

Making Household Microsimulation of Travel and Activities Accessible to Planners

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ABSTRACT

There is a large gap between the aggregate, trip-based models used by transportation planning agencies and the activity-based, microsimulation methods being espoused by those at the forefront of research. The modeling environment presented here aims to bridge this gap by providing a palatable way for planning agencies to move towards advanced methods. Three components to bridging the gap are emphasized, including an incremental approach, demonstration of clear gains, and providing an environment that eases initial implementation and allows for expansion. The modeling environment (called STEP2) is a household microsimulator developed in TransCAD, which can be used to implement a 4-step model as well as models with longer term behavior and trip chaining. An implementation for Southern Nevada is described and comparisons are made with the region's aggregate 4-step model. The models perform similarly on numerous counts. A key advantage to the microsimulator is that it provides impacts by socio-economic group (essential for equity analysis) and individual trip movements (for use in a vehicle microsimulator). A sensitivity analysis indicates that the microsimulation model has less inelastic cross elasticity of transit demand with respect to auto travel times than the aggregate model (aggregation error). The trade-off is that microsimulators have simulation error; results are presented regarding the severity of this error. This work shows that shifting to microsimulation does not necessarily require substantial investment to achieve many of the benefits. One of the greatest advantages is a flexible environment that can expand to include additional sensitivity to demographics and transportation policy variables.

INTRODUCTION

While the theoretical advantages of an activity-based, microsimulation approach to travel demand modeling are well known, the techniques have not been widely implemented by transportation planning agencies. Furthermore, the gap is growing as researchers introduce more complexity (effectively raising the bar of entry). This paper presents a household microsimulator environment for travel demand modeling, which aims to bridge this gap by providing a palatable way for planning agencies to take a step towards advanced methods without necessarily adding significant complexity or expending significant resources. The environment is called STEP2 and is developed in TransCAD.

The paper begins by discussing key aspects to bridging the gap and motivating the focus on microsimulation. The household microsimulation environment is then described, and an implementation for Southern Nevada is presented. This implementation is then used to make comparisons with an aggregate model and to highlight advantages of microsimulation.

BRIDGING THE GAP

There are numerous reasons for slow adaptation of advanced travel demand modeling techniques. One is that the methodologies require more expertise for development. Another is that there is little evidence of realized gains, a fact that will change if such tools are more accessible to planners. The focus of this paper is on lowering the technical bar of entry for practitioners to work with advanced techniques. With the objective of bridging the gap, three aspects are of prominent importance:

- Using an incremental approach,
- Demonstrating clear gains (as well as alleviating fears), and
- Providing an environment that eases implementation and allows for expansion.

In terms of taking an incremental approach, it is important to separate the concept of microsimulation from activity-based modeling. Microsimulation refers to applying models to individuals (rather than zones), and it can be applied to any model including a simple 4-step model as well as more complex activity-based models. (1) note in their *Research Agenda of the TRB Committee on Demand Forecasting* that “Simulation-based approaches have come to dominate the field of travel behavior and forecasting.” While this may be true for researchers, it is not true for practitioners who are predominantly using aggregate techniques. The fact that microsimulation is little used in practice is troubling because it is a well-studied, superior, and feasible method. The modeling environment presented here focuses on microsimulation as it represents a critical and nontrivial step necessary for the use of advanced modeling.

The household microsimulator described here provides for a flexible environment that can use as its foundation behavioral models from a simple 4-step model and can expand to richer specifications including longer-term behavior such as residential location and auto ownership and activity-based concepts such as trip chaining and scheduling. This modeling environment is called STEP2, because it builds upon the STEP policy analysis tool created by Greig Harvey in the 1970s and enhanced by him and Elizabeth Deakin through the 80s and 90s (2,3). The original STEP grew out of a project for the San Francisco Bay Area’s MTC that proposed both an aggregate implementation and a microsimulation implementation of the developed model system (4,5). Harvey’s philosophy with STEP was to develop microsimulation tools that would be accessible to transportation planning agencies without overly burdensome commitments of time and money. This philosophy is at the heart of this development effort, in which the STEP modeling tool has been revived and enhanced.

STEP2 has gone beyond STEP in numerous ways. STEP was a sketch planning tool with no explicit network and no equilibrium assignment. The effort presented here incorporates realistic transportation networks and traffic assignment (increasing capabilities for long-range planning), it is run within a GIS environment, and was developed with generic modules that can be more easily replaced with new models as they are developed. The work described here continues the work that Caliper performed to integrate STEP’s home-based work models into a GIS environment using realistic networks and apply the models to an environmental justice study in Baltimore (6). This paper describes the household microsimulation modeling environment that has been developed as well as a particular implementation that was developed for the Las Vegas region.

MICROSIMULATION OF TRAVEL AND ACTIVITY BEHAVIOR

Microsimulation provides a practical method to implement probabilistic models (such as logit) at the level of the individual. The use of microsimulation policy analysis tools was pioneered by the economist Guy Orcutt in the late 1950s (7). The motivation is that aggregate demand is made up of decisions made by individuals, and therefore it is necessary to do behavioral modeling at the level of the individual. That is, one person is processed at a time, and

then these individual decisions are summed up to produce summary statistics on the behavior (including the impacts of policies). It has long been recognized in transportation (since the 70s) that there is great value in modeling transportation at the level of the individual. The basic argument is that people travel, not zones, and by averaging to the level of the zones, much information is lost and the aggregation bias is significant.

There has been much discussion in the research community on the microsimulation of travel and activities, see, for example, (8-14). Advantages of microsimulation include the ability to tabulate impacts for subgroups of the population (for example, low income or elderly), the capability of explicitly modeling realistic travel behavior patterns such as trip chaining and activity scheduling, and the ability to better reflect heterogeneity (and segmentation). Also important is that while aggregate applications have aggregation bias (error induced by applying the model based on average characteristics of the population), a microsimulation approach does not have aggregation bias. Rather, with microsimulation there is simulation bias, which is also not desirable but has the advantage of being able to estimate the magnitude of the error. The issue of aggregation bias has led the state of best practice aggregate 4-step models to introduce significant socio-economic segmentation on variables such as income, auto ownership, household size and transit access. While adding additional socio-economic explanatory variables in an aggregate setting is extremely cumbersome, adding them in a microsimulation setting is straightforward as any number of socio-economic characteristics is trivially associated with each individual in the synthetic population.

The original STEP implementation represents one of the earliest applications of microsimulation to a full travel demand modeling system. Today, simulation-based models dominate the research community (1). The intricacies of the travel and activity behavior represented in these state of the art model systems vary substantially. For example, the original STEP was trip-based, the Dutch National (15) and Stockholm models (16) are tour-based, the Portland (17) and San Francisco (18) models are day schedule-based, the Columbus model includes the added wrinkle of explicit household interactions (14), and the Canadian ILUTE system (12) integrates land use and activity scheduling with travel demand, just to list a few. In this paper, we take a step back from this seemingly unstoppable growth in complexity to look at what can be done with microsimulation at a more modest scale, exploring advantages as well as comparing to a traditional aggregate approach.

A HOUSEHOLD MICROSIMULATION MODELING ENVIRONMENT

The objective of this environment is to develop a flexible platform that can be used to implement a variety of travel demand microsimulators such as a simple 4-step model to more complicated models that incorporate longer term decisions as well as trip chaining and scheduling. Two such frameworks are shown in Figure 1. Microsimulation models are typically implemented with custom, model specific programs, which are costly to develop and require expertise to modify. An emphasis of this research was to develop the modeling environment such that it can be incrementally improved and updated as new models or datasets become available. TransCAD is used as a platform for the environment, which provides numerous travel demand modeling procedures, database management, scripting language, a scenario manager, and GIS tools for visualization and spatial analysis. Many generic procedures were developed as building blocks of a microsimulation model. For example, a flexible population synthesizer and logit and nested logit routines that can be applied to individuals, are straightforward to set up for destination and mode/destination models, apply Monte Carlo to simulate realizations, and produce logsums for use in other modeling steps higher in the hierarchy. Furthermore, these routines were developed with windows-based interfaces, from which script can be captured. In addition to creating generic procedures, tools were created to aid in processing household travel and activity surveys. These include tools to process household travel and activity diary data into trips by trip purpose and also to produce home-based tour and work-subtour information. Examples of these interfaces are in Figure 2. The user interface for the Southern Nevada implementation is shown in Figure 3, which allows the user to straightforwardly run the full model or a subset of models with the click of a button. The interface also provides tools for file and scenario management.

AN IMPLEMENTATION FOR SOUTHERN NEVADA

An implementation using the microsimulation modeling environment was developed for Southern Nevada, which made heavy use of pre-existing models for the region. The implementation is built from models developed for the region by PB Consult and Caliper for the Regional Transportation Commission of Southern Nevada's (RTC) latest aggregate 4-step travel demand model. Since these models were all estimated with disaggregate data, application in a microsimulation setting is feasible and appropriate. [All references to the aggregate model in this paper refer to the "RTC Phase 2 Model in TransCAD" (19).] Also used are models from Harvey's original STEP system as well as new models estimated from PUMS data and the 1996 Las Vegas Region household survey. The modeling framework and models are briefly described below; more detail may be obtained from the project report (20).

Model Framework for the Southern Nevada Implementation

The Southern Nevada implementation is a trip-based, microsimulation model with a step towards a tour-based implementation. It follows a 4-step process similar to the RTC aggregate model. Trip generation is the step that is most different, because it is necessary in microsimulation to generate an integer number of trips by purpose for each individual. The destination and mode choice models apply the same nested logit models used in the aggregate implementation, although they are applied to individual trips rather than aggregate zones. The model was developed using the highway and transit networks and taz database (1218 zones) from the region's aggregate 4-step model. All of the scripts used for network processing and highway and transit assignment are taken from the aggregate model. The microsimulator uses the same trip purposes as in the aggregate model, including home-based shop, home-based school, home-based other, and non-home-based, as well as a set of journey to work (jtw) trip purposes including jtw home-work, jtw home-other, jtw work-other, and journey away from work (not to home). The microsimulator models trips made by residents, and takes the visitor, external, and truck trip projections generated by the aggregate model as inputs.

There are three major components to the household microsimulation model:

1. Population Synthesis

Generates a representative population of specific (but synthetic) individuals and their personal and household characteristics.
2. Household Behavior

Simulates travel-related behavior for each individual (age 16 and older) in the synthetic population via a series of behavioral models. The framework is as shown in Figure 1 (right). Specific travel patterns as well as other travel-related behavior are simulated for each individual in the synthetic population, including:

 - For a set of “movers”, the TAZ to which the household moves.
 - Whether or not each person is a worker, retired, or other non-worker
 - For workers, the TAZ in which the person's work is located
 - Detailed travel patterns for a particular day:
 - For workers, whether the person goes to work.
 - For those who go to work, whether they make a stop on the way to work, on the way home from work, or a mid-workday stop.
 - All other trips made in the day, including home-based shop trips, home-based other trips, and non-home-based trips.
 - The location of each activity, and the timing and mode of each trip.
3. Aggregation, Network Performance, and Analysis

Aggregates the individual trip behavior to generate trip matrices by trip-type and/or socio-economic characteristics (for reporting purposes) and assigns the vehicle and transit trip matrices to the transportation and transit networks to generate link/route flows and level of service.

In theory, all of the household behavior that is listed above is inter-related. The degree to which the interdependencies are captured in the modeling is directly correlated to the complexity of the model. Therefore, the approach is to simplify the problem by representing it as a sequence of choices in a choice hierarchy (see (4) for more discussion). This implementation is a typical example of a choice hierarchy, in which the longer term decisions are at the top of the hierarchy, and the shorter-term and more flexible daily travel decisions are below and conditional on the long-term decisions. Furthermore, within the daily decisions, the work trip and its characteristics are higher in the hierarchy, and the non-work trips are lower. Behavior that occurs lower in the hierarchy is conditional on decisions that are made above it in the hierarchy, and decisions that are made higher in the hierarchy can be influenced by the potential of decisions made lower in the hierarchy. Increasing the degree of conditionality and feedback lead to more behaviorally realistic models, but also increase the model's complexity.

Modules in the Southern Nevada Implementation

Each of the individual components of the Southern Nevada implementation is described below, including the source of the model, the type of model, the explanatory variables, and the method for calibration. At each model stage, Monte Carlo simulation is used to generate a realized choice for each individual (or household), and all subsequent models are conditioned on these choices. The key in terms of making microsimulation accessible to planners is that it is a sequence of fairly straightforward models, many of which were taken directly from the aggregate model and others that were developed from a household survey or census data. Furthermore, while many simplifications were

made in this particular implementation, the structure was implemented in a modular fashion so that specific components can be replaced when resources and necessity arise.

Population Synthesis

Generates a synthetic population of households (and persons in households) using the inputs of PUMS data and aggregate zonal data on number of households by income (4 categories), household size (4 categories), and age of head of householder (4 categories). The routine uses iterative proportional fitting to generate the joint distribution of household characteristics for each zone, and then Monte Carlo simulation to draw a set of households from PUMS that are consistent with the joint distribution.

Residential Location

The inclusion of a residential location component is an important improvement over the RTC aggregate model. For a set of “movers” (determined based on an input parameter), a multinomial logit residential location model is applied. The model is a function of job accessibility (the logsum from the work destination-mode choice model), average rental or home ownership cost in relation to household income, residential density, manufacturing jobs, violent crimes, and a size variable (log of the number of housing units). The model specification was obtained from the original STEP model, and it has not yet been calibrated.

Labor Force Participation

A binary logit model is used to determine whether each person is a worker or not. The model is a function of gender and household structure (single/married, male/female, with/without children and age categories of children), age, and race. The model was estimated using PUMS data, and calibrated to match Census statistics on labor force.

Retirement Status

For non-workers age 30 and over, a binary logit retiree model is used to determine whether each person is retired or not. The model is a function of gender and household structure (as for the labor force participation model) and age. The model was estimated using the 1996 Las Vegas Region Household Survey, and calibrated to match the retirement percentage reported in the local household survey.

Workplace Location

For each worker, a multinomial logit work location model is used to determine the work location. The model is a function of transportation level of service (the logsum from the home-work mode choice model), three dummy variables for the CBD, the Las Vegas Strip, and intra-TAZ trips, and a size variable (the log of the number of HBW trips generated by a trip attraction model). The model is conditioned on auto ownership and income through the size variable and the logsum from the mode choice model. The model specification was taken from RTC's aggregate 4-step model, and calibrated to match average home-work statistics from the local household survey.

Work Participation on a Given Day

For each worker, a binary logit model is used to determine whether a worker goes to work on a particular day. The model is a function of income, gender and household structure (live alone, male/female, with/without children and ages of children), employment sector, and the ratio of peak highway travel time to work divided by free flow highway travel time to work. This model was obtained from the original STEP model, and calibrated to match work participation reported in the local household survey.

Work Tour Type

For those workers who go to work, a naïve multinomial logit model is applied to determine the type of work tour for each person. There are 8 possible work tours, including each combination of stopping on the way to work, stopping on the way home from work, and making a trip in the middle of the work day. The model was calibrated to match the work tour type frequency reported in the local household survey.

Non-work Tour Trip Frequency

Trips that occur outside of the work tour are generated from a naïve multinomial logit model that is based on trip-making rates observed in the survey. For students, there is a naïve binary logit model to determine whether the student goes to school on the simulated day, which is calibrated to match the percentage of students who reported going to school in the local household survey. For home-based shop, home-based other, and non-home based trips (and not part of the work tour), a naïve multinomial logit model with 295 alternatives is used in which each

alternative consists of {the number of home-based shop trips, the number of home-based other trips, and the number of non-home based work trips}. A different model is used for those who make a work trip in the day and those who do not, and the models were calibrated to match the trip rates reported in the local household survey.

Work Tour Timing and Non-work Tour Trip Timing

The time of day modules determine the hour of the day in which each trip commences. Similar to the model used the aggregate Las Vegas region model, the microsimulation model uses time of day distribution lookup tables to determine the timing of each trip. For the work tour, first the start time and end time of the work day are determined from a lookup table containing the frequency of all start/end time combinations. If the tour includes a stop on the way to or on the way from work, lookup tables are used to determine how many hours before or after the work day the stop occurs. For all other trip purposes (including work-based midday stops), the timing is determined from direction- and purpose-specific time of day distribution lookup tables. All of the lookup tables were developed from the local household survey.

Destination and Mode Choice

Destination/mode choice is implemented via nested logit models, which are specific to each purpose. They are applied sequentially in which first the location of the activity is simulated (incorporating the logsum from the mode choice model), and then the mode is simulated conditioned on location. The destination/mode choice models are those used in the RTC aggregate model, there are different parameters for each trip purpose, and the models were calibrated to match average trip lengths and mode shares as reported in the local household survey.

Destination of all activities other than home and work activities (fixed based on residential and workplace location models) are determined in this module. For the stops on the way to or from work, the activity location is conditioned only on the home location (a limitation of the available models). For each individual, home-based shop and home-based other trips are paired into *from home* and *to home* trips, and only one shop/other destination zone is simulated for each pair of trips. The destination choice models are similar to the work destination choice model described above in that they are a function of the logsum from the mode choice model, a set of area-specific dummy variables, and a size variable generated from a trip-attraction model.

The mode choice models are applied to each trip separately (a limitation of the available models). The mode choice model is a nested logit model with the alternatives drive alone, 2-person shared ride, 3-or-more person shared ride, walk to transit, drive to transit, and non-motorized. The utility of each mode is a function of level of service (in-vehicle time, walk time, wait time, transfers, drive access time), cost (operating cost, parking cost, fare), zone characteristics (residential density, CBD and Strip dummy variables), and auto ownership.

Assignment

The highway and transit assignment procedures from the aggregate model are used in the microsimulation model. Individual trips produced by the household microsimulator are aggregated into a vehicle trip matrix and a transit trip matrix, and the visitor, external, and truck trips from the aggregate model are added. These matrices are input into traffic assignment and transit assignment to produce link/route flows and level of service. The highway assignment is User Equilibrium, and is applied to each of 3 peak hours during the day (AM, PM, mid-day). Note that this aggregate approach for highway assignment could be replaced by a vehicle microsimulator.

ALLEVIATING FEARS AND ESTABLISHING CLEAR GAINS

An important part of bridging the gap is to be able to both alleviate fears and establish clear gains. The incremental approach, emphasized above, is important as it adds perspective that advanced techniques are not necessarily so different from traditional models. The extent of the differences will, of course, vary based on the extent of complexity in the aggregate and microsimulation models. Since the microsimulation implementation described here and the RTC aggregate model were developed for Southern Nevada using similar data sources and share many of the same behavioral models, it is a nice opportunity to compare the performance of the two models and to assess the advantages of microsimulation. This section begins by discussing the similarities of the two models, and then presents some key advantages of microsimulation.

Similarities Between Microsimulation and Aggregate Model

Data Requirements

While the data processing that is required by the two models is different, both models make use of approximately the same underlying data sources. These sources include the same household travel diary, the same auto and transit

network, the same zone geography and similar land use and demographic information. The only additional data sources that the microsimulator requires are the PUMS dataset for population synthesis and additional zonal data for the residential choice model. Like the aggregate model, the microsimulation model relies heavily on a local household travel and activity survey, although the manner in which these data are processed and used may be quite different. Therefore, generic procedures such as those shown Figure 2 are important.

Calibration and Performance for the Base Case

Both models perform approximately the same for the base case as each model is calibrated to match base conditions (traffic counts and aggregate travel statistics from the survey). At this time, the aggregate model has been more carefully calibrated than the microsimulator. The calibration of the microsimulation model is not unlike calibrating an aggregate model. For each individual model component, the base model is applied and adjustments are made such that target aggregate characteristics are achieved. In the description of each of the modules for the Southern Nevada implementation provided above, the aggregate statistic to which the calibration was performed is mentioned. Each module requires a calibration step (whether in an aggregate setting or a microsimulation setting), and so the more modules in the microsimulator, the more steps that require calibration. In many cases, the calibration is a simple adjustment of the constant in the logit equation.

Computation time and disk space

Both the aggregate and microsimulation models run on a single PC. The computation time and disk space for the microsimulator varies depending on the size of the sampled population as well as whether or not multiple runs are needed to average the results in order to minimize simulation error. In this particular implementation, a run with 100 thousand households (20% of the population) leads to the same run time as the aggregate model and uses approximately the same disk space. The microsimulation run time increases linearly with the size of the synthetic population. As elaborated further below, the size of the synthetic population and the number of runs that are required is based on the statistic of interest for the analysis (21). For urban-wide statistics (for example, total VMT), one run using 20% population appears to be sufficient. However, zone-level or link-level statistics may require numerous runs (10 or as many as 20) and may require a larger synthetic population, which places the run time of this microsimulator an order of magnitude (or two) slower than the aggregate model. The caveat is that run times are highly dependent on the efficiency of the coding, and implementations can always be further optimized often leading to quite dramatic results. Furthermore, there are two obvious modifications that can significantly decrease the run time of the microsimulator. One is the use of multiple processors, for which household microsimulation is a perfect application. The second is to use intelligent sampling strategies in creating the synthetic population, for example, sampling at different rates by TAZ or by socio-economic groups. Naively using either the size and distribution of the true population (as in (21)) or drawing the same proportion of the true population for each zone (as used in this paper) are inefficient approaches.

Clear Gain 1: Additional Outputs

The microsimulation model includes all of the same outputs of the aggregate model, including link flows and level of service as displayed in Figure 3. Beyond these outputs, an advantage to microsimulation is that the entire richness of the population is preserved throughout the process. This permits tabulations of impacts for any subgroup, which is vital for environmental justice studies. For example, Figure 4 displays mode share statistics for the base year by income group and race. Another output from the microsimulation is a detailed list of trips by purpose, time period, and individual characteristics, which can be used as an input to a vehicle simulator.

Clear Gain 2: Elimination of Aggregation Error (and Understanding Simulation Error)

An issue with aggregate models is that there is error in the forecast due to aggregation (see (4)). To compare the forecasting performance across the two models and the severity of aggregation error, a sensitivity analysis was performed in which auto travel times were incrementally changed at 10% intervals. The change impacts the destination and mode choice modules. The microsimulation implementation borrowed its mode and destination choice model from the aggregate model, and so all but the calibration parameters are identical.

The results from the sensitivity analysis are in Figure 5, which displays the percent changes in VMT and number of transit trips resulting from the change in auto travel times. A sample size of 500,000 households was used for the microsimulation run, and the microsimulation forecast includes 95% confidence bars (calculated as described in the next section). Both models exhibit inelastic behavior. The VMT projections for the two models seem to be similar, although the microsimulator shows slightly greater impact on VMT as travel time increases. However, the cross elasticity of transit ridership is different, with the microsimulator indicating a stronger shift to transit as a result

of the change in travel time. While there may be nuances that are contributing to this difference, including calibration issues, a likely candidate for this difference is the aggregation bias. While microsimulation eliminates the problem of aggregation error, the trade-off is that it contains simulation error.

Understanding Simulation Error

An issue with microsimulation is that the results are stochastic, meaning that the forecast changes each time the seeds to the random number generators used in the Monte Carlo simulation change. The advantage of sampling error (as opposed to aggregation error) is that one can estimate the size of the error and generate confidence intervals. (21) presented a thorough analysis of sampling error resulting from microsimulation runs of the San Francisco model. They used a full synthetic population, and show that the magnitude of the sampling error varies based on the characteristics of the statistic of interest. They found that region-wide and neighborhood level statistics are quite stable and one model run is sufficient, and that estimates of zone-level statistics with minimal sample error can be obtained by averaging the results from 10 model runs. While (21) used a full synthetic sample of households, this is not always necessary and computation time can be saved by using fewer households than in the whole population. The sampling error (variance) of any statistic will decrease at a rate proportional to the inverse of sample size, and the necessary size of the sample depends on the statistics of interest and the precision required.

The results in Figure 6 provide insight into sampling error. Figure 6a shows how the sampling error dissipates as the size of the sample increases. To generate this plot, the microsimulator was run 10 times each for four different sample sizes. The plots show the range of the VMT and transit trip statistics that were generated for each sample size as well as an estimate of the standard deviation. The sample standard deviation shown here for 500,000 households was used to calculate the confidence intervals in Figure 5. These results suggest that there may be some bias when a small number of households is used, but the bias dissipates by 50,000 households and the simulation error is negligible with 500,000 households. One can synthesize more than the full population to decrease the sampling error even further, and more efficiency can be gained by using intelligent sampling strategies.

Figure 6b indicates that, as expected, the size of the sampling error is proportional to the inverse of the square root of the sample size. This property allows one to trivially determine the size of the sample necessary to generate a desired level of confidence. Also note that the size of the error is *not* a function of the true size of the population.

There are actually two types of sampling error that influence the precision of the forecasts. One is the sampling error present in application via the Monte Carlo simulation, which is displayed in Figure 6a/b. The second is the sampling error present in estimation of the models due to the limited size of the household survey. Figure 6c is included to examine the properties of this second type of sampling error versus the simulation error. Consistent with the analysis in Figure 6a/b, the estimation error is examined only from the perspective of the destination and mode choice model (although clearly it is present in all stages). In the destination and mode choice model, the magnitude of this estimation sampling error is indicated by the t-statistics (or standard errors) of the logit parameter estimates. The standard errors were not available to generate the precise estimation sampling error, and therefore it is approximated by assuming t-statistics of 3.0 (midway between 2.0 and 4.0, which is the likely range of the true t-statistics) on all level of service variables that are in the mode and destination choice models. Figure 6c indicates two important things: one, that estimation sampling error does not dissipate with simulation sample size, and two, that estimation sampling error dwarfs application sampling error for any reasonable application sample size. This is an underestimate of the estimation error as only errors in destination and mode choice were included.

There are other types of forecast errors to keep in mind that are not included in this analysis, for example the errors associated with the input zonal household and employment data and transportation network attributes.

Clear Gain 3: Expandability

Microsimulation is a flexible and expandable method that can be used to develop behavioral models based on a rich description of demographic and travel characteristics. Once practitioners become comfortable with microsimulation, they can more easily transition to other advanced travel demand modeling techniques and the various advantages therein. In terms of the level of richness incorporated in the models, there is a wide range of detail that can be captured, from the most basic independent trip assumption to a day activity schedule model that aims to model realistically all of the movements a person makes during the day. This microsimulation implementation falls between these extremes. It can be improved by improving the behavioral components, increasing the level of detail in the choice hierarchy, and improving the feedback and linkages among the modules.

CONCLUSION

In developing this environment for household microsimulation models, we take to heart conclusions from a 1996 workshop on microsimulation in activity analysis that there is “institutional fear” of microsimulation and activity models and that “first and foremost it is essential that we need to take an incremental approach in implementing the potential new planning tools” (8). This modeling environment aims to lower the bar of entry and has shown that the shift to microsimulation does not necessarily require substantial investment or complexity to achieve many of the purported benefits. Perhaps one of the greatest advantages of using this approach is that it is a flexible and expandable method that can be modified to include additional sensitivity to demographics and transportation policy variables by incorporating more detailed representation of travel and travel behavior.

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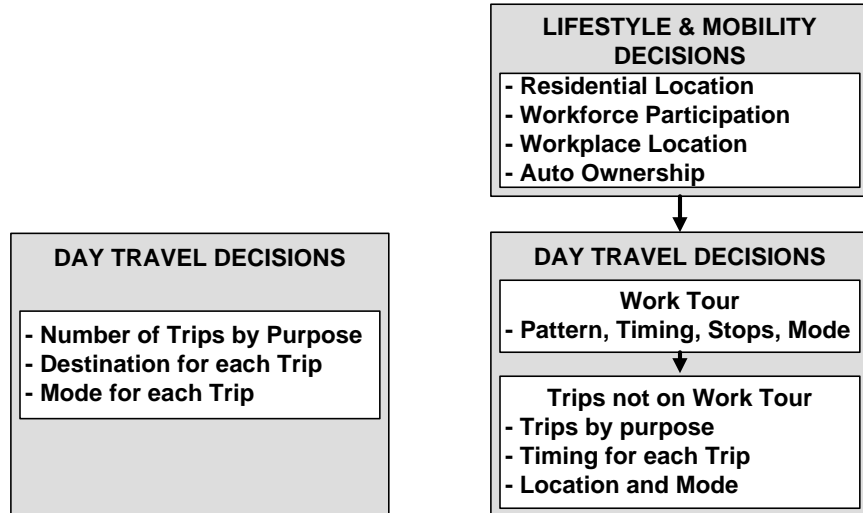
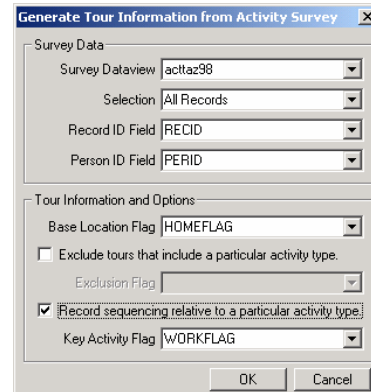
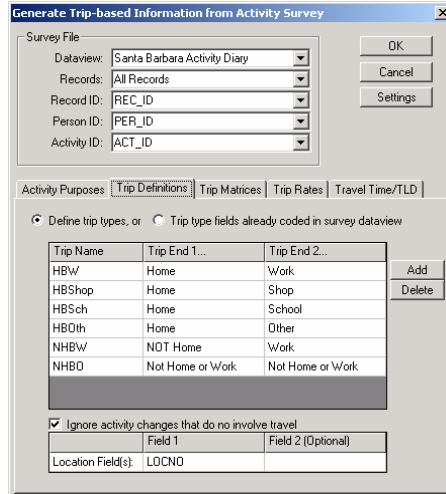
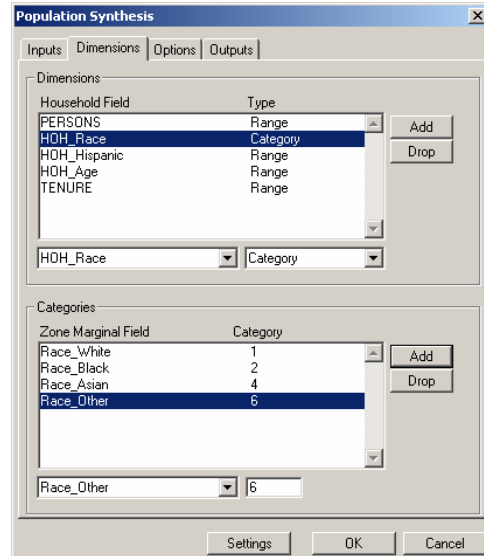
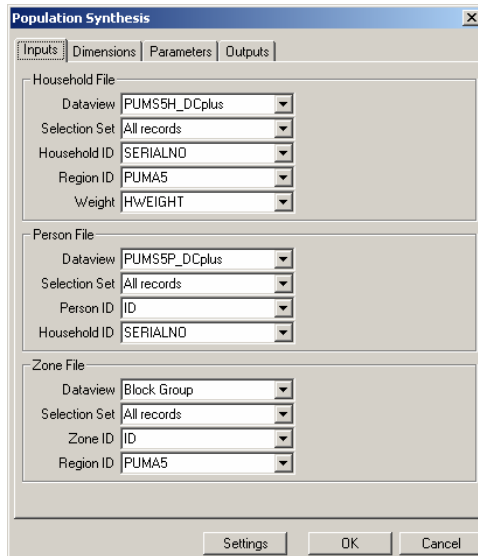


Figure 1 Demand modeling frameworks from a simple 4-step (left) to increasing behavioral realism (right).

Survey Processing



Population Synthesis



Logit for Microsimulation

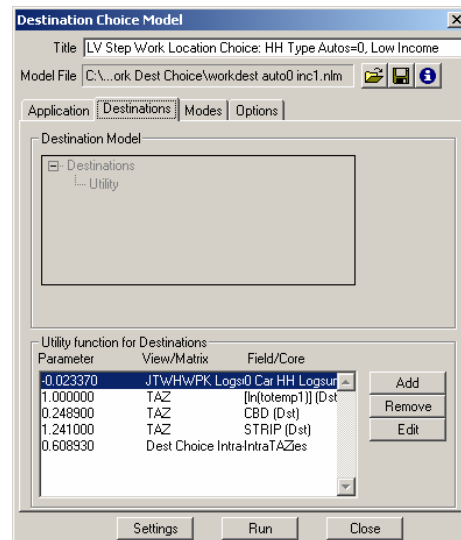
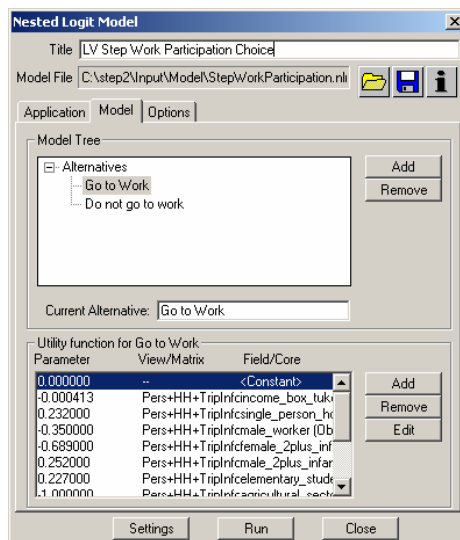


Figure 2 Examples of generic and flexible interface modules to support microsimulation models.

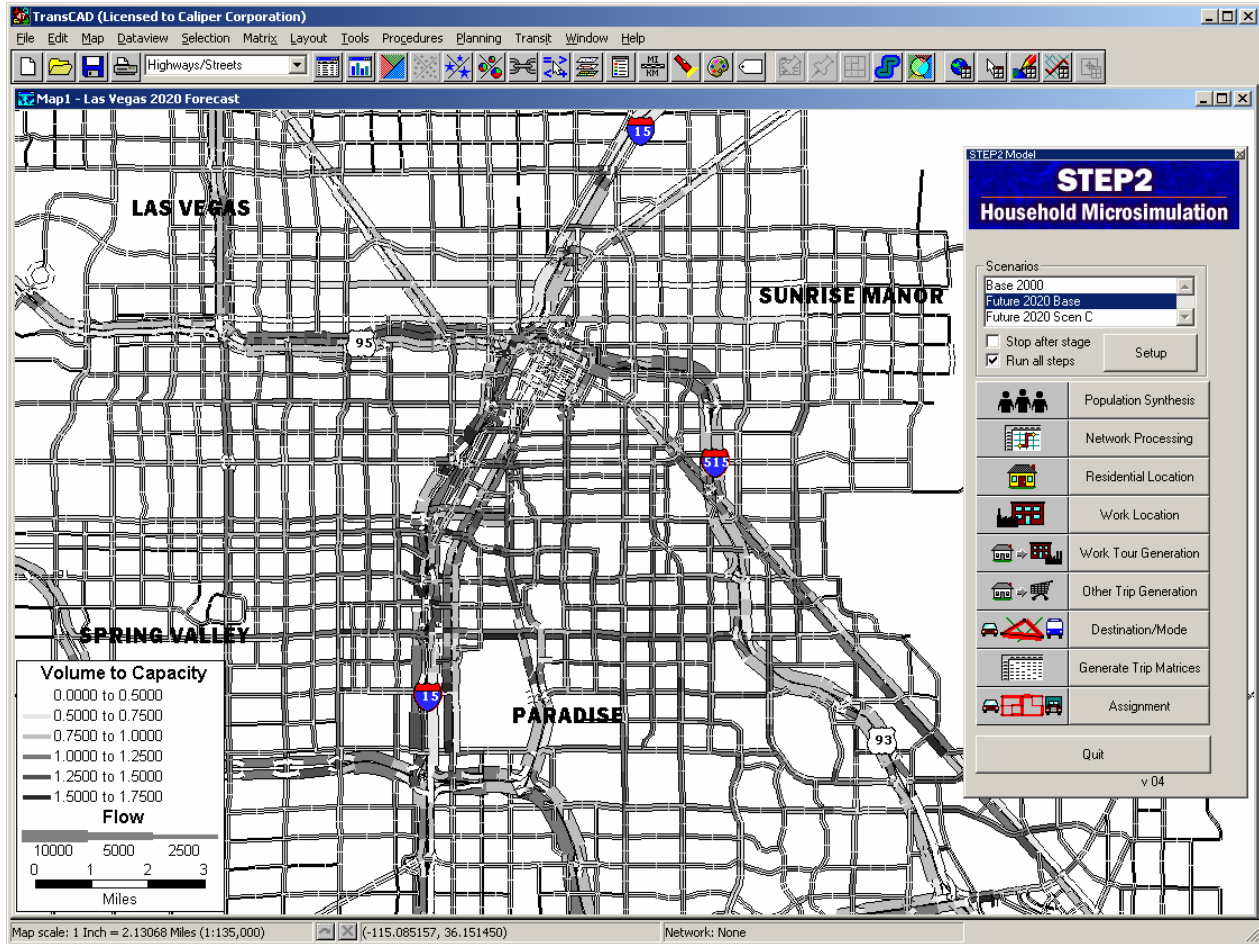


Figure 3 The Southern Nevada implementation.

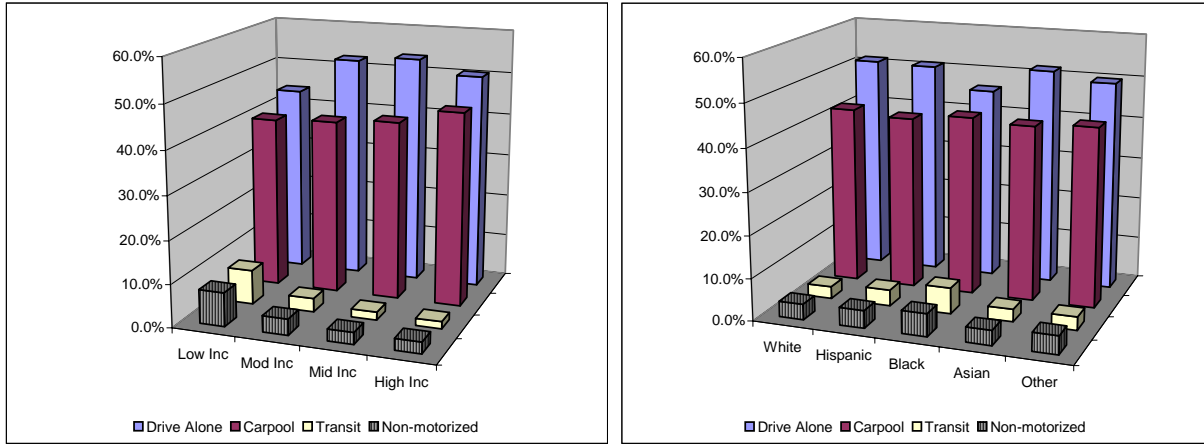


Figure 4 Tabulation of statistics by socio-economic characteristics.

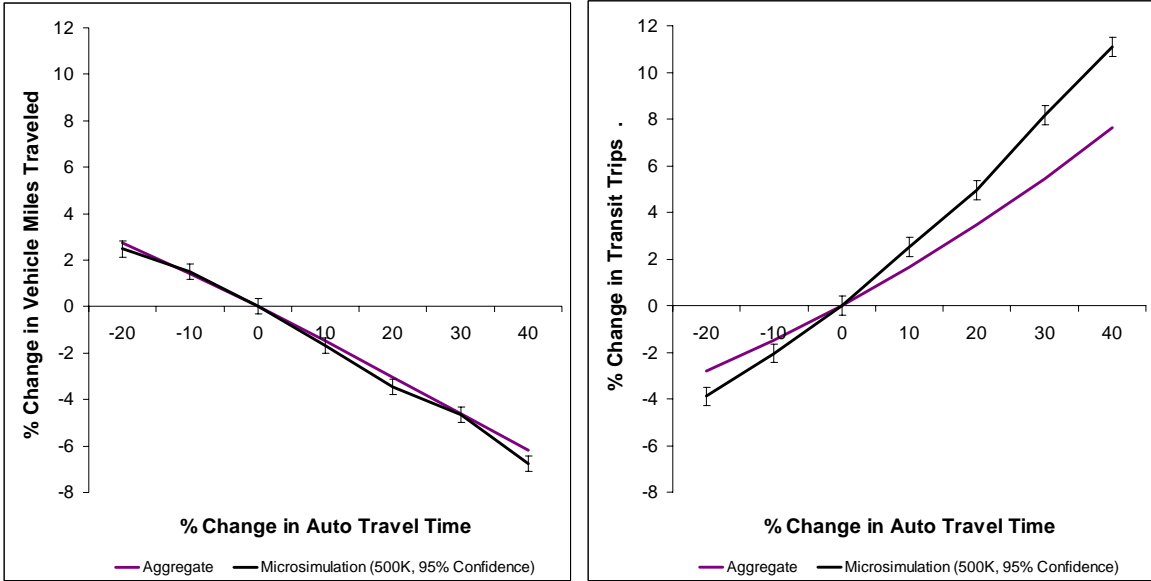
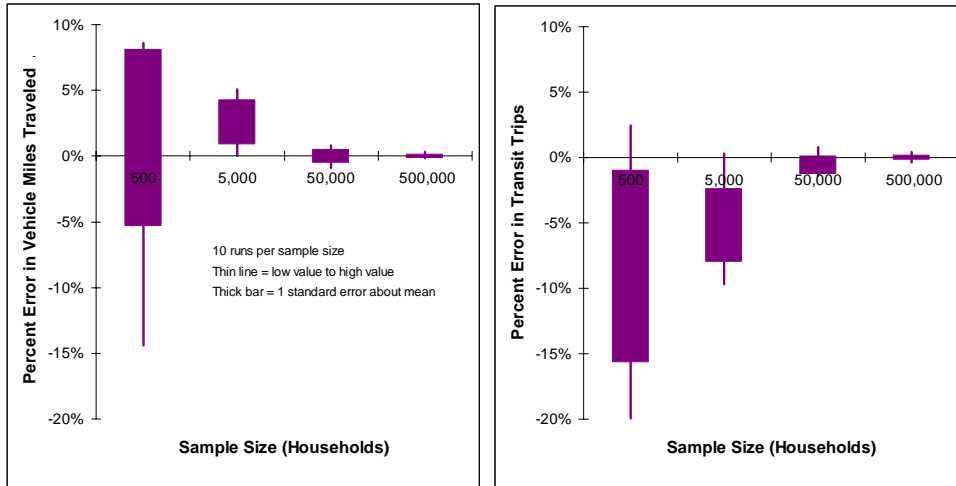
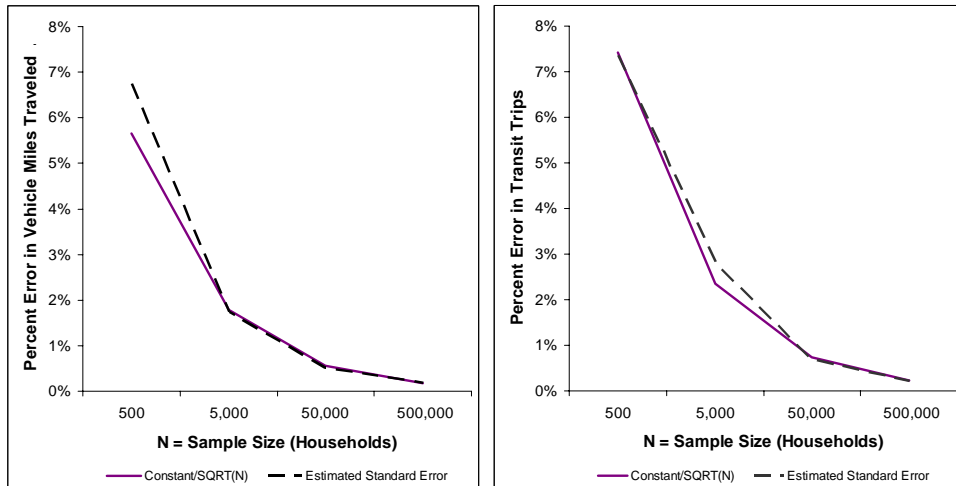


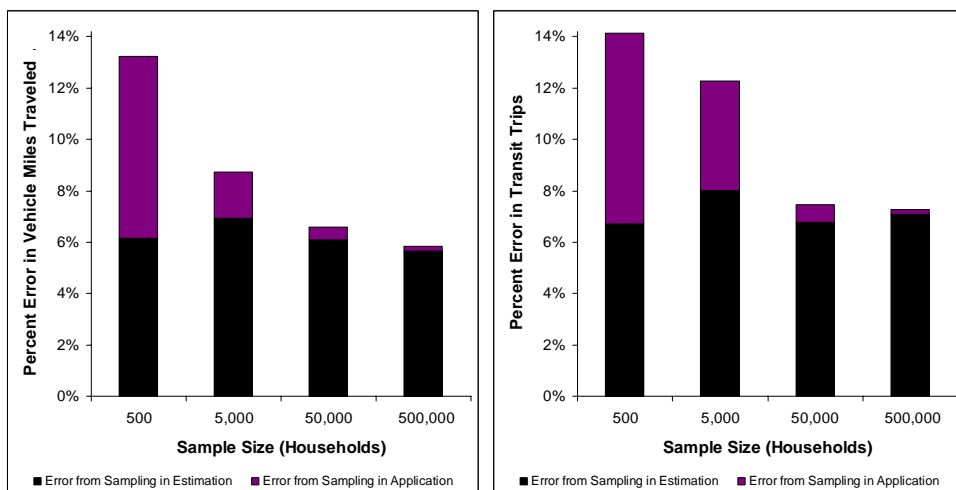
Figure 5 Sensitivity analysis and aggregation error.



6a: Estimation of Application Sampling Error as a Function of Sample Size



6b: Application Sampling Error is Proportional to $1/\sqrt{N}$



6c: Application Sampling Error versus Estimation Sampling Error

Figure 6 Investigation of sampling errors.