1+ vehicles and less vehicles then drivers (model/census)	0.79	1.01
HH with 1 vehicle per driver (model/census)	1.10	0.99
HH with more vehicles than drivers (model/census)	1.09	1.00
HH with 0 vehicles residing downtown (model/census)	1.03	1.06
HH with 0 vehicles residing in Davis (model/census)	1.21	1.81
HH with 0 vehicles residing in rural RADs (model/census)	0.18	0.93
HH with 0 vehicles %rmse among RADs (model vs census)	62%	29%
HH with 0 vehicles % RADs within 15% (model vs census)	1%	39%

5.3. Prediction validation

Prediction validation involves using SacSim to forecast from a base year of 2000 to a forecast year of 2005, and comparing the results to estimates of actual 2005 transport system performance. It also involves using SacSim to forecast under various scenarios and comparing its sensitivity to reasonable expectations. This work has just begun. Some preliminary results, based on application of DaySim without SacSim equilibration, are provided in Section 6.

6. SENSITIVITY TESTS

To illustrate some of the policy analysis capabilities of the model, we ran two scenarios and compared them to a base case scenario for the year 2000. The policy scenarios are:

- Cordon pricing: A toll of $5.00 is charged for any drive alone (SOV) trip entering the Sacramento city CBD area during the AM peak period (6:30 am to 9:30 am).
- Increased connectivity: Regionwide, the density of 3-node and 4-node street intersections is increased by 10% and the density of 1-node intersections (dead ends and cul-de-sacs) is decreased by 10%.

These policies may or may not be feasible in reality. Given that the models have not yet been completely calibrated to base year conditions, and that these sensitivity runs were not done with full iterative feedback of travel times, our purpose in running these scenarios is solely to illustrate the type of results the model generates, and not to provide accurate forecasts for any specific policies.

One of our main interests in performing the sensitivity tests was to investigate how random stochastic simulation error could affect the results of analyzing policy scenarios for a given synthetic sample and forecast year. Ideally, when one is comparing a base case forecast and a policy scenario forecast for the same population and year, the only changes in the forecasts will be directly related to the changes in the input data related to land use, pricing or level of service. In this way, one can expect the changes in the forecasts to be less prone to modeling errors than the absolute forecasts, because many of the errors will be the same in both the base and policy cases and will thus cancel out when computing the difference. One could expect this same aspect to apply to microsimulation models so that the random simulation error will also cancel out between two runs on the same sample. A potential problem arises, however, if different random number sequences are used for the base case run and the policy scenario. In that case, the difference in the predictions resulting from changing the random numbers—and thus the sequence of stochastic choices—will be mixed with the differences resulting from changes in the policy variables, with no way of separating the two.

The way in which most random number generators work is to always use the current random value as the seed for generating the next random value. If this feature is used throughout the simulation, then a change in just <u>one</u> decision by <u>one</u> individual will change the entire sequence of random numbers that are used for all subsequent simulated individuals. For example, if a person is predicted to make two intermediate stops on a half tour instead of one, then more random numbers will need to be used to predict the location and timing of that additional stop, and those random numbers would have otherwise been used to predict choices for the next individual, and so on.

To address this problem, we have programmed DaySim so that a given random number seed at the beginning of the run will cause a specific random value to be used for each resident/tour/trip/model combination. For example, for a given initial random seed, the random seed used to predict the mode of the 2nd trip on the 1st half of the 2nd tour for the 100,000th person in the sample is always the same, no matter what choices are predicted for preceding persons in the sample or for preceding tours for that same person. If the person is predicted to make less than 2 tours, then the random seeds assigned for tours 2 and upwards are not used. This feature does <u>not</u> mean that a given person will be predicted to make the same choices in both scenarios, but it <u>does</u> mean that most changes in a person's predicted travel and activities will be due to changes in the modeled utilities and probabilities and not due to the random number sequence used.

Table 8 shows the difference that coordinating the random seeds makes in the predictions at the individual level. For the cordon pricing policy, only about 1% of the regional trips in the base case (roughly 60 thousand out of 6 million) are predicted to enter the cordon CBD area during the AM peak. As a result, we would expect this policy to influence the choices of very few of the simulated individuals, even when accounting for any indirect effects. When the random seeds are coordinated, 98.6% of the simulated individuals are predicted to perform identical activity patterns in the base case and the cordon pricing scenario. (“Identical” means no changes in the number of tours made, the number of trips on each tour, or the destination, mode and departure time of each trip.) Of the 1.4% who change behavior, there is a mix of changes seen, with the most common change (0.9%) including only a shift in departure time to avoid the AM peak pricing period.

Table 8: Percent of simulated individuals who change behavior relative to the base case

Policy scenario	Cordon pricing	Higher connect-ivity	Base case	Cordon pricing	Higher connect-ivity
The same random numbers?	Yes	Yes	No	No	No
No changes in the simulated day	98.58%	75.76%	22.67%	22.67%	22.61%
Different number of tours	0.00%	5.54%	63.80%	63.80%	63.85%
Same # of tours, but different number of stops	0.23%	9.85%	13.09%	13.09%	13.12%
Same # of tours & stops, but different purpose(s)	0.03%	4.55%	0.37%	0.37%	0.35%
Same tours, stops, purposes / different location(s)	0.21%	3.96%	0.07%	0.07%	0.07%
Same tours, stops, purp, loc. / different mode(s)	0.02%	0.06%	0.00%	0.00%	0.00%
Same except for different departure time(s)	0.93%	0.28%	0.00%	0.00%	0.00%

The “higher connectivity” policy was specified to affect every neighborhood in the region rather than just a specific area. The table shows that, as a result, even when the random number sequence is the same, only 76% of individuals maintain travel patterns identical to the base case. “Walkability” and connectivity directly and indirectly affect every decision in the model, possibly including the longer terms decisions of work location and auto ownership, and thus it is not surprising that a ubiquitous change in this variable can influence such a large number of simulated individuals to at least some extent.

When the random seeds are not coordinated, as shown in the last three columns, only 23% of individuals follow the same simulated travel pattern as in the base case. Many of these are the simplest case—no intra-regional tours or trips made in the day—which is easiest to match. Also note that for the other 77% with different travel patterns, the patterns tend to be very different from the base case, almost always including a different number of tours or stops on a tour. When a different random number sequence is used, we get approximately the same number of change patterns regardless of which policy is simulated, even including re-simulating the Base Case, where <u>nothing</u> has been changed except the random numbers. With different random sequences, we are relying completely on the law of large numbers when we compare aggregate results from two scenarios, as the individual-level forecasts are rarely related to one another.

How does this strategy of using the same random numbers influence the predicted policy results? First, we will focus on the “cordon pricing” scenario. The first column of Table 9 shows how much the predicted number of regional trips changes from the base case, first for all regional trips, and then for regional trips broken down one at time by time of day, mode, destination type and trip purpose. Looking at the entire region, we see that the AM peak trips in the region go down noticeably in the cordon pricing scenario, by about 1.7%. Because we are looking at total regional trips, the numbers are quite small. If we focused only on trips to the CBD (results not shown here), then we would see that more than 40% of those trips are predicted to change time of day in response to the $5.00 AM SOV peak toll, with some switching earlier and some switching later. Some other travelers switch mode as well. Very few switch destination, due to the fact that most of the AM peak CBD-bound trips are work trips, and the work location model is a longer-term model with base year constraints that all jobs in the CBD be filled. Also notice that the PM peak trips are predicted to go down somewhat as well, particularly when the random seeds are coordinated. This is because it is a tour-based model that also considers duration of stay at the destination, so if some workers shift out of the AM peak, they may also shift out of the PM peak in order to maintain a similar number of work hours. On a regional level, the cordon pricing policy causes very little shift out of drive alone trips or away from trips entering/leaving the CBD.

Table 9: Changes in regional trips relative to the base case, by choice dimension

Policy scenario	Cordon pricing	Higher connectivity	Base case	Cordon pricing	Higher connectivity
The same random numbers?	Yes	Yes	No	No	No
All regional trips	0.01%	0.26%	-0.26%	-0.26%	0.13%
<u>Time of day choice….</u>					
AM peak trips	**-1.71%**	0.31%	**0.25%**	-1.40%	0.43%
Midday trips	**0.55%**	0.40%	**-0.27%**	0.23%	0.22%
PM peak trips	-0.20%	-0.02%	-0.84%	-0.99%	-0.43%
Other trips	**1.00%**	0.27%	**-0.11%**	0.86%	0.29%
<u>Mode choice…</u>					
Drive alone trips	-0.03%	0.17%	-0.26%	-0.31%	-0.12%
Shared ride trips	0.05%	-0.01%	-0.35%	-0.30%	-0.19%
Transit trips	0.02%	-0.75%	1.01%	1.01%	0.44%
Walk/bike trips	0.04%	**2.55%**	**-0.26%**	-0.24%	3.06%
<u>Destination choice…</u>					
Totally within CBD	0.25%	0.45%	0.37%	0.46%	0.72%
Entering/leaving CBD	-0.45%	0.24%	-0.26%	-0.74%	-0.63%
Near (but not entering) CBD	0.09%	0.23%	-0.36%	-0.25%	0.15%
Other locations	0.03%	0.26%	-0.25%	-0.23%	0.18%
<u>Activity/trip generation…</u>					
Home-based work trips	0.00%	0.07%	-0.34%	-0.34%	-0.31%
Home-based school trips	0.00%	0.48%	0.12%	0.12%	0.17%
Home-based escort trips	0.01%	0.56%	0.45%	0.45%	0.92%
Home-based personal business trips	0.00%	0.38%	-0.47%	-0.47%	0.25%
Home-based shopping trips	0.00%	0.45%	0.37%	0.39%	0.99%
Home-based meal trips	0.00%	0.12%	-1.56%	-1.56%	-0.16%
Home-based social/recreation trips	0.00%	0.67%	0.53%	0.52%	1.17%
Work-based trips	0.02%	0.14%	-0.76%	-0.73%	-0.81%

Other non-home-based trips	0.05%	-0.18%	-0.90%	-0.89%	-0.03%

In the second column of Table 9 for the “higher connectivity” scenario, the number of trips goes up during all periods of the day, and overall regional trips increase by about 0.3%. As shown in the mode choice changes, this is mainly due to an increase in the number of walk/bike trips, and in spite of a small decrease in the number of transit trips. The destination choice changes show that the increase is for all area types, but is largest for trips in the CBD, as the increase is mainly for shorter distance trips that can be made by walking. The increase in trips is greatest for school, escort, personal business, shopping and social/recreation trips, and smallest for work and work-based trips. A slight decrease in non home-based trips is due to the fact that higher walkability tends to increase the number of short walk-only tours with few stops, rather than chaining many trips together by car.

With a change in intersection density of 10% providing an increase in walk trips of 2.5%, this is an elasticity of about 0.25. In a recent tour-based mode choice analysis for Seattle which used the same variable (Frank, et al. 2006), elasticities were calculated in the range of 0.28 to 0.43. The Seattle models also include variables related to mixed distributions of land use, and it would be an interesting further sensitivity test to change land use mixes in the Sacramento input data.

The key result in Table 9 is that the difference in results for the same scenario but with different random numbers is typically greater than the difference in results for different scenarios. The only cases where the policy differences with the same random numbers are much larger than the Base Case difference due to changing random numbers are those shown in bold. Because most policy differences at the regional level are quite small, it does not take a great deal of random error to outweigh the policy effect, and thus the “law of large numbers” is not sufficient if different random sequences are used.

For example, when the cordon pricing scenario is run with a different random number sequence, we obtain the illogical result that regional shared ride and walk/bike trips go down due to an increase in SOV price, whereas we get a shift in the logical direction (and much smaller) when the same sequence is used. One might erroneously assume that the results in the last two columns are valid policy outputs of the model rather than random noise. Also note that cordon pricing has almost no impact on trip generation by purpose when the same random numbers are used, but does appear to have some impact when different random numbers are used. This type of difference will be even more important when analyzing results at the sub-regional level based on smaller sample sizes, where random simulation error has a larger relative impact.

7. CONCLUSIONS

The overarching contribution of this project is to demonstrate a working real world implementation of a travel forecasting model system based on the day activity schedule approach, incorporating several advanced features, including:

- disaggregate treatment of purpose (7 purposes), time (48 half-hour time periods), and space (parcels)
- extensive downward and upward vertical integration:
    - lower level models conditioned by upper level models, with extensive use of space and time constraints
    - sensitivity—in all component models, including upper level pattern model—to network accessibility and spatial attributes via the use of mode choice logsums, approximate logsums encapsulating differences across modes, destinations and times of day for different types of persons
- a parametrized equilibration algorithm that requires only two day-activity-schedule simulations per person to achieve a reasonably high degree of convergence. This is achieved by (a) using iterations with successive averages that simultaneously stabilize results across assignment iterations and demand-assignment iterations, and (b) using partial population simulations of the demand model during early iterations.
- a random seed coordination method that removes much of the random simulation error when comparing results of two policy scenarios

This paper has described in some detail (a) the formulation and results of the time of day models, (b) the equilibration procedure, (c) the calibration and validation procedure, along with partial results, and (d) the results of sensitivity tests that illustrate sensitivity throughout the model system to transportation policy, and how the coordination of seeds can help remove the effect of random simulation error when two scenarios are compared.

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