FROM AGGREGATE METHODS TO MICROSIMULATION: ASSESSING THE BENEFITS OF MICROSCOPIC ACTIVITY-BASED MODELS OF TRAVEL DEMAND

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The following paper is a pre-print and the final publication can be found in
Transportation Research Record No. 1994: 80-88, 2007.
Presented at the 86th Annual Meeting of the Transportation Research Board,
January 2007

ABSTRACT

Two competing approaches to travel demand modeling exist today. The more traditional "4-step" travel demand models rely on aggregate demographic data at a traffic analysis zone (TAZ) level. Activity-based microsimulation methods employ more robust behavioral theory while focusing on individuals and households. While the vast majority of U.S. metropolitan planning organizations (MPOs) continue to rely on traditional models, many modelers believe that activity-based approaches promise greater predictive capability, more accurate forecasts, and more realistic sensitivity to policy changes.

Little work has examined in detail the benefits of activity-based models, relative to more traditional approaches. In order to better understand the tradeoffs between these two methodologies, this paper examines model results produced by both, in an Austin, Texas application. Three scenarios are examined here: a base scenario, a scenario with expanded capacity along two key freeways, and a centralized-employment scenario. Results of the analysis reveal several differences in model performance and accuracy, in terms of replicating

travel survey and traffic count data. Such distinctions largely emerge through differing model assumptions. In general, activity-based models are more sensitive to changes in model inputs, supporting the notion that aggregate models ignore important behavioral distinctions across the population. However, they involve more effort and care in data manipulation, model calibration and application in order to better mimic behavioral processes, at a finer resolution. Such efforts help ensure that synthetic populations match key criteria and that activity schedules match surveyed behaviors, while being realistic and consistent across household members.

Keywords: Travel demand modeling, microsimulation of travel demand, activity-based models, tour-based models, model comparison

INTRODUCTION

Traditional travel demand models (TDMs) use a four-step process based on demographically (and spatially) aggregate data. While widely used for many years, this method has many drawbacks, including limited behavioral theory, disregard of intra-household constraints, and neglect of tour-based dependencies in mode, departure time, and destination choice. Continuity in activity participation and recognition of the various interdependencies in activity timing and other travel attributes allow greater realism in models of travel demand. Methods that allow for this continuity, such as activity-based modeling and microsimulation, are heralded as offering a considerable advantage over traditional methods. Moreover, activity-based modeling is better suited to current transportation planning interests, as emphasis has switched from long-term capital improvement projects to shorter-term congestion management strategies, such as alternative work schedules and congestion pricing (Bhat and Koppelman 1999). While substantial effort has been devoted to developing activity-based models and application of microsimulation methods, little research has focused on comparing these to more traditional model specifications. This work undertakes such a comparison for the region of Austin, Texas.

This paper compares trip-based to tour-/activity-based models, as well as traditional aggregate methods to microsimulation techniques. The results of applying a microsimulation activity-based TDM to a synthetic Austin population are compared to those of a relatively traditional model, offering insights into the tradeoffs between such approaches, in terms of accuracy, both in development and application. Other differences examined here include modeling sensitivities to policies and investments that should affect travel behavior. Comparisons include estimates and observations of traffic flows during peak hours and off-peak hours, total vehicle hours traveled during peak and off-peak hours, and mode shares. Such relationships are important when considering a variety of potential strategies for managing traffic congestion, improving quality of life, and forecasting a region's future.

One way in which the models differ is their required inputs. The aggregate model uses zonal averages for household information. Households were assigned to different types based on three household characteristics: household size, the presence of children, and household income. A total of 27 household types were considered. The activity-based model relies on disaggregate socioeconomic information (such as household size and composition, income, age, gender, and employment status of household members). Both rely, to some extent, on aggregate zonal land use data for trip generation models; and, for their sub-models' estimation, both rely on the same network and system level-of-service (LOS) characteristics (of interzonal costs and times across two time of day/periods [peak and off-peak]).

The following sections discuss related investigations, the data and model specifications used here, and the scenarios evaluated for results comparison across both TDM approaches. The final section offers some conclusions as well as recommendations regarding modeling directions.

LITERATURE REVIEW

A key feature of the newest TDMs is their use of disaggregate data, synthesis of micro-population features, and simulation of individual behaviors. This enhancement allows for greater precision (and stratification) in results and a greater reliance on behavioral theory. Microsimulation of travelers and their regional perambulations is the focus of this paper. Microsimulation involves the sampling of individual households and persons using multivariate distributions for base demographic data. This population of travelers may be assigned both home and job locations as well as a series of simulated daily activity patterns. Detailed travel itineraries, including mode and route assignments, strive to mimic realistic activity patterns while recognizing the travel choices of other household members. Existing models include MORPC (PB Consult Inc. 2005), TRANSIMS (http://tmip.fhwa.dot.gov/transims/), ILUTE (Miller and Salvini, 2001), CEMDAP (Bhat, et al., 2001), and ALBATROSS (Arentze and Timmermans, 2000), among others. Activity-based models in practice today include Columbus, Ohio's MORPC, the San Francisco Bay Area's SFCTA, New York City's NYMTC, Atlanta's ARC, and Portland's METRO (Vovsha, et. al, 2004). While all these models share certain characteristics, their details differ. Additionally, none offers a clear, applications-based comparison to a traditional TDM, as sought here.

The Mid-Ohio Region Planning Commission (MORPC) model has generated a lot of interest, and was the basis for the activity-/tour-based model structure used here. It relies on a nested logit framework for all its main modules (Anderson, 2005). And its tour production module recognizes the interdependence of household members, unlike many current models (which determine trip and tour attributes independently across household members [Vovsha, et al., 2003]).

While the MORPC and other models incorporate various emerging aspects of microsimulation and activity-based modeling, there is very little research directly comparing traditional, aggregate methods and microscopic modeling techniques. Walker's (2005) models of Las Vegas, Nevada offered a direct comparison, though the microsimulation model relied on a trip-based format (which does not allow for mode, scheduling or intra-household consistency). Walker (2005) capably illustrated how the two approaches' computation time and calibration efforts were quite similar, yet the microsimulation model offered the additional benefits of preserving demographic distinctions across the population, thus allowing for analysis of sub-group impacts (of transportation policies and investments, for example). In addition, the microsimulation approach eliminated aggregation errors (spatial and demographic), while allowing for calculations of the associated simulation errors/variability (Walker, 2005). The current paper expands this comparison to a microscopic model with tours, rather than trips, as the basic unit of analysis, and utilizing more sophisticated methods to incorporate intra-household constraints and activity scheduling.

DATA AND SCENARIOS

To ensure the greatest consistency between the traditional and microscopic TDMs used here, both primarily rely on data collected in the 1996-1997 Austin Travel Survey (ATS 1997) for model estimation. The Capital Area Metropolitan Planning Organization (CAMPO) provided interzonal travel time and cost data during peak and off-peak periods of the day, along with year 2000 zonal employment counts. The three-county household population (of 1.2 million people) was synthesized for both models using the three-county region's 2000 Census Public-Use Microdata Sample (adjusting from the region's 709 Census block groups to its 1,074 TAZs).

Since both models were calibrated using the same datasets, it is hoped that any differences in their predictions are due largely to the models themselves. The governing hypothesis is that a microscopic, activity-based approach should more accurately identify behavioral shifts in travel caused by changes in urban form, transportation policy, system investment, and other factors.

To fully examine the responsiveness of the models, three scenarios were analyzed. These include the base scenario (for year 2000, status quo conditions), capacity expansion (of two key freeways), and centralized employment. The expanded capacity scenario adds a lane (in both directions) to each of the two most important corridors in the region: Interstate Highway 35 (I-35, over its entire 85-centerline-mile length) and Loop 1 (also known as MoPac, from Parmer Lane to U.S. 290, comprising 16-centerline miles). Given that both presently are congested corridors, such lane additions (providing 36% capacity increases for both corridors) represent a reasonable (though unlikely in the near-term) expansion project for the system.

In order to appreciate the impacts of changing job locations, an employment density scenario assumes a land use system with jobs more highly concentrated in Austin's central business district and other key locations in the region. To accomplish this, non-educational, non-airport employment levels were modified in all zones. For the 506 (47% of total) zones classified (by CAMPO) as rural, 50% of such jobs were moved to the 201 urban- or 25 CBD-classified zones (representing an average 44% loss of jobs in rural zones). For the 342 zones classified as suburban, 30% of employment was moved (representing a 28% loss, on average). These removed jobs were allocated across all urban and CBD-classified zones in proportion to their 2000 employment totals, raising those zones jobs totals by 58%, on average. This job-relocation example and the capacity-expansion example make for interesting case studies of Austin's travel conditions, while permitting a comparison of model performances.

METHODOLOGY

In order to further enhance consistency between the two models, they were estimated using similar sets of explanatory variables, and employed weights in model estimation (using the ATS's population expansion factors). Due to the distinctive nature of the two approaches, there are obvious differences in the number and types of variables used for the models, as well as the model specifications themselves. In general, however, the variables used for the traditional TDM formulation are a subset of those used in the microscopic model. The basic modeling steps are summarized here.

Population Synthesis

To ensure consistency in inputs, population synthesis was performed similarly for both models. The aggregate model uses a subset of the outputs of this analysis. The population synthesizer builds zonal populations based on local and regional Census data. The inputs to this synthesis process, for each zone, are zonal population, household population, labor force population, and average annual household income. Only average values for household size are available at the Census tract level, so shifted Poisson were used to generate marginal distributions for household size. Marginal distributions for income are given directly by the Census data. PUMS data then were used to seed a process of iterative proportional fitting (IPF), in order to reconcile zonal information with the multi-dimensional nature of these distributions. For the microscopic model, draws of actual values from the closest-matching PUMA household then provided demographic information on individual household members, household auto ownership, and a continuous value of household income. The output is a list of specific households in each zone, characterized by size and composition (i.e., worker/student status, age, and gender of household member), income, and auto ownership.

The microscopic model uses the complete set of individual and household characteristics throughout the model system (e.g., household size, worker/student status, age, gender, income, and auto sufficiency). For the aggregate TDM, the data set was aggregated by household type at the zonal level, using only the household size, income, and presence-of-children variables from the synthesis.

Traditional, Aggregate Model Specification

The traditional TDM employed here relies on techniques used in several existing TDMs for the Austin region, all based on data in the 1996-1997 ATS (CAMPO 2000, Smart Mobility 2003, Gupta 2004, Kalmanje and Kockelman 2004, and Kalmanje 2005), as well as many standard techniques outlined by Martin and McGuckin (1998). All components were estimated to facilitate comparison with the activity-based model, while maintaining a rather traditional (though not highly simplistic) structure. The model uses rather standard and streamlined approaches: regression models for trip generation, fixed rates of trip productions (as a function of household and employment counts [by type]), multinomial logit models for destination and mode choice, fixed time of day and vehicle occupancy trip apportionments, and static traffic assignment routines. For consistency, it also features a vehicle ownership model upstream of trip production. Due to space limitations, many of the details of the models are not included here. For a more detailed discussion of the model estimation results, please refer to Lemp (2007).

Auto Availability

While auto availability does not comprise one of the four steps in the basic four-step modeling procedure (as outlined by Martin and McGuckin (1998)), auto availability plays a key role in travel behavior (Smart Mobility 2003). For this reason, an auto ownership model was estimated and placed upstream of more traditional steps offering consistency with many of the better TDMs in practice today. Due to the implicit ordering of alternatives from 0 to 1 and then 2 or more autos, an ordered-probit model was used. Here, it was assumed that households with more than two autos behave in ways similar to those with two; hence, three choice alternatives are offered.

Trip Generation

Using linear regression techniques, home-based trip productions were modeled at the household level based on four characteristics: the presence of children under 18 years of age, annual household income categories ($0-29,999, $30,000-74,999, and over $74,999), household size, and auto availability. The first three of these characteristics come directly from the synthesized household types, and auto availability comes from the three choice probabilities of the auto availability model. Work and non-work trips were modeled separately.

Non-home based (NHB) trips – both work and non-work types (separately) – were modeled at the zonal level (rather than at the household level) using zonal housing and employment characteristics. Again, linear regression techniques were used. The model parameter estimates are relevant only for the sample. For model application, parameter estimates were inflated to represent the total population. It was assumed that zones with no households and no employment will not produce any trips; hence, constants were not used in the two NHB trip-generation regression equations. Scatter plots of NHB trips (work and non-work in nature) versus each of the explanatory variables support this notion.

Mode Choice

Multinomial logit models of mode choice were estimated for each of the four trip types. Because of the unreasonably low value of travel time implied by the models (which may come from poor traveler perception of actual times and costs across modes)[1], and the desire for time-sensitive travel patterns (in mode, route, and destination choices), value of travel time was assumed to be \$9 per hour per person for work trips and \$4.50 per hour per person for non-work trips. A generalized cost term was then formulated based on total travel time and cost using CAMPO's peak and off-peak travel cost and time matrices (by mode type).

Indicator variables for whether the individual lives in a household with one or more vehicles per household member were devised. This was done using the categorical values for household size (1, 2, 3, 4, and 5+) and number of autos (0, 1, and 2+). Therefore, there are some households that in actuality have one or more vehicles per person, but have a value of 0 assigned for the indicator variable (e.g., 3 autos and 3 persons), but these were relatively few. It was assumed that marginally relevant vehicle operating costs (for purposes of mode choice) were \$0.10 per mile, which approximate gasoline costs.

Destination Choice

While destination choice precedes mode choice in the standard four-step model, here a nested formulation is used, since a logsum (expected minimum cost) formulation across modes and times of day was used to estimate (and then apply) the multinomial model of destination choice. For time of day purposes, two travel time skims were performed for peak and off-peak periods. The logsum from origin i to destination j for trip purpose p is computed as shown in equation (1) across all modes m and time periods t. The β's in the formula represent coefficients estimated in the mode choice model.

$$LOGSUM_{ijp} = \ln\left(\sum_{m,t \in C} \exp\left[\alpha_{tp} GenCost_{ijmt} + \beta_{mp}\left(Indicator_{veh}\right) + \gamma_{mp} \right] \right) \quad (1)$$

where $GenCost_{ijmt}$ is the generalized cost (logsum) term from zone i to zone j using mode m during time period t, $Indicator_{veh}$ is an indicator variable taking a value of 1 if the household has 1 or more vehicles per household member, and γ_{mp} is an alternative-specific constant for each mode-trip purpose combination (and zero for the base mode).

For purposes of estimation, not all choice alternatives could be used since the total choice set includes over 1,000 possibilities. Instead, 30 choice alternatives were generated at random, plus the chosen alternative, for a total of 31 choice alternatives used in model estimation (as per McFadden's [1978] finding that such sampling results in consistent estimators). These models were estimated using a multinomial logit framework.

Time of Day and Vehicle Occupancy

For time of day analysis, four time periods were used: AM peak (6 am – 8:59 am), PM peak (3 pm – 6:59 pm), midday/evening (9 am – 2:59 pm and 7 pm – 8:59 pm), and overnight (9 pm – 5:59 am). Fixed proportions (specific to each of the four trip types) were obtained from the (population-weighted) ATS to use in application. Home-based trips were split by departure trips and return trips. Similarly, vehicle occupancy rates were derived from the travel survey for application to shared ride trips. These rates were also derived specific to trip type.

Traffic Assignment

Truck trips and external trips were handled outside the TDM. Origin-destination (O-D) tables for both were taken directly from CAMPO estimates and added to the vehicle O-D tables before the assignment phases of both the aggregate and microscopic models. These 460,000 trips were handled statically using (fixed) ATS trip distributions across times of day. They represented approximately 5 million vehicle miles traveled (VMT), or about 15% of the region's total VMT. (A 15% share of VMT is substantial, but considering that I-35 is one of the nation's busiest corridors for international trade and that Austin is home to the state capitol, various state agencies, and the University of Texas, the truck/external trip share appears realistic.) Taken as given, these externally related trips are presumed to be non-responsive to system changes, which is an imperfect (though common) assumption.

Deterministic user-equilibrium traffic assignment was performed for both models in an identical manner. Shortest-paths were found using generalized cost functions, and, in the case of the aggregate TDM, this information was fed back (to destination and mode choice models) using the method of successive averages (MSA), until system convergence (using a TransCAD gap criterion of 0.02). Unfortunately, due to time constraints, full feedback was not possible for the activity-based model (whose data development and model run times were on the order of days).

Microscopic Activity-Based Model Specification

The microsimulation model was structured in a manner similar to MORPC's activity- and tour-based framework (PB Consult, 2005), though it does not employ the same nested logit framework. As described earlier, this model synthesizes the Austin population and uses a series of logit model results to simulate the daily activity patterns and travel decisions made by each individual in the synthesized population. The model consists of a population synthesizer, primary activity pattern (PAP) generator, maintenance and discretionary tour allocation model, activity scheduler, primary activity and secondary activity destination choice, and mode choice models, as well as network assignment, as shown in Figure 1. Each model was tested for inconsistencies with sampled data to ensure targets were met. With the exception of the destination choice sub-models (discussed in more detail below), no inconsistencies were found. A more complete description of the model system can be found in McWethy (2006) and Lemp (2007).

Mandatory Activities
The PAP model system determines the number and type of mandatory activities that each individual will undertake that day, including work, university, and school. It is comprised of MNL models specific to six person types: pre-driving school-age children (ages 5 through 15 [since persons under 5 years of age were not sampled]), driving-age children (ages 16 and 17), non-working adults, adult students, part-time working adults, and full-time working adults. This system incorporates household interactions via a sequential modeling format, which models the person types in order of their (assumed) dependence on other household members, thus accounting for other members' PAPs. This ordering is adapted from the MORPC model (PB Consult, 2005) and is as follows: pre-driving age children and driving age children are assigned PAPs first, then adult students, full-time working adults, part-time working adults, and finally, non-working adults. The explanatory variables used in this model include household size and composition, traveler demographics, auto "sufficiency" (i.e., having at least one automobile per adult), a variety of area type characteristics of the home zone (including employment numbers by type, area type indicators [rural, suburban, urban, and CBD], and transit availability), and indicator variables for PAPs chosen by household members already modeled.

Non-Mandatory Activities
The non-mandatory activity model is comprised of three MNL sub-models, which run at the household level, and two individual-level sub-models. The household-level models determine the number of escort activities (parents chauffeuring children, typically), shopping activities and other maintenance activities (0 through 3+ for each tour type). The individual-level models allocate household maintenance activities (to household members) and determine the number of discretionary activities undertaken by each household member. The explanatory variables used for these models include the individual's person type and PAP, household size and composition, auto sufficiency, household income, land use, and transit accessibility.

Activity and Trip Scheduling
The activity scheduler draws from the actual ATS activity diaries, in order to fit the individual's PAP, the number of escorting, shopping, other maintenance, and discretionary activities for the individual, and the area type of the home zone. This diary is comprised of all activities undertaken, including work, school, all types of maintenance activities and discretionary activities, as well as the activity's start time and duration. The start time for each activity is key here, and activity durations are then adjusted to allow for different travel times.

Primary Destination Choice
There are two destination choice models in the microscopic model. The first determines the location of the primary activity (typically a mandatory activity) of each tour. It is a MNL model with attraction measures (including residential, commercial and employment intensities, zone area, mode choice logsums, and population density) for each destination zone serving as the explanatory variables. There are separate models for mandatory and non-mandatory activities.

Mode Choice
Once a destination is chosen for the primary stop of the tour (i.e., randomly sampled from among all options, according to the associated logit probabilities), tour mode is chosen, ensuring consistency of mode use across all tour segments. Mode choice relies on an MNL model with

both time and cost parameters, as well as travel-purpose and mode-specific constants, number of other activities by type undertaken on the tour, person-type constants indicating age and employment status, household income, auto sufficiency and household composition. (For example, the presence of children increases the likelihood of carpooling/shared ride.) The four mode alternatives are drive-alone, shared ride, transit, and non-motorized modes. Logsums across these mode alternatives are used in the destination choice model.

Secondary Destination Choice

Once the mode for each tour is determined, the secondary activity destination choice model is applied. This model is similar to the primary activity destination choice model, but it controls for the location of the primary activity (via distances to both home zone and primary activity zone) and the chosen mode. This is done by controlling for the generalized costs, specific to the chosen mode, from the home zone and from the primary activity destination.

Similar to the conventional model's applications, these microsimulated tours were loaded onto the Austin network, using standard assignment methods, at the TAZ level, in TransCAD. Trips with at least one external end zone and commercial vehicle trip matrices were loaded as well. Unlike in the conventional model, feedback of travel times and costs to models of primary activity destination choice, mode choice, and secondary activity patterns was not performed in the microscopic model's application. The effort required to perform these hierarchical tasks in this microscopic paradigm is significant (requiring at least one person-day). If the 1.2-million person population could be efficiently tracked and all the behavioral models easily coded into GIS-DK, for use in the network assignment package (TransCAD), this iterative feedback-till-convergence would be feasible.

RESULTS

The performance of the two models was compared on the basis of predictive accuracy (both in model development and application), modeling sensitivities to policies and investments that affect the timing and cost of travel, using the direct observations of traffic flows during peak hours and off-peak hours and mode splits forecasted by each model.

VMT and Mode Share Comparisons

In order to examine the accuracy of the two models, actual link flow data were compared to those predicted by the models using the base scenario (Table 1). The actual data come from 1997 traffic counts performed by CAMPO on 6,606 of the network's 7,203 coded, non-centroid-connecting links. (2,436 [or 25%] of the coded-network's links are centroid connectors.) Of course, the models were applied using 2000 Census data, rather than 1997 travel data, so one expects somewhat higher model-predicted counts (due to population, job and income growth during the 1997-2000 period – which was a time of significant economic expansion for the U.S. and Austin economies). Moreover, the TDMs assume a school day, whereas CAMPO's counts are for an average day (including weekends and summertime), over the course of a year. Estimates of network VMT (on the links with traffic counts) are approximately 14% greater (3.8 million VMT per day) with the aggregate model and 27% greater (7.1 million VMT per day) with the microscopic model.

After recognizing the growth in population, employment and travel during the 1997-2000 period, and the emphasis of school days in the TDM, the traditional model appears to be performing

reasonably, in general, system-level performance terms. However, the microscopic model is not. Upon closer inspection, the microscopic model results were found to suffer from long travel distance predictions, with most of this error (65% of the excess VMT, as compared to the aggregate model predictions) occurring in return trips to home. Essentially, after all activity locations for a tour are chosen, the synthetic travelers tend to locate their final tour stop (prior to returning home) too far from their home zone. One possible source of this error stems from the estimation of the destination choice model with 30 randomly chosen alternatives rather than the entire set of 1,074. While this method of model estimation is extremely common and statistically consistent (see McFadden 1978), the fact that many legitimate choice alternatives are not considered could reduce the magnitude of level-of service parameter estimates (biasing the impedance term's coeffiicient towards zero, essentially). Preliminary investigations indicate that the model parameters for level-of-service variables do, in fact, rise when more alternatives are used in model estimation.
Model-predicted mode shares also were compared to the (population-corrected) ATS shares (Table 2). In the aggregate model, transit and walk/bike mode shares are significantly less than that of the population weighted ATS (0.9% and 2.6%, rather than ATS shares of 2.0% and 4.3%). For walk/bike trips, this may be a result of the low (4 mph) speed assumption, made during model estimation, which may not apply for Austin. In contrast, the microscopic model estimates of transit share (1.9%) are very close to the ATS. The microscopic model estimates of walk/bike trips are almost identical to those of the aggregate model. Of course, these are minor modes, so mis-predictions will not really affect most/many applications of the model. Fortunately, the mode shares for both shared ride and drive alone appear reasonable, under both model formulations.

Scenario Evaluations via Model Responses

To investigate model sensitivities to scenario assumptions, three measures were used for comparison, to the base scenario's outputs: VMT by roadway type, VMT and vehicle-hours traveled (VHT) by time of day, and mode split. Changes in these variables (from the base case outputs for both models) were used to assess scenario results, across the two modeling frameworks.

Results of the Expanded-Capacity Scenario

Table 3 provides VMT and VHT estimates by time of day for both models under expanded link capacities for I-35 and Loop 1. As expected, for the traditional model, total VHT estimates fell for the (AM and PM) peak time periods. With reduced travel times, VMT is predicted to increase anywhere between 0.55% (off-peak) and 9.13% (in the AM peak period). Of course, the critical question is how these compare to the microscopic model's estimates model. The activity-based model shows similar results for both the off-peak and PM peak periods, but the effects in the AM peak period are smaller while the effects in the midday period are greater. Both models predict a slight increase VMT over all time periods: 2.62% and 3.17% for aggregate and activity-based, respectively. In addition, both models predict almost an identical overall increase in speeds of about 5%.

It is expected that with increased capacity, people will shift to routes that offer higher speeds under free-flow and regular traffic conditions (in this case, I-35 or Loop 1). The traditional model results (Table 4) suggest just that: people shift their destination and route selections in favor of these higher speed freeways. Other roadways still receive significant use, but people tend to drive further distances, relying more on the additional capacity offered by I-35 and Loop 1. The microsimulation model forecasts indicate similar patterns, but with slightly larger magnitudes. Both models suggest a higher shift towards Loop1 as compared to I-35, as shown in Table 4. The shift is also more evident from frontage roads to the freeways in the microscopic model than for the traditional model.

The mode splits for the aggregate model are very close to those of the base scenario, suggesting that both models are largely insensitive to network speeds. This is due to the substantial alternative-specific constants in both model's mode choice settings, which generally are two or three times as high as the cost and time component contributions to systematic utility.

Results of the Centralized Employment Scenarios
Table 3 provides the VMT and VHT results by time of day for both models under the centralized employment location scenario. The results of the traditional model show little impact for this scenario, with a slight decrease in VMT and VHT over all time periods, except the AM peak, which exhibits a VHT increase of 3.24%. This can be explained as more commuters are concentrated on the routes heading into the CBD. The microscopic model also predicts an overall decrease in VHT and VMT across all time periods with the exception of the off-peak period. The magnitude of the overall daily VMT decrease is substantially larger in the microscopic model (2.54%, compared to 0.60% in the traditional model). The reason for this may be explained by the linking of trips in the microscopic model. While the distance between home and primary activity location choices in the microsimulation model may be longer, the secondary activities are concentrated near the primary activity. This ultimately reduces VMT.

With more centralized employment, one may expect longer-distance trips (of all types) and greater use of arterials, since Austin's downtown is not served by many of the region's freeways. However, in both models VMT reductions are predicted on almost every roadway type, as shown in Table 4. This can be explained by higher frequencies of trips originating from (and destined for) urban and CBD zones. Trip distances may be longer for home-based trips, but much shorter for non-home-based trip types.

As in the expanded capacity scenario, the mode splits for the aggregate model are very close to those of the base scenario, again indicating an insensitivity and heavy weight of alternative-specific constant terms. While the microsimulation model predicts little change in transit use, the share of walk/bike mode increases by 19%. This is likely a result of households in the urban and CBD zones choosing destinations very close to home. In any case, it seems the microscopic model is more sensitive to the impacts of policy changes on travel, as expected – thanks to the explicit chaining of linked trips, mode consistency requirements within a tour, and so forth (see, e.g., Bowman and Ben-Akiva, 1997).

CONCLUSIONS
The question of how much "better" activity-based microsimulation models perform relative to traditional aggregate approaches is controversial – and to date largely overlooked. The widespread endorsement by the academic community of activity-based, microscopic models has had little empirical foundation. This paper addresses this issue by calibrating and then applying two such models, using identical data sets with application to the same study area for the base case, expanded-capacity, and centralized employment scenarios.

The calibration of the microscopic model is necessarily more time-consuming for multiple reasons. Traditional travel surveys are coded as trip data, as opposed to tour data, and so the data needs to be converted before the models can be calibrated. While seemingly trivial, linking trips into tours requires careful treatment. Moreover, in order to represent intra-household interdependencies, assembly of the variables used in the microsimulation model requires additional time. In total, data assembly for the microsimulation model was roughly four to five times greater that that required by the traditional model set-up. The microsimulation model is also more complex, requiring estimation and application of 17 different sub-models (rather than the 13 used under the conventional modeling approach) and estimation of 307 individual parameters (rather than the 177 required by the traditional model used here). Complexity of such models is a key cost that may be over-ridden by the detailed results that can be acquired and policy issues that can be analyzed through these models. However, the analysts must first be confident that their simulation methods and activity-pattern, trip timing and other specifications are error-free and appropriately reflect actual travel patterns. If the experience of this research team is any indication, the added effort (and skill requirements) of activity-based models may not be feasible for most MPOs, particularly in the near term. This particular microscopic model has been under development for over a year and still exhibits many "bugs". Its predictions and specifications suggest many areas for model improvement and validation.

The results indicate that activity-based models do indeed perform rather differently than traditional aggregate approaches. The microscopic model proved more sensitive to capacity expansion and employment location tests. Unfortunately, appraising the accuracy of the models under changes to model inputs (relative to actual traffic patterns) is not possible (without actually undertaking such a policy and collecting new traffic and travel data). Moreover, the microscopic model was far trickier to estimate in such a way that reasonable behaviors emerged. Nonetheless, it seems that the more exhaustive behavioral theory incorporated in the microscopic, activity-based models may offer significant benefits for scenario analysis, an important component of the planning process. Far more investigation is needed, to ascertain the true benefits of such modeling methods, and the extent to which they warrant the expertise and effort that they require.

ACKNOWLEDGEMENTS

The authors wish to thank CAMPO's Daniel Yang and SmartMobility's Norm Marshall for valuable data sets and GISDK code, Oregon DOT's Brian Gregor for helpful suggestions on R programming, Howard Slavin for Caliper's contributions, Saurabh Kumar for various computing contributions, and Annette Perrone for editing assistance. We also wish to thank the Southwest University Transportation Center and the U.S. Environmental Protection Agency's STAR Grant program for their sponsorship. The STAR grant's multi-team project is titled "Predicting the Relative Impacts of Urban Development Policies and On-Road Vehicle Technologies on Air Quality in the United States: Modeling and Analysis of a Case Study in Austin, Texas."

REFERENCES

Anderson, R. (2005). Implementation of a Tour-based Microsimulation Regional Travel Demand Model: Mid-Ohio Region. Proceedings of the 9th Transportation Research Board Conference on the Application of Transportation Planning Methods, Baton Rouge, LA

Arentze, T. and H. Timmermans, (2001). *ALBATROSS: A Learning Based Transportation Oriented Simulation System*. Technische Universiteit Eindhoven, Netherlands.

ATS (1997). *Austin Travel Study*. Capital Area Metropolitan Planning Organization (CAMPO). Austin, TX.

Bhat, C. and F. Koppelman (1999). Activity-Based Modeling for Travel Demand. *Handbook of Transportation Science*, R.W. Hall (ed.), Kluwer Academic Publisher.

Bhat, C., S. Srinivasan, and J. Guo (2001) Activity-Based Travel-Demand Modeling for Metropolitan Areas in Texas: Model Components and Mathmatical Formulations. Report 4080-2. Prepared for the Texas Department of Transportation.

Bowman, J. and M. Ben-Akiva (1997) Activty-Based Travel Forcasting. Working Paper. Travel Model Improvement Program (TMIP).

CAMPO (2000). *1997 Base Year Travel Demand Model Calibration Summary for Updating the 2025 Long Range Plan*. Transportation Planning and Programming Division, TXDOT.

FHWA (2006). TRANSIMS Home Page. URL: http://tmip.fhwa.dot.gov/transims/ (Accessed July 2006)

Gupta, S. (2004). Road Pricing Simulations: Traffic, Welfare, Home Value and Land Use Impacts for Austin, Texas. Master's Thesis. Department of Civil Engineering. The University of Texas at Austin.

Kalmanje, S. U. and K. M. Kockelman (2004). Credit-Based Congestion Pricing: Travel, Land Value and Welfare Impacts. *Transportation Research Record No. 1864*: 45-53.

Kalmanje, S. U. (2005). Toll Roads in Texas: Traffic and Welfare Impacts. Master's Thesis. Department of Civil Engineering. University of Texas at Austin.

Lemp, J. (2007). Quantifying the Benefits of Activity-Based Microsimulation Models of Travel Demand: A Case Study of Austin, Texas. Master's Thesis. Department of Civil, Architectural, and Environmental Engineering. University of Texas at Austin.

Martin, W. A. and N. A. McGuckin (1998). *Travel Estimation Techniques for Urban Planning*. NCHRP Report 365. National Research Council, Washington, D.C.

McFadden, D. (1978). Modeling the Choice of Residential Location. In *Spatial Interaction Theory and Planning Models* (A. Karlquist, L. Lundquist, F. Snickbars, and J. W. Weibull, eds.). North-Holland, Amsterdam, p. 75-96.

McWethy, L. (2006). Comparing Microscopic Activity-Based and Traditional Models of Travel Demand: An Austin Area Case Study. Master's Thesis. Department of Civil, Architectural, and Environmental Engineering. The University of Texas at Austin.

Miller, E. and P. Salvini (2001) The Integrated Land Use, Transportation, Environment (ILUTE) Microsimulation Modelling System: Description and Current Status. *Travel Behavior Research.* Ed. David Hensher, p. 711-723. Oxford: Elsevier Science Ltd.

PB Consult (2005). *The MORPC Travel Demand Model Validation and Final Report*. Prepared for the Mid-Ohio Region Planning Commission. (https://ftp.pbworld.com/GetFile.aspx?fn=1941597264.zip Accessed November 2005).

Smart Mobility (2003). *Envision Central Texas Transportation Model: Technical Documentation*. Prepared for Envision Central Texas. Smart Mobility, Inc, Norwich, VT.

Walker, J. L. (2005). Making Household Microsimulation of Travel and Activities Accessible to Planners. *Transportation Research Record*, 1931, p. 38-48.

Vovsha, P., M. Bradley, and J. L. Bowman (2004). Activity-based Travel Forecasting Models in the United States: Progress since 1995 and Prospects for the Future. Presented at the EIRASS Conference on Progress in Activity-Based Analysis, May 28-31, 2004, Masstricht, The Netherlands.

Vovsha, P., E. Petersen, and R. Donnelly (2003). Explicit Modeling of Joint Travel by Household Members: Statistical Evidence and Applied Approach. *Transportation Research Record* 1831, Washington, D.C., 1-10.

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Table 1: Comparisons of Model-Predicted VMTs and Actual Counts

Functional Class	Count-based VMT (1996)	Traditional Model		Microscopic Model	
		VMT (2000)	% Increase from Count	VMT (2000)	% Increase from Count
I-35	6,903,589	8,161,105	18.22	9,522,073	37.93
Loop 1	1,633,263	1,820,105	11.44	2,086,808	27.77
Other Freeway	2,109,803	2,023,125	-4.11	2,169,954	2.85
Arterial	13,721,103	16,266,494	18.55	17,591,369	28.21
Collector / Local	173,489	166,167	-4.22	162,658	-6.24
Ramps	315,711	302,569	-4.16	317,938	0.71
Frontage Roads	1,455,020	1,364,576	-6.22	1,595,624	9.66
TOTAL	26,311,978	30,104,141	14.41	33,446,423	27.11

Table 2: Comparisons of Model Mode Splits to ATS Data

Model	Mode	ATS (pop. weighted)	Base		Expanded Capacity		Centralized Employment	
			Share	% Change from ATS	Share	% Change from Base	Share	% Change from Base
Traditional TDM	Drive Alone	0.539	0.598	10.93	0.596	-0.33	0.598	-0.01
	Shared Ride	0.398	0.367	-7.82	0.367	-0.07	0.367	-0.07
	Transit	0.020	0.009	-54.34	0.012	32.11	0.009	0.86
	Walk / Bike	0.043	0.026	-39.30	0.025	-2.65	0.026	1.05
Microscopic TDM	Drive Alone	0.539	0.544	1.00	0.543	-0.20	0.526	-3.41
	Shared Ride	0.398	0.411	3.37	0.413	0.48	0.425	3.41
	Transit	0.020	0.019	-7.50	0.018	-1.72	0.018	-2.29
	Walk / Bike	0.043	0.026	-40.28	0.025	-2.06	0.031	19.26

Note: ATS stands for Austin Travel Survey. Mode splits were computed based on personal travel only.

Table 3: Time of Day Traffic Comparisons for Traditional Model and Microscopic Model

Time of Day	Measure	Traditional Model					Microscopic Model				
		Base Case	Expanded Capacity		Centralized Employment		Base Case	Expanded Capacity		Centralized Employment	
		Value	Value	% Increase from Base	Value	% Increase from Base	Value	Value	% Increase from Base	Value	% Increase from Base
AM Peak	VMT	6,675,489	6,865,325	2.84	6,658,345	-0.26	5,957,981	6,267,892	5.20	5,653,217	-5.12
	VHT	230,412	217,130	-5.76	228,148	-0.98	180,095	182,917	1.57	170,088	-5.56
	Avg. Speed	28.97	31.62	9.13	29.18	0.73	33.08	34.27	3.58	33.24	0.47
Midday	VMT	11,576,376	11,857,974	2.43	11,469,935	-0.92	14,686,892	15,047,325	2.45	14,264,262	-2.88
	VHT	263,204	263,566	0.14	260,216	-1.13	362,322	351,379	-3.02	349,850	-3.44
	Avg. Speed	43.98	44.99	2.29	44.08	0.22	40.54	42.82	5.64	40.77	0.58
Off-Peak	VMT	2,322,750	2,363,700	1.76	2,318,697	-0.17	2,529,603	2,550,763	0.84	2,647,652	4.67
	VHT	51,025	51,639	1.20	50,920	-0.21	54,003	54,289	0.53	56,204	4.08
	Avg. Speed	45.52	45.77	0.55	45.54	0.03	46.84	46.99	0.31	47.11	0.57
PM Peak	VMT	9,529,527	9,805,398	2.89	9,476,500	-0.56	10,271,946	10,642,098	3.60	10,030,750	-2.35
	VHT	255,812	249,793	-2.35	253,796	-0.79	297,373	289,804	-2.55	288,484	-2.99
	Avg. Speed	37.25	39.25	5.37	37.34	0.23	34.54	36.72	6.31	34.77	0.66
Daily	VMT	30,104,141	30,892,397	2.62	29,923,477	-0.60	33,446,423	34,508,078	3.17	32,595,882	-2.54
	VHT	800,452	782,128	-2.29	793,081	-0.92	893,793	878,389	-1.72	864,626	-3.26
	Avg. Speed	37.61	39.50	5.02	37.73	0.32	37.42	39.29	4.98	37.70	0.74

Table 4: VMT by Roadway Type for Traditional and Microscopic Model Applications with Expanded Capacity and Centralized Employment Scenarios

	Expanded Capacity Scenario Results				**Centralized Employment Scenario Results**			
	Traditional TDM		Microscopic TDM		Traditional TDM		Microscopic TDM	
Functional Class	VMT	% Increase from Trad. Base	VMT	% Increase from Micro. Base	VMT	% Increase from Trad. Base	VMT	% Increase from Micro. Base
I-35	9,043,058	10.81	10,845,345	13.90	8,144,657	-0.20	9,416,018	-1.11
Loop 1	2,130,064	17.03	2,470,387	18.38	1,814,136	-0.33	2,084,277	-0.12
Other Freeway	1,992,374	-1.52	2,141,734	-1.30	2,010,251	-0.64	2,115,511	-2.51
Arterial	15,995,370	-1.67	17,149,740	-2.51	16,126,088	-0.86	16,929,385	-3.76
Collector / Local	164,536	-0.98	156,201	-3.97	163,601	-1.54	152,257	-6.39
Ramps	316,424	4.58	338,611	6.50	301,102	-0.48	321,588	1.15
Frontage Roads	1,250,570	-8.35	1,406,060	-11.88	1,363,642	-0.07	1,576,846	-1.18
TOTAL	30,892,397	2.62	34,508,078	3.17	29,923,477	-0.60	32,595,882	-2.54

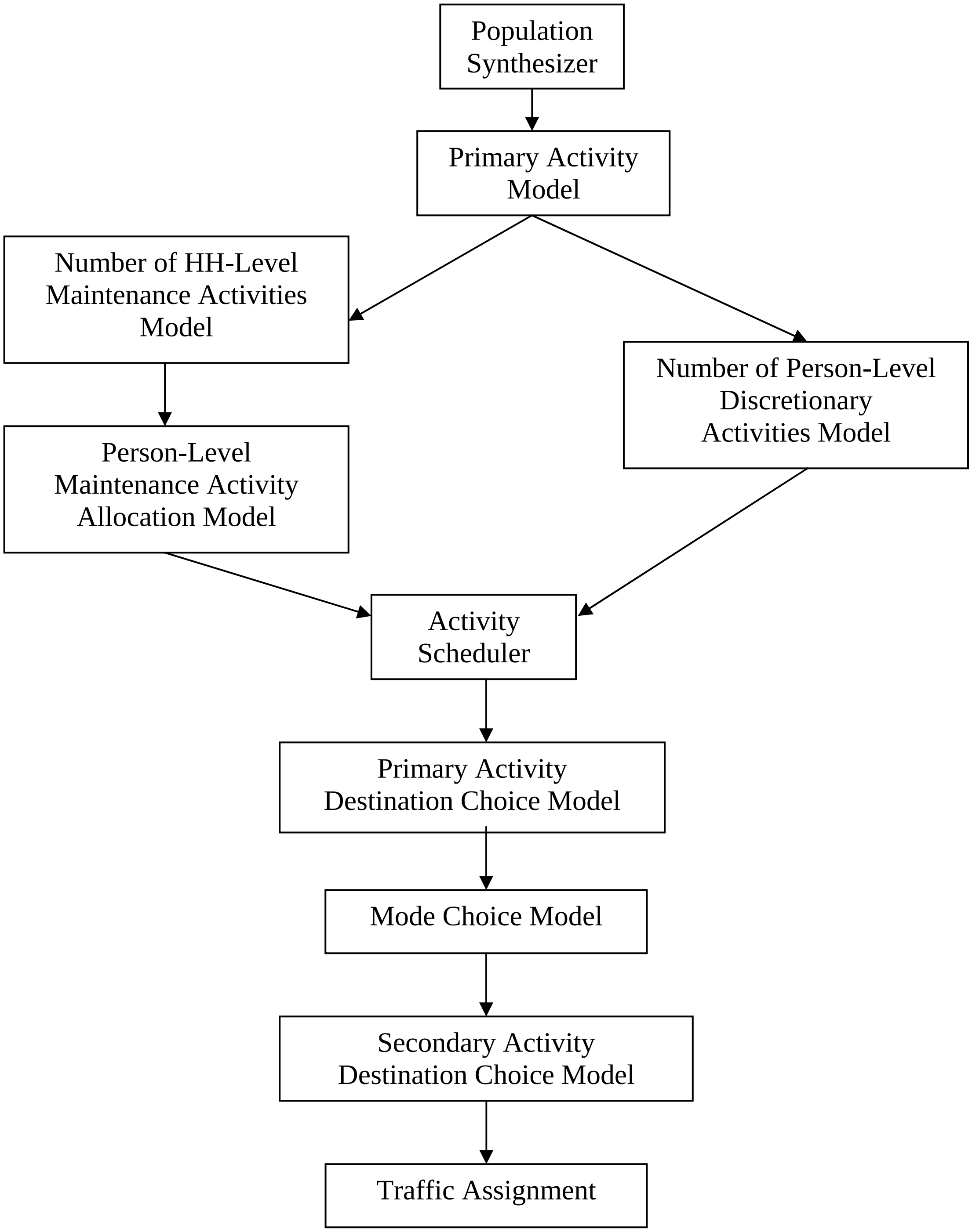

Figure 1: Microscopic (Activity-/Tour-Based) Model Structure