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CONFERENCE PROCEEDINGS 42

Innovations in Travel Demand Modeling

Summary of a Conference

VOLUME 2: PAPERS

May 21–23, 2006
Austin, Texas

Sponsored by

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This report has been reviewed by a group other than the authors according to the procedures approved by a Report Review Committee consisting of members of the National Academy of Sciences, the National Academy of Engineering, and the Institute of Medicine.

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Preface

On May 21 through 23, 2006, the Transportation Research Board (TRB) convened the Innovations in Travel Demand Modeling Conference in Austin, Texas. The conference was sponsored by the following agencies, organizations, and companies to provide an opportunity for a frank exchange of ideas and experiences among academics, model developers, and practitioners: TRB, FHWA, FTA, the Central Texas Regional Mobility Authority, the Capital Metropolitan Transportation Authority, PBS&J–Austin, URS Corporation, and HNTB Corporation.

Approximately 220 individuals from across the transportation research community—at national, state, regional, and local levels and from the public and private sectors and academia—participated.

BACKGROUND

The last major conference on specialty travel demand modeling was held as part of the U.S. Department of Transportation’s Travel Model Improvement Program (TMIP) in the fall of 1996. At that time, there was little research and no practical application of land use models and activity-based travel demand models and their integration with demographic, economic, and network modes. Since then, there has been a literal revolution in travel demand forecasting. In particular, significant advances have been realized over the past decade in survey methods and analysis tools available to the travel demand modeling profession.

CONFERENCE PLANNING

To plan this conference, TRB assembled the Committee for Innovations in Travel Demand Modeling: A Conference,

appointed by the National Research Council. Under the chairmanship of Chandra R. Bhat, University of Texas at Austin, and Ken Cervenka, North Central Texas Council of Governments, the planning committee identified three objectives for the conference. The first was to examine advances in travel demand modeling. The second was to facilitate the sharing of ideas and information among academics and practitioners on the opportunities and the challenges associated with the implementation of advanced travel models. The third was to identify additional needs for research, education, and training to ensure that the travel demand modelers of today and tomorrow are adequately prepared to apply the new model techniques.

After identifying the three main objectives and, hence, topic areas, the committee issued a call for papers, seeking high-quality white papers of three to five pages addressing the themes of the interactive sessions. The themes included

- Data needs to support activity-based and land use microsimulation models;
- Innovations in survey data collection to support travel demand forecasting;
- Population and household synthesis;
- Validation and assessment of activity-based travel models;
- Implementation of activity-based models;
- Emerging traffic microsimulation applications;
- Innovations in traffic assignment and improvements of forecast speeds;
- Institutional, monetary, staff, data, hardware, and training resources needed to move innovative approaches to practice; and
- The role of models in decision making in the contemporary decision-making context.

The final versions of these papers are reproduced in Volume 2.

CONFERENCE FORMAT

The conference opened with two workshops: Innovations in Practice and FTA Findings for Meaningful Forecasts. Two plenary sessions at the beginning of the conference framed the underlying policy issues that drive model development and the issues associated with moving innovative modeling techniques into practice. Following these plenary sessions, 11 breakout sessions were held. These sessions were largely based on the papers, although several presentations not based on papers were included when the committee felt that additional information was required to cover a topic. The breakout sessions were designed to allow for lively discussion. A final plenary session focused on the institutional issues that must be faced to move research into practice.

CONFERENCE PROCEEDINGS FORMAT

Volume 1: Session Summaries

Volume 1 contains summaries of the plenary and breakout sessions. The conference summary was prepared by Katherine F. Turnbull, Texas Transportation Institute. The appendix contains a list of all conference participants.

Volume 2: Papers

This volume contains 31 full papers from the breakout sessions.

PEER REVIEW PROCESS AND ACKNOWLEDGMENTS

Of the more than 65 full papers (of five to six pages) that were initially received in response to the call for papers, the committee selected 31 for conference presentation. Breakout session moderators provided review comments and worked with the authors to make improvements to the papers. After the conference, authors submitted their final papers, updated on the basis of the comments received and discussion held at the conference.

The conference planning committee wishes to thank the TRB Transportation Demand Forecasting Committee, the Traveler Behavior and Values Committee, the Travel Survey Committee, and the Moving Activity-Based Modeling into Practice Task Force. The leadership and members of these committees and task force were important contributors to the conference.

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WORKSHOP

INNOVATIONS IN PRACTICE

Levels of Disaggregation and Degrees of Aggregate Constraint in Transportation System Modeling

J. Douglas Hunt, *University of Calgary*

This paper compares modeling approaches used in transportation system modeling and in system modeling more generally. It considers two dimensions: (a) the level of disaggregation in the representation of system elements and (b) the degree of aggregate constraint on the system. Furthermore, it incorporates both the equilibrium and the process simulation approaches and thereby enters the debate concerning the relative merits and (perceived?) flaws of these two approaches. The intentions of this paper are (a) to engender a greater appreciation for the advantages and disadvantages within the range of available techniques and the potential for matching technique with context in a given instance and (b) to present a more complete view of the linkages among techniques and the scope for hybrid approaches. Coverage includes some new, emerging approaches, including the combination of an activity-based model with equilibrium treatments for both land use and network assignment. Therefore, the paper provides the framework for a discussion of the opportunities and challenges arising with the implementation of activity-based models and transportation system models more generally, helping progress beyond the standard positions taken in the debate about equilibrium versus process simulation and aiding the consideration of appropriate directions for further research and development work.

A standard view in transportation system modeling—almost a central tenet in the orthodoxy—is that two basic types of modeling approach are available: equilibrium and process simulation.

With the equilibrium approach, a particular state of the system with certain properties is identified, a calculation process is used to bring (iteratively) the system to this state (sometimes called the equilibrium solution), and then other aspects of the system at this state are examined and perhaps compared with what they are at that same state under other conditions. The standard four-step modeling system (with feedbacks) uses the equilibrium approach.

With the process simulation approach, an explicit reproduction of certain elements of the behavior of the system is developed, including representation of the separate actions and reactions involved (often involving a direct representation of behavior through time). A calculation process is used to work through the sequence of combined actions that arise under specific initial conditions. Aspects of the system through this sequence are examined and perhaps compared with what they are through the same sort of sequence under other starting conditions. The activity-based approach and the latest in traffic microsimulation modeling use this approach. Each approach has advantages and disadvantages.

EQUILIBRIUM VERSUS PROCESS SIMULATION

For the equilibrium approach,

- A well-defined system state is considered that is at least identifiable and in many cases unique, allowing re-identification and reexamination;

- The solution point can have certain properties that allow theoretical extensions or reinterpretation of results, such as socially desirable allocations of resources in welfare economics analysis, pricing strategies and second-best approaches, non-Walresian or reduced assumptions, contestable markets, and the property that all used paths have the same minimum cost with transport networks in certain forms of equilibrium;
- The solution point can have certain properties that make it relatively easy (or quick) to find (such as with the Frank–Wolfe algorithm);
- The defined equilibrium state generally does not exist in reality for most systems of interest, except with more generalized and extended (perhaps sometimes even tortured) definitions of equilibrium, such as spatially or temporally dynamic equilibrium that may also give up something related to the benefits of the properties already listed, including the potential instability and nonuniqueness of equilibrium points; and
- Failure to reach the defined equilibrium point within a sufficient tolerance can lead to difficulties when results are being interpreted, particularly when results are being compared for different input conditions, leading to the potential for large calculation burdens such that iteration “recipes” are a poor compromise.

For the process simulation approach,

- It provides a more direct match with actual system mechanics;
- It generally can draw on a wider range of understanding and appreciation of the elements of behavior involved;
- It does not require the definition of an equilibrium state or even rely on the concept of equilibrium;
- It incorporates path dependencies that complicate understanding and evaluation;
- It can display emergent aggregate behavior, leading to a greater appreciation of system dynamics;
- It typically involves random elements in its calculation processes (by using Monte Carlo techniques) with the implication that the calculated output values also have random components (sometimes called simulation error or microsimulation error) with distributions that vary with level of aggregation and often are not well understood; and
- The calculation of expectations for outputs in general requires multiple simulation runs, leading to the potential for large calculation burdens.

These two approaches have their proponents, and the debates that arise about the approaches’ relative merits can sometimes be heated. This is hardly surprising, as these two approaches arise from different viewpoints, and the strength and even the relevance of the advan-

tages and disadvantages vary according to theoretical perspective and modeling context more generally. In essence, the equilibrium approach facilitates a more wide-ranging theoretical consideration of the cross-sectional tendencies of the system, whereas the process simulation approach allows a more empirical exploration of the actual dynamic behavior of the system.

Two common misconceptions (among many potential ones) are that

1. The iterations used in a calculation process to find the equilibrium solution in some way mimic the real-world behavior of the system, which would be the case only by coincidence, and
2. The simulation error in some way mimics the variation in system behavior even when the random elements involved in the calculation process reflect analyst uncertainty rather than variation in system behavior, which again would be the case only by coincidence.

DEGREE OF AGGREGATE CONSTRAINT AND LEVEL OF DISAGGREGATION

The equilibrium approach and the process simulation approach are two points (or perhaps regions) on a continuum of the degree of aggregate constraint on the modeling system. At one end is a complete lack of any aggregate constraints or restrictions on the system, and at the other is a full set of such constraints. Specific modeling approaches can be placed along this continuum, with the recognition of a range of levels of such constraints and even of types of equilibrium as different forms of such constraint. There is a similar continuum in relation to the level of representation of the individual behavioral agents in the system and the distributions of their interactions, from the explicit treatment of each agent as a unique object to the handling of aggregate quantities representing groups or flows of agents as specific entities.

Specific modeling approaches can be placed jointly along these two continua in a two-dimensional plane. Figure 1 shows these placements for a selection of modeling approaches.

Figure 1 also shows regions with aggregate behavior that is chaotic, emergent, or both. This representation is based on the recognition that chaotic behavior tends to arise when there are comparatively fewer agents—consistent with the idea that a larger number of individual objects with a comparatively wide distribution of responses results in a dissipation of impact that dampens the system. It is also based on the recognition that emergent aggregate behavior arises in a meaningful sense only when there are enough individual agents to allow for the interactions among the agents to develop into something beyond what they explicitly specify.

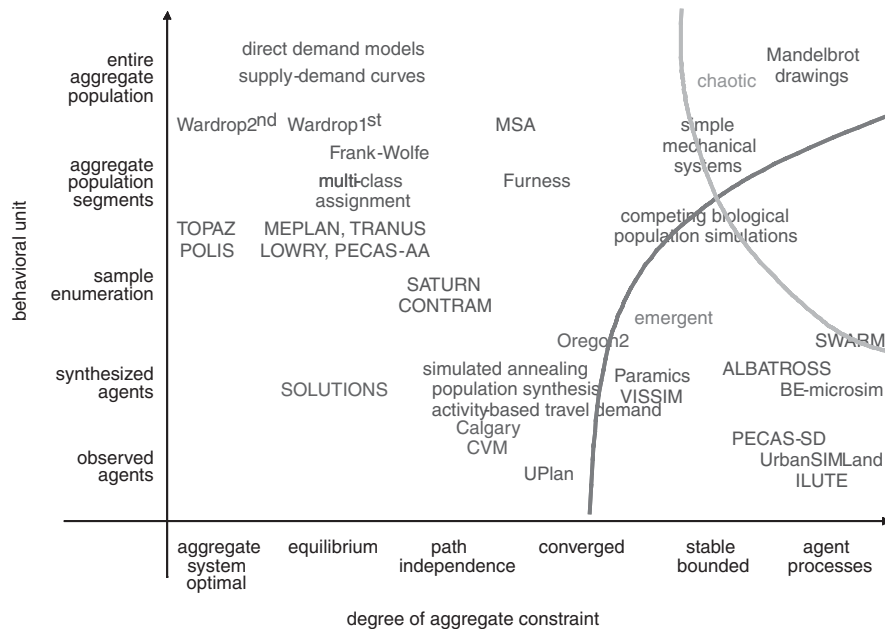


FIGURE 1 Comparison of modeling approaches for level of aggregation (i.e., behavioral unit) and degree of aggregate constraint (i.e., aggregate behavioral construct).

TAXONOMY OF TRANSPORTATION SYSTEM MODELING APPROACHES

The existing approaches in transportation system modeling tend to sit along a diagonal from upper left to lower right in Figure 1; the recent increasing use of process simulation has arisen in conjunction with a swing to greater use of explicit representation of individual agents. Clearly, the ability to handle systems with large numbers of interacting agents (with the advent of increasing computing capabilities) has led to more attempts at explicit representation of the behavioral processes involved at the individual level. It appears that more and more analysts—at least implicitly—are taking the view that enough is known about the nature of individual agents' behavior (possibly in part because these analysts are such agents themselves in the real world and thus have insight gained by experience) to result in modeling systems that provide more accurate, or at least more faithful, representations of reality.

A range of other combinations off the diagonal are available in transportation system and related modeling. Some of these other combinations are now being explored so as to gain some of the available advantages. Examples of these other combinations are

1. Cambridge Solutions modeling system (Caruso 2005): This system uses a bid-choice framework to allocate individual households to residential locations within a particular transportation analysis zone consistent with the results of a combined land use transport model that

is equilibrium based (that uses the MEPLAN framework) to refine the search for the equilibrium solution and to explore further the aspects of this equilibrium solution at the level of individual households. A detailed resolution is provided without giving up desirable equilibrium properties.

2. Calgary commercial vehicle movement model (Stefan et al. 2005): This model uses a tour-based microsimulation framework with Monte Carlo simulation in which logit choice models provide the sampling distributions to simulate the movements of commercial vehicles in the delivery of goods and services. It runs in combination with an equilibrium-based model of household travel demands. Trip tables from multiple runs of the commercial movement model are averaged to obtain a trip table of expected movements, and this table is combined with trip tables from the household demands model and then assigned to road networks by means of techniques for stochastic user equilibrium. The resulting congested travel times are fed back to both the household demands model and the commercial vehicle movements model in an iterative process that runs to a convergence. A converged system is obtained with a household demands model at equilibrium and a process simulation tour-based microsimulation representation of commercial vehicle movements.

3. Oregon2 integrated land use transport model (Hunt et al. 2001): This model includes a spatially disaggregated input-output model that is based on equilibrium to represent industrial and government activity, process-oriented microsimulations of household demo-

graphics, travel activities (activity-based), and land development activity. The interface between these occurs at the represented markets, where elasticities in both the provision of labor by workers and the use of developed space by activities allow for consistent market clearing.

The situation with activity-based models is likely to warrant similar combined treatments in some instances in which an assignment process is used to identify an equilibrium state between supply and demand for the network. Expectations of the quantities of household travel demand are the quantities being loaded to the network, with those developed by use of a component of the activity-based model run multiple times within each iteration of the assignment process. Through use of the definitions established earlier, such a combined treatment would constitute less of a process simulation and more of a disaggregation of the household demand side of the network equilibrium. To date, there has been little in the literature about the issues arising with such a combined treatment; at least, it should be acknowledged that there is still a reliance on the concept of equilibrium when an activity-based model is being used in this way.

In this light, the debate over equilibrium versus process simulation seems misdirected, and effort should be focused on establishing how to gain the possible benefits of each and how to use the two in combination most appropriately.

CONCLUSIONS

In model systems, the level of disaggregation and the degree of aggregate constraint are two separable characteristics. Separation of the two is useful when one considers the properties of these systems, as it can help in the understanding of the model system dynamics and in the identification of alternative, more suitable modeling approaches and the aspects of the solutions provided by these approaches.

Much of the practical work in transportation system modeling tends to sit very broadly along a diagonal in these two dimensions that runs from the combination of aggregate and equilibrium to that of disaggregate and process simulation. A range of other approaches, including some more-novel ones that sit off this diagonal, is also available, as are examples of their use in practical work. One such example is the Cambridge Solutions model system, in which an equilibrium approach is used in combination with a representation of individual agents at the disaggregate level.

The practical implementation of model systems that use combinations of process simulation and equilibrium techniques now under way is being guided largely by intuition and some potentially relevant previous experi-

ence. Little is understood from a more general theoretical perspective. Some more generalized theoretical research is required so as to consider the issues involved, including these:

- The uniqueness of converged solutions,
- The extent to which equilibrium properties apply,
- The possible combinations and variations in techniques and the advantages and disadvantages arising with each,
- The relevant attributes to use in the definitions of the relevant categories properties, and
- The potential linkages among the “strange attractors” in chaotic systems.

The results of this more generalized theoretical research then need to be converted into appropriate guidance for practical modeling work. Practice is moving ahead with activity-based modeling (although perhaps not as fast as some would like), and theory needs to catch up. The definitions provided here, and the resulting taxonomy for sorting model systems along relevant dimensions, is intended as a starting point for such an examination.

The issue of the degree of aggregate constraint on the model system needs to be taken into account more completely in much of the current practical work that is using activity-based models. The focus in such work often seems to be the complexity of the representation of the behavior of the individual agents. Certainly, this aspect of the model is important. But the behavior of the model system in relation to the degree of aggregate constraint is equally important. Practice is moving ahead with activity-based modeling (although perhaps not as fast as some would like), and theory needs to catch up and provide some important support.

The region definitions presented here along the two dimensions are intended to illustrate the range and potential resolution of model system properties. While it has been judged that they provide mutually exclusive and collectively exhaustive coverage, they are not intended to be the final, authoritative definitions. It certainly may be the case that somewhat different groupings and distinctions would be more appropriate in a given instance, and thus it would make sense to modify the ones presented here.

REFERENCES

- Caruso, G. 2005. *SOLUTIONS Micro-Scale Modeling: Method and Initial Results*. Draft Working Paper. Martin Centre for Land Use and Built Form Studies, University of Cambridge, United Kingdom. www.suburbansolutions.ac.uk.

Hunt, J. D., R. R. Donnelly, J. E. Abraham, C. Batten, J. Freedman, J. Hicks, P. J. Costinett, and W. J. Upton. 2001. Design of a Statewide Land Use Transport Interaction Model for Oregon. *Proc., 9th World Conference for Transport Research* (CD-ROM), Seoul, South Korea, July.

Stefan, K. J., J. D. P. McMillan, and J. D. Hunt. 2005. Urban Commercial Vehicle Movement Model for Calgary, Alberta, Canada. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1921, Transportation Research Board of the National Academies, Washington, D.C., pp. 1–10.

BREAKOUT SESSION
TOUR-BASED MODELS

Design Features of Activity-Based Microsimulation Models for U.S. Metropolitan Planning Organizations

A Summary

Mark Bradley, *Mark Bradley Research and Consulting*
John L. Bowman, *Bowman Research and Consulting*

This paper provides a concise summary of important design features of various activity-based model systems that have been implemented or have recently been designed for planning agencies in the United States. The models described are for Portland, Oregon; San Francisco, California; New York; Columbus, Ohio; Atlanta, Georgia; Sacramento, California; the Bay Area of California; and Denver, Colorado. These models were selected because they are in the same family of activity-based models, and one or both of the authors have been involved in the design of all of them except for New York. Two other examples have also been included in the summary table and supplementary text of activity-based models in the United States: the CEMDAP model for Dallas, Texas, and the FAMOS model for southeast Florida (see sidebars, pages 14 and 17). Not included is the TRANSIMS model or the TLUMIP model for Oregon. Although those models share some of the features discussed here, the authors are not sufficiently familiar with them to compare them at the level of detail included here; that, however, could be a useful extension of this paper. All model systems described in this paper share a similar overall structure, with a hierarchy of levels from top to bottom, with the lower choices predicted conditionally on higher-level choices. The levels are

- Population synthesis: geographic allocation of households;
- Longer-term decisions: auto ownership and (in some cases) work and school locations;
- Person-household day level: number of tours and activities made for various purposes;

- Tour level: main destination and mode, begin and end times, and number of stops; and
- Trip level: intermediate stop location and the mode and departure time of each trip.

Within this structure, several important design features distinguish the models, and these are summarized in Table 1. The models are listed in the table roughly chronologically, with the earliest ones on the left and the later ones on the right. At the time of writing, the Bay Area Metropolitan Transit Commission (in California) and the Denver (Colorado) Regional Council of Governments models are in the design stage; therefore, the design characteristics shown for these models are those currently envisioned. Each following paragraph is a more detailed annotation of a row in the comparison table.

CONTROLS AND CATEGORIES FOR POPULATION SYNTHESIS

All model systems simulate persons one by one and require a representative sample of households and persons for the base year and forecast years. All regions use zone-level data and forecasts of household size and income as control variables for sampling households from the regional Public Use Microdata Samples households. In addition, most regions have used the number of workers in the household as a third control variable, both because it is important

TABLE 1 Comparison of Design Features of Various Activity-Based Model Systems

Model Design Feature	Portland METRO	San Francisco SFCTA	New York NYMTC	Columbus MORPC
Controls and no. of categories for population synthesis	4 household sizes, 4 incomes, and 4 ages	4 household sizes, 3 no. of workers, 4 incomes, and 3 ages	5 household sizes, 4 no. of workers, and 4 incomes	5 household sizes, 4 no. of workers, and 4 incomes
“Usual” work and school locations at top level?	No–yes	Yes	No	No
Number of out-of-home activity purposes	3 / 8	3	4	7
Number of in-home activity purposes	3	1	1	1
Day pattern type linked explicitly across HH?	No	No	No	Yes, sequential
Joint activities linked explicitly across HH?	No	No	No	Yes
Allocated HH activities allocated explicitly?	No	No	No	Yes
“Escort” trips linked explicitly across HH?	No	No	No	No
Level where stop purpose and frequency modeled	Person-day	Person-day	Tour	Tour
Network zones used (approx.)	1,250	1,900	6,000	2,000
Smaller spatial units used below zones?	No–yes, 20K blocks	No	No	No
Mode and destination model estimation	Simultaneous	Sequential	Sequential	Sequential
Network time periods per day	5	5	4	5
Modeled time periods	5 per day	5 per day	4 per day	1 hour
Use of time window duration in scheduling?	No	No	No	Yes
Tour time of day relative to mode and destination	Above both	Above both	Between them	Between them
Departure time modeled separately at trip level?	No	No (may be added)	No	No
Accessibility measures in upper level models	Person-specific mode–destination logsums	Jobs reached by zone–mode–time band	Destination choice logsums by zone–mode–segment	Destination choice logsums by zone–mode–segment

^a These model systems are currently in the design phase. HH = households.

behaviorally and because Census Transportation Planning Package Table 1-75 provides a useful three-way joint distribution of household size, number of workers, and income for 2000. The Portland Metro and San Francisco County Transportation Authority models have also used age of head of household as a control variable, and the Atlanta Regional Commission, the Bay Area (California), and Denver are all considering using age or age-related variables as well (e.g., presence of children, senior citizens, or both). The sample-generation software created for Atlanta has a flexible system for designating and combining control variables, as well as facilities for testing how well the synthetic population matches other variables for which there has not been explicit control. An important test will be how well the age distribution is matched when age is not one of the explicit control variables.

“USUAL” WORK AND SCHOOL LOCATIONS MODELED AT TOP LEVEL

The research community recognizes that the choices of where to work and go to school are longer-term decisions that are not adjusted day to day, similar to the choice of residence (which is implicitly modeled in the synthetic sample). In most models, and all the more recent ones, the “usual” work and school places are modeled at the top level, meaning that these are predicted before any choices specific to the travel day are predicted. The home location is typically one of the alternatives in the choice set for people whose main workplace is at home or who are homeschooled. Certain types of individuals, such as construction workers or traveling salespeople, may not have a usual workplace. And this model formulation requires that data be collected on each worker’s most frequent work location, even if that person does not visit

Atlanta ARC	Sacramento SACOG	Bay Area MTC ^a	Denver DRCOG ^a	Dallas CEMDAP	SE Florida FAMOS
100+ combination of h'hold size, no. of workers, income, and age	4 household sizes, 4 no. of workers, 4 incomes	4 household sizes, 4 no. of workers, 4 incomes, age (?)	4 household sizes, 3 no. of workers, 4 incomes, age (?)	6 h'hold types, 7 h'hold sizes, 2 children, 2 genders, 7 races, 10 ages	4 household sizes, 2 dwelling unit types, 4 vehicle ownerships, 6 ages
Yes	Yes	Yes	Yes	Yes	Yes
8	7	7 or 8	7 or 8	11 for adults, 3 for children	6
1	1	1 or 2	1	1	2
Yes, simultaneous	No	Yes, simultaneous	No	Yes, sequential	Yes, sequential
Yes	No	Yes	No	Yes (between parent and child)	Yes
Yes	No	No	No	Yes	Yes
No	No	No	No	Yes	Yes
Tour 2,500	Person-day and tour 1,300	Person-day and tour 1,600	Person-day and tour 2,800	Person-day and tour 4,800	Person-day and tour 3,000
No	Yes, 700K parcels	Transit accessibility subzones (?)	Yes, buildings	No	No
Sequential	Sequential	Sequential	Simultaneous for nonwork	Sequential	Simultaneous
4	4	5	10	5	3
1 hour	30 min	30 min (?)	30 min	Continuous time, 1 min	Continuous time, 1 min
Yes	Yes	Yes	Yes	Yes	Yes, time-space prisms
Between them	Between them	Between them	Above both for nonwork	Between them	Above both
Yes, lowest model	Yes, lowest model	Yes, lowest model	Yes, lowest model	Yes, before stop-location	Yes, lowest model
Destination choice logsums by zone-mode-segment	Mode and destination logsums by zone-segment	Mode and destination logsums by zone-segment	Mode and destination logsums by zone-segment	In person-level activity generation models: Hansen-type measure	Time-space prism accessibility; mode-destination logsums

that location on the survey diary days. The destination for any particular work tour will most often be the usual work location but may be another location instead (a business meeting, for example), and that choice is modeled accordingly at the tour level. School tours nearly always go to the usual school location, so a separate school tour destination model may not be needed. In the future, it would be ideal for the population synthesis and longer-term models to be replaced by a dynamic, integrated land-use model that includes joint prediction of residential and workplace (re)location decisions.

NUMBER OF OUT-OF-HOME ACTIVITY PURPOSES

The simplest purpose segmentations are in the first version of the Portland model, with three purposes

(work-school, maintenance, and discretionary), and in San Francisco, also with three purposes (work, school, and other). Most other model systems have included at least seven activity purposes: work, school, escort (serving a passenger), shopping, meals, personal business (or other maintenance), and social-recreation (or other discretionary). In some cases, social visit has been separated from recreation. The main reasons for splitting out the meal activity are that it tends to be done at certain types of locations and that it has very specific time-of-day and duration characteristics. The escort activity also tends to be to specific locations at specific times for driving children to or from school. In tour-based models, there is no need to treat nonhome trips as if they are separate purposes, although all the systems have separate tour-level models for work-based tours (often called subtours because they are tours within tours). In most model systems, the division of the school purpose into university,

K to 12, and preschool is made in the lower-level models on the basis of the age and enrollment type of the particular person in the sample.

NUMBER OF IN-HOME ACTIVITY PURPOSES

In the Portland models, in-home activities are distinguished on three purposes (work–school, maintenance, and discretionary), but this distinction is made only for the primary activity of the day and is predicted only when the person has no out-of-home activities. This distinction did not appear to add substantially to the

explanatory value of the models. That information, coupled with the fact that most survey respondents are reluctant to provide much detail about their in-home activities, explains why none of the other models distinguishes between types of in-home activities. Some of the models predict which people work primarily at home: that provides some substitution between in-home and out-of-home work. It does not, however, handle the phenomenon of part-time telecommuting, which is the focus of some transportation demand management policies. As a result, there is some interest in predicting work at home as a separate activity type in the Bay Area model if the data will support it.

Brief Description of CEMDAP Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns

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The synthetic population generator (SPG) in Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) uses census tract–block group–block level summary tables as control totals for synthesizing households and individuals from the 2000 5% Public Use Microdata Samples (PUMS) data. Some of the summary tables contain the distribution of a single variable, while other tables describe the joint distribution of multiple variables. These tables are used to construct a full multiway distribution by using a recursive merge procedure and the iterative proportional-fitting procedure. The SPG allows the user to specify the choice of control variables from a wide range of census variables at run time.

Currently, for the Dallas–Fort Worth (DFW) application, four household-level variables and three individual-level variables, are used as controls. The household-level variables are household type (six categories), household size (seven categories), presence of children (two categories), and age of householder (two categories). The individual-level variables are gender (two categories), race (seven categories), and age (10 categories). All other variables in the PUMS data that are required for the activity travel pattern simulator, but not controlled during the population synthesis, are not directly used. Instead, their values are simu-

lated on the basis of a suite of models estimated by using PUMS and other sources of data.

SCHOOL AND WORK LOCATIONS

The “usual” school and work locations are modeled at the “top” level. Every work location zone is considered as an alternative in the choice set (i.e., to avoid large prediction bias, the work location model is not applied to just a sample of zones). However, home location zone, adjacent location zone, and central business district zones are given higher preference in the utility functions. In addition to modeling the “fixed” school and work locations at the top level, work-related activity (business meeting, etc.) destination choice models are implemented at the activity stop level.

OUT-OF-HOME AND IN-HOME ACTIVITIES

CEMDAP application for the DFW area includes 11 out-of-home activity types for adults (work, school, work-related, drop-off at school, pickup from school, joint discretionary activity with children, grocery

DAY-PATTERN TYPE LINKED EXPLICITLY ACROSS HOUSEHOLD MEMBERS

This and the following three sections are concerned with the modeling of explicit linkages between the predicted activities and travel of different members of the same household. All the models treat such linkages implicitly through the use of a wide variety of person type and household composition variables, and indeed one of the main advantages of the microsimulation approach is the ability to reduce aggregation bias by including such case-specific variables. The use of explicit linkages takes that ability one step further and reduces aggregation bias

even more. One of the key linkages is fairly simple: if each person's full-day activity pattern is classified into three main types—stay at home, go to work or school, or travel for some other purpose—then strong similarities can be seen between the patterns of members of the same household, ones even stronger than the similarities that would be predicted indirectly. The Columbus model system includes a sequential model of these linkages, simulating children first and then adults conditional on what the children do. The Atlanta model system includes a similar model that is estimated simultaneously across all household members, avoiding the need to assume the order in which they are simulated and thus the direction

shopping, household and/or personal business, social-recreational, eat out, and other serve passenger activities) and three for children (school, joint discretionary activity with parent, and independent discretionary activities). CEMDAP does not distinguish between types of in-home activities.

INTRAHOUSEHOLD INTERACTIONS AND EXPLICIT ALLOCATION OF ACTIVITIES

In CEMDAP, the activity generation and allocation decisions are simulated in the following three sequential steps: (a) the generation of work and school activity participation, (b) the generation of children's travel needs and explicit allocation of escort responsibilities to one of the parents, and (c) the generation of independent activities for personal and household needs.

Linkage of joint activities, travel, or both is implemented between parents and children (in single-parent and nuclear-family households) in two ways: drop off at or pick up from school and joint discretionary activities. Due to data limitations, the nature of these interactions is currently restrictive. For instance, CEMDAP does not consider the case of one of the parents dropping off or picking up multiple school children at multiple locations. There is also an "other serve-passenger" activity type recognized in CEMDAP, but the activity-travel pattern linkage across household members is not now explicitly implemented for this activity type because of lack of data.

The grocery shopping activity is modeled to be generated at the household level and is allocated to one of the adults. Joint participation of adults in activities is currently not considered because of lack of good data to estimate these models in the Dallas-Fort Worth, Texas, area.

LEVEL AT WHICH INTERMEDIATE STOP PURPOSE AND FREQUENCY ARE MODELED

Activity travel patterns are modeled separately for workers (adults who go to school or work on travel day) and nonworkers (adults who neither go to work nor attend school during the day). The daily pattern of workers is characterized by four subpatterns: before-work pattern, which represents the activity-travel undertaken before leaving home to work; commute pattern, which represents the activity-travel pursued during the home-to-work and work-to-home commutes; work-based pattern, which includes all activity and travel undertaken from work; and after-work pattern, which comprises the activity and travel behavior of individuals after arriving home at the end of the work-to-home commute. Within each of the before-work, work-based, and after-work patterns, there might be several tours. Each tour, the home-to-work commute, and the work-to-home commute may include several activity stops. In the case of nonworkers, the activity-travel pattern is considered as a set of tours, each of them comprising a sequence of out-of-home activity stops.

The number of tours is predicted at the subpattern level for workers (pattern level for nonworkers), while the tour mode and the stop frequency are predicted at the tour level. The activity purpose, activity duration, home stay-work stay duration before the activity, travel time to the activity stop, and destination are predicted for each of the individual activity stops. In essence, the stop purpose is modeled at the stop level, and the stop frequency is modeled at the tour level. The purpose and frequency of stops are modeled conditional on a higher-level choice of each person to undertake activities of various types (activity generation models).

(continued on next page)

of causality. A similar model is planned for the Bay Area system.

JOINT ACTIVITIES LINKED EXPLICITLY ACROSS HOUSEHOLD MEMBERS

Joint activities are those in which two or more household members travel together to and from an activity location

and participate in the same activity while at that location. In the lower-level models, such as mode and destination choice, it is best to model such cases as a single joint decision rather than as independent decisions made by different people. The Columbus and Atlanta model systems include models of household joint-activity generation and participation. The application of the Columbus model has shown that predicting joint travel can have significant implications for mode choice, so this type of model has

BRIEF DESCRIPTION OF CEMDAP

(continued from page 15)

TIME OF DAY, MODE, AND DESTINATION CHOICE MODELING SEQUENCE

The work and school locations are predicted at the top level, while the work start and end times and work commute mode choice are modeled in sequence at the travel day level. The school start and end times are also predicted before the to- and from-school mode choice models. For all other activities, the tour mode is predicted at the tour level, followed by predicting the time of day and then the destination choice at the activity stop level. The departure time is derived from the predicted home stay-work stay duration before each tour, activity duration at—and travel time to—each stop.

NETWORK FEATURES, LEVEL OF SERVICE VARIABLES, AND MODELED TIME PERIODS

CEMDAP can be used with any level of spatial resolution of zones and any number of time periods for level-of-service (LOS) variables. The DFW application uses a system of 4,784 traffic analysis zones for spatial representation and five time-of-day periods (a.m. off peak, a.m. peak, midday off peak, p.m. peak, and p.m. off peak) for LOS characteristics. No finer spatial units are used for land use variables.

The effect of time-varying LOS characteristics is considered directly in work scheduling and indirectly in activity generation models through accessibility measures. The LOS attributes are also used in models of commute mode choice and nonwork-activity stop-location choice.

Any time-of-day feature in CEMDAP is predicted in continuous time. The simultaneous prediction of work

start and end times is currently implemented at 30-min periods, but it can be implemented at any finer time intervals. The school start and end times are predicted in continuous time by using hazard-based duration models. The departure time for all other activities is also scheduled in continuous time. Available time windows are used in both the worker and nonworker scheduling models at the subpattern, tour, and stop levels.

ACCESSIBILITY MEASURES

Measures of accessibility from the home zone are used in activity generation models. The accessibility of a zone to another zone is calculated as the ratio of an attraction measure in the other zone relative to an impedance measure between the two zones (which is a function of travel times and costs). The parameters of these attraction and impedance functions were predetermined from a destination choice model. The overall accessibility of a zone is then calculated as the average of the zone-to-zone accessibility measures.

REFERENCES

- Bhat, C. R., J. Y. Guo, S. Srinivasan, and A. Sivakumar. Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1894, Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 57–66.
- Guo, J. Y., S. Srinivasan, N. Eluru, A. Pinjari, R. Copperman, and C. R. Bhat. *Activity-Based Travel-Demand Analysis for Metropolitan Areas in Texas: CEMSELTS Model Estimations and Prediction Procedures, 4,874 Zone System CEMDAP Model Estimations and Procedures, and the SPG Software Details*. Report 4080-7. Texas Department of Transportation, Oct. 2005. www.ce.utexas.edu/prof/bhat/REPORTS/4080_7.pdf.

been recommended for the Bay Area. However, in a wider sense, the final decision has not been made on the extent to which the additional accuracy of explicitly modeling household interactions will merit additional complexity. For that reason, such models will not be included in the Denver system, at least in the initial version.

ESCORT TRIPS LINKED EXPLICITLY ACROSS HOUSEHOLD MEMBERS

Another type of joint travel, known as an escort trip, occurs when two or more household members travel together to or from (or both to and from) an activity location but do not participate in the same activity there. The most common example is a parent driving a child to school and then either returning home (an escort tour) or else driving on to work (an escort stop on a work tour). Because these types of tours are partly joint and partly independent, it can be very complex to link them explicitly across persons. For that reason, explicit modeling of escort linkages has not been done in any of the applied models or recommended for the models under design. Most of the models, however, do include a separate escort purpose, so that the most important special characteristics can be captured—particularly the fact that the mode is nearly always by automobile, with the exception

of infrequent cases of walk escort. Furthermore, children's school locations can easily be included as special alternatives in the parents' escort tour destination choice sets, so that at least the location is accurate, even if the exact trip timing and car occupancy are not matched.

ALLOCATED ACTIVITIES DIVIDED EXPLICITLY AMONG HOUSEHOLD MEMBERS

Certain types of activities, such as grocery shopping, escorting, and some other maintenance chores, are likely to be allocated across individuals in a household, showing a negative correlation across frequencies within a household day. The Columbus and Atlanta model systems include explicit models of the generation of these activities at the household level and then allocation to particular individuals. In the Atlanta case, this model was estimated jointly with the model for household joint travel generation. Compared with explicitly linking people who make joint tours together, predicting which people within a household perform allocated activities appears less important to the model results: nothing fundamental about the tours is being changed, only which person makes them. So, in relation to the tradeoff between accuracy and complexity, these models seem less crucial than the joint travel models, and thus they

Brief Note on FAMOS Florida Activity Mobility Simulator

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The Florida Activity Mobility Simulator (FAMOS) was completed in 2004 with a full-fledged development and application in southeast Florida. Since that time, work has progressed to reengineer FAMOS and integrate it with the land use model UrbanSim in conjunction with an ongoing 3-year EPA project. Table 1 (page 12) compares model features of FAMOS and various models from other locations throughout the United States.

REFERENCES

Pendyala, R.M. *Phased Implementation of a Multimodal Activity-Based Travel Demand Modeling System*

in Florida. Final Report, Volume II: FAMOS Users Guide. Research Center, Florida Department of Transportation, Tallahassee, 2004. www.eng.usf.edu/~pendyala/publications/report/FAMOS%20Users%20Guide.pdf.

Pendyala, R. M., R. Kitamura, A. Kikuchi, T. Yamamoto, and S. Fujii. FAMOS: The Florida Activity Mobility Simulator. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1921*, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 123–130.

have not been recommended for the Bay Area models. In addition, the limited number of activity categories offered in most surveys makes it rather difficult to determine which activities are most likely to be allocated. For example, grocery shopping is mainly an allocated activity, while shopping for a good book is an individual activity, but both are usually coded the same.

LEVEL AT WHICH INTERMEDIATE-STOP PURPOSE AND FREQUENCY ARE MODELED

When the models in an activity-based system are ordered from top to bottom, it is not always clear which decisions should be modeled conditionally on which other decisions. A prime example is the generation of intermediate stops made during tours. Are activities planned and combined into trip chains when a person is planning a day (in which case the mode, timing, and location of the tours may depend on which stops they contain)? Or, conversely, do people make tours and then decide during the tour how often and where to make stops, depending on their mode and location? Clearly, both of these situations describe real behavior, and which description is more accurate depends on the particular person and the types of activities they are carrying out. The Portland and San Francisco models follow closely the original Bowman and Ben-Akiva day-pattern approach, in which the number and purpose of any intermediate stops are predicted at the person-day level before any particular tours are simulated. In contrast, the Columbus, New York, and Atlanta models predict only the number and purpose of tours at the person-day level, and then the number and purpose of intermediate stops on any particular tour are predicted at the tour level once the tour destination, time of day, and main mode are known. In the Sacramento models, an intermediate approach is used. Some information about stop-making is predicted at the person-day level, predicting whether or not any intermediate stops are made for each activity purpose during the day (seven yes–no variables). These are predicted jointly with the choice of whether or not to make any tours for each of the activity purposes (seven more yes–no variables), thus capturing some substitution effects between the number of tours and the number of trips per tour. Then, when each tour is simulated, the exact number and purpose of stops on each tour are predicted conditional on both the mode and destination of that tour and the types of stops that still need to be simulated to fulfill the person-day level prediction. There is no obvious behavioral reason for this structure other than that it balances the model sensitivities between the two types of behavior described earlier. A similar approach is planned for Denver and recommended for the Bay Area.

NUMBER OF NETWORK ZONES USED

This and the next two sections discuss spatial aspects of the model systems. In all cases, the zone system for model development and application is the same as that used for trip-based models. The automobile and transit networks and assignments are also the same as those in the trip-based models. This fact has facilitated the transition to activity-based models, but at the same time, the microsimulation framework can also be used with more detailed spatial systems and would support more accurate traffic simulation methods as well.

SMALLER SPATIAL UNITS USED BELOW ZONES

Because the microsimulation framework is not tied as strongly to zone definitions, it is possible to use the zones only to provide the level-of-service variables for roads and transit paths, while variables related to land use, parking, and walk access (which do not need to be stored as matrices) can be specified at a finer level. The Portland model uses such an approach for roughly 20,000 “blocks,” while the Sacramento models use over 700,000 parcels. The Denver metropolitan planning organization is also planning to predict demand at the parcel or building level by means of a model framework for two-stage destination choice. An intermediate approach, which has been recommended for the Bay Area models, is to divide zones with heterogeneous transit and walk accessibilities into more homogeneous subzones, but with assignments and skims still done at the larger zone level.

SIMULTANEOUS MODE AND DESTINATION CHOICE MODEL ESTIMATION

It has become a sort of tradition in modeling to condition mode choice upon a known destination, sometimes by using a sequential nested structure in which the mode choice log sum is used in the destination choice model. That is probably appropriate for purposes such as work and school. For purposes such as shopping, however, the choice of store may depend more upon the mode used than vice versa. Simultaneous estimation of mode and destination choices allows the modeler to test different nesting hypotheses. Such an approach was used in the Portland model and may be used in Denver as well.

NETWORK AND MODELED TIME PERIODS

Most four-step models only use two times of day—peak and off peak—and use fixed time-of-day factors. All the activity-based models contain tour time-of-day models

that allow some sensitivity of time-of-day choice to network conditions. All the models have used at least four network assignment periods: a.m. peak, midday, p.m. peak, and off peak. In some cases, free-flow conditions are assumed for the off-peak period, so no traffic assignment is needed for it. In some models, a fifth period has been added by splitting the off-peak period into early morning and evening–night. The more recent models, beginning with Columbus, use more precise time windows so as to schedule each tour and trip consistently during the day. This scheduling involves keeping track of the available time windows remaining after blocking out the time taken by each activity and associated travel. The time windows can also be used in the activity generation models. The Sacramento model and perhaps other models are moving to half-hour periods to provide even more detail. The main constraint on how small the time periods can be is the adequacy of the self-reported times in the diary survey data. There is evidence that people often round clock times to 10-, 15-, or 30-min intervals.

TOUR TIME-OF-DAY RELATIVE TO MODE AND DESTINATION CHOICE MODELS

It is not obvious whether activity and departure times should be predicted before both mode and destination choices, between them, or after both. There is some empirical evidence that shifts in time of day occur at two levels: the choice between broad periods of the day (e.g., morning, afternoon, etc.) is made fairly independently of accessibility, while smaller shifts of up to an hour or two are more sensitive to travel times and costs—the peak-spreading effect. Because all the models use broad network time periods, the tendency has been to model the choice of these periods for tours at a fairly high level above mode and destination choices (although in most cases the usual destination for work and school tours has already been predicted). In some models, time-of-day choice is predicted between the destination and mode choice levels, which allows the use of destination-specific mode choice log sums in the time-of-day model but requires that the destination choice model assumes (or stochastically selects) a specific time of day for the impedance variables.

DEPARTURE TIME CHOICE MODELED SEPARATELY AT TRIP LEVEL

Perhaps the placement of the model that predicts the choice of times for the overall tour is not as crucial if there is a separate model that predicts the departure time for each trip to the more detailed periods, conditional on the mode and origin–destination of each trip. Some

model systems include such a model as the “lowest” one in the system. It is also possible to include such a model for car trips only so as to predict the shape of the demand profile within the broader peak periods.

ACCESSIBILITY MEASURES IN UPPER-LEVEL MODELS

Last, but certainly not least, is the issue of how to include most accurately the accessibility and land use effects in the upper-level models. Calculation of full log sums across all possible nests of lower-level alternatives is clearly infeasible with so many levels of choices. The earliest Portland models came the closest to including “proper” individual-specific logsums, but the structure of that model was relatively simple and the effect on model run time severe. The San Francisco models include mode-specific measures with set boundaries, such as the number of jobs accessible within 30 min by transit. The rather arbitrary cutoff boundaries in such measures can result in unexpected sensitivities when the models are applied. The New York and Columbus models use mode-specific travel-time decay functions that approximate the log sum from a simple destination choice model. Such measures perform better but still have the problem that they are mode specific and that automobile and transit accessibility tend to be correlated, so it is difficult to estimate model parameters for both of them. A method that solves this problem and is more consistent with discrete choice theory is to approximate joint mode–destination choice logsums. However, the mode choice log sums tend to vary widely across the population, so it is best to calculate different accessibility measures for different population segments. The Sacramento models use such an approach, with aggregate accessibility logsums for each combination of seven travel purposes, four car availability segments, and three walk-to-transit access segments—as those tend to be the most important segmentation variables in the mode choice models.

REFERENCES

- Bowman, J., and M. Ben-Akiva. Activity-Based Disaggregate Travel Demand Model System with Activity Schedules. *Transportation Research A*, Vol. 35, 2001, pp. 1–28.
- Bradley, M., J. Bowman, and K. Lawton. A Comparison of Sample Enumeration and Stochastic Microsimulation for Application of Tour-Based and Activity-Based Travel Demand Models. Presented at European Transport Conference, Cambridge, United Kingdom, 1999.
- Bradley, M. A., J. L. Bowman, Y. Shiftan, K. Lawton, and M. E. Ben-Akiva. *A System of Activity-Based Models for Port-*

- land, Oregon. Travel Model Improvement Program, FHWA, U.S. Department of Transportation, 1998.
- Bradley, M., M. Outwater, N. Jonnalagadda, and E. Ruiter. Estimation of an Activity-Based Microsimulation Model for San Francisco. Presented at 80th Annual Meeting of the Transportation Research Board, Washington, D.C., 2001.
- Jonnalagadda, N., J. Freedman, W. A. Davidson, and J. D. Hunt. Development of Microsimulation Activity-Based Model for San Francisco: Destination and Mode Choice Models. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1777, TRB, National Research Council, Washington, D.C., 2001, pp. 25–35.
- Progress Report for the Year 2003: Modeling Task 2—Activity/Tour-Based Models. Regional Transportation Plan Major Update Project for the Atlanta Regional Commission*. PB Consult, New York, 2004.
- Vovsha, P., and M. Bradley. Hybrid Discrete Choice Departure-Time and Duration Model for Scheduling Travel Tours. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1894, Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 46–56.
- Vovsha, P., E. Petersen, and R. Donnelly. Microsimulation in Travel Demand Modeling: Lessons Learned from the New York Best Practice Model. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1805, Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 68–77.
- Vovsha, P., E. Petersen, and R. Donnelly. Experience, Tendencies, and New Dimensions in the Application of Activity-Based Demand Modeling Systems for Metropolitan Planning Organizations in the United States. Presented at 10th International Conference on Travel Behavior Research, Lucerne, Switzerland, 2003.
- Vovsha, P., E. Petersen, and R. Donnelly. Explicit Modeling of Joint Travel by Household Members: Statistical Evidence and Applied Approach. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1831, Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 1–10.
- Vovsha, P., E. Petersen, and R. Donnelly. Impact of Intra-household Interactions on Individual Daily Activity-Travel Patterns. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1898, Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 87–97.
- Vovsha, P., M. Bradley, and J. Bowman. Activity-Based Travel Forecasting Models in the United States: Progress Since 1995 and Prospects for the Future. Presented at EIRASS Conference on Progress in Activity-Based Analysis, Maastricht, Netherlands, 2004.

Development of New York Metropolitan Transportation Council Tour-Based Model

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The New York Metropolitan Transportation Council (NYMTC) is responsible for transportation improvement programming activities in the greater New York Metropolitan Region, including the preparation of plans that comply with the requirements of both the Intermodal Surface Transportation Efficiency Act of 1991 and the Clean Air Act Amendments of 1990. The New York model developed for NYMTC in the period 2000 to 2002 (actual modeling work period, though the data collection and network preparation stages started in 1994) is the first comprehensive multimodal model developed for the New York Metropolitan Region, which encompasses an entire 28-county, three-state region that includes portions of Connecticut and New Jersey, with a total population of 20 million residents. The NYMTC model's success has proven that the concept of a microsimulation activity- and tour-based model can be applied for a large metropolitan area with a unique level of complexity for the transportation system.

The NYMTC model structure appears in Figure 1. It has four major consecutive modules:

- Tour generation, which includes household synthesis, automobile ownership, and journey frequency choice models;
- Tour mode and destination choice, which includes premode choice, primary destination choice, entire-tour mode combination choice, stop-frequency choice, and stop-location choice;
- Time-of-day choice and preassignment processor, which includes tour time-of-day choice for outbound and inbound directions, trip mode choice, and construc-

tion of mode-specific and time-of-day period-specific trip tables; and

- Traffic and transit simulation, which is implemented by time-of-day periods.

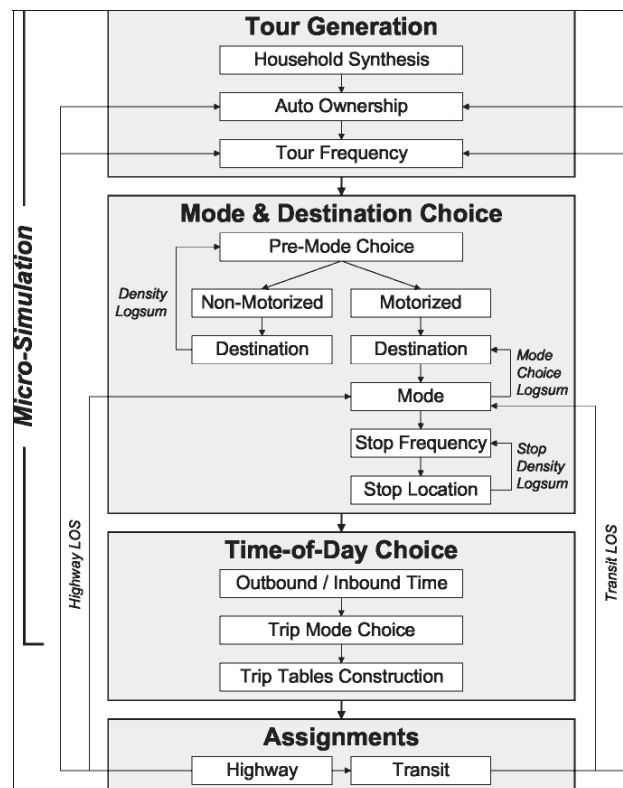


FIGURE 1 Structure of NYMTC model (New York).

The first three modules are implemented as fully disaggregate microsimulation procedures working with individual records for the synthesized population (households, persons, or tours). The last module is currently based on standard aggregate (zone-to-zone) assignment algorithms built in TransCAD. The developed software allows for numerous feedbacks to be implemented until equilibrium is reached. Level-of-service skims after the last stage can be fed back to the mode and destination modules as well as to the tour-generation components through accessibility indices.

The New York Best Practices Model has the following basic structural dimensions:

- Almost 4,000 traffic zones, and thus a full origin–destination matrix has almost 16 million cells;
- 11 travel modes (drive alone, shared ride-2, shared ride-3, shared ride-4+, transit (including bus, subway, and ferry) with walk access, transit with drive access, commuter rail (with transit feeder lines) with walk access, commuter rail with drive access, taxi, school bus (for journeys to school only), and walk (the only nonmotorized mode);
- More than 100 population slices including a combination of dimensions like three household income groups (low, medium, and high), four household car-sufficiency groups (without cars, cars less than a number of workers, cars equal to workers, cars more than workers), and three personal categories (worker, nonworking adult, child);
- Six travel purposes (work, school, university, household maintenance, discretionary activity, and non-home-based at-work sub-tours); and
- Four time-of-day periods (a.m. peak, 6:00 to 10:00; midday, 10:00 to 16:00; p.m. peak, 16:00 to 20:00; and night, 20:00 to 24:00 and 0:00 to 6:00).

The tour generation module of NYBPM consists of three successive models that include household population synthesizer, automobile-ownership model, and tour frequency choice model. The household synthesis is based on the predetermined socioeconomic controls (number of households, population, and labor force) for each zone. The automobile ownership choice model is applied for each household and is sensitive to the household characteristics and residential zone accessibility by automobile and transit, respectively. The tour-frequency model is implemented at the person level. There are three person types and six travel purposes that finally yield 13 tour frequency models; these take into account that children cannot implement journeys to work, at work, and to the university and that nonworking adults cannot implement journeys to work and at work. Each model is essentially a multinomial logit construct having three choice alternatives (no tours, one tour, two or more

tours). A set of the tour frequency models is ordered and linked in such a way that choices made for some purposes and household members have an impact on the other choices of the same person as well as those of the other household members.

The mode and destination module starts with pre-mode choice, in which each tour is assigned to either a motorized or a nonmotorized mode of travel. Density of nonmotorized attractions is essentially a log sum from the subsequent destination choice model for nonmotorized travel with individual attractions available in a 3-mi radius around the tour origin. If the motorized option is chosen, then the motorized branch of the algorithm is activated. First, the mode and primary destination choice for the entire journey is modeled (without intermediate stops). It can be thought of as a nested structure in which destination choice comes at the upper level of hierarchy while mode choice is placed at the lower level, conditional upon the destination choice.

The motorized destination choice model has been calibrated by eight purposes (six original purposes with additional subdivision of work tours by three income categories). In a microsimulation framework, the destination choice model is applied as a doubly constrained construct (either fully constrained or relaxed–constrained). Constraint of the destination ends is achieved by removing the chosen (taken) attraction from the zonal size variable after each individual journey simulation. For fully constrained mandatory purposes (work, school, and university), an entire attraction unit is removed. For relaxed–constrained nonmandatory purposes (maintenance, discretionary, and at work), only a part (0.5) of the attraction unit is removed.

The mode choice model has been calibrated by six purposes as a nested logit construct with differential nesting, depending on the purpose. In most cases, drive-alone and taxi modes proved to be in separate nests, while transit and shared-ride modes were nested in different combinations.

At the second stage of the motorized branch of the algorithm, intermediate stops are modeled conditional upon the chosen mode and primary destination for the tour. Stops are modeled by means of two linked choice models: stop frequency and stop location. The stop location model includes a zonal stop-density size variable that is similar to the attraction size variable. The composite log-sum from the stop-location model is used in the upper-level stop-frequency model.

The stop frequency model has been calibrated for six purposes as a multinomial logit construct. After observed stop frequencies from the survey were considered (it was found that an absolute majority of journeys have not more than one stop on each leg, 90% to 95% depending on the journey purpose), a decision was made to limit a number of choice alternatives to the following four:

- 1 = no stops on either outbound or inbound direction;
- 2 = one outbound stop leg, no inbound stops;
- 3 = no outbound stops, one inbound stop; and
- 4 = one stop in each direction.

The proposed stop location choice model is also a multinomial logit construct. Similar to the destination-choice model, the stop-location model requires a procedure for selecting a limited subset of relevant zones (for both model calibration and application) to reduce computational burden. In the case of the stop-location model, however, both origin and destination of the journey are known; thus, effective rules were applied to build a “spatial envelope” that reflects the observed traveler’s behavior.

The current version of the NYMTC model has a time-of-day choice model based on a set of predetermined time-of-day distributions segmented by travel purpose,

mode, and destination area. One of the ongoing works of PB Consult for further enhancement of the NYMTC model includes replacement of the time-of-day distribution with a time-of-day choice model sensitive to person, household, and level-of-service variables. Time-of-day choice is followed by trip mode choice (in most cases predetermined by the entire-tour mode) and a preassignment processing procedure that constructs mode-specific and period-specific trip tables.

In the period from 2002 to 2006, the New York model had been used by NYMTC for more than 30 local planning agencies for various projects, including environmental conformity analysis, a Tappan Zee bridge study, a Goethals bridge study, a Manhattan, New York, area pricing study, and many others. Since 2002, PB Consult has been constantly supporting NYMTC and the other users through an ongoing model support contract with NYMTC.

The San Francisco Model in Practice

Validation, Testing, and Application

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The San Francisco County Chained Activity Modeling Process (SF-CHAMP) was developed for the San Francisco County Transportation Authority (SFCTA) to provide detailed forecasts of travel demand for various planning applications (1). These applications included developing countywide plans, providing input to microsimulation modeling for corridor and project-level evaluations, transit planning, and neighborhood planning. The objective was to represent accurately the complexity of the destination and the temporal and modal options and to provide detailed information on travelers making discrete choices. These objectives led to the development of a tour-based model that uses synthesized population as the basis for decision making rather than zonal-level aggregate data sources.

Most of the tour-based model's nine components were estimated by means of household survey data for San Francisco, California, residents only that were collected by the Metropolitan Transportation Commission (MTC). Each model component was calibrated by using various observed data sources, and then the full model was validated with traffic count and transit ridership data for each of five periods. The model is applied as a focused model that combines trip making from the entire Bay Area (derived from the MTC's BAYCAST trip tables) with the travel demand from San Francisco residents produced by the tour-based model.

ORIGINAL APPROACH AND LIMITATIONS

Modeling Process

The main feature of the full-day pattern approach is that it simultaneously predicts the main components of all of

a person's travel across the day. This approach includes the frequency of five types of tours:

- Home-based work primary tours,
- Home-based education primary tours,
- Home-based other primary tours,
- Home-based secondary tours, and
- Work-based subtours.

A home-based tour includes the entire chain of trips made between leaving home and arriving back at home. The primary home-based tour is defined as the main home-based tour made during the day. If a worker makes a work tour or a student makes an education tour, then that is always the primary tour. If there are no work or education tours, the primary tour is the tour with the highest-priority activity at the destination (shopping–personal business followed by social–recreation followed by serve passenger). If there are two or more tours with the same activity priority, then the one with the longest duration of stay at the destination is the primary tour. All other home-based tours are designated as secondary tours. A special type of tour is a work-based subtour, defined as the entire chain of trips made between leaving the primary workplace and returning to that workplace in the same day. By using tours as a key unit of travel, the interdependence of different activities in a trip chain is captured. This method provides a better understanding of non-home-based trips, especially in the case of the work-based subtours that represent a significant proportion of non-home-based travel.

The study area for the model is the nine-county San Francisco Bay Area, which is represented by the MTC's regional travel demand forecasting model, BAYCAST. The study area is divided into two parts, so the San Fran-

cisco tour-based model can be used to predict travel by San Francisco County residents, while the BAYCAST model can be used to predict travel by residents from the other eight counties.

Figure 1 presents a schematic diagram of SF-CHAMP. This diagram includes the model components and data inputs for these components. A synthesized population of San Francisco residents is input into each model component to estimate choices for work location; vehicle availability; and tours and trips by time of day, destination, and mode of travel. The synthesized tours and trips are aggregated to represent flows between traffic analysis zones before traffic assignment. A separate model of visitor travel is estimated as to incorporate trips made by tourists and business travelers visiting San Francisco County. The model system also incorporates trips made by non-San Francisco residents by merging regional trip tables into the process for assignment.

Limitations of Approach

There were a few limitations of this approach that were a result of the available time and resources of the project:

- Initially, there was no onboard survey data available for validation of the mode choice model. There was a discrepancy between the U.S. Census journey-to-work data and the observed transit boarding data; this discrepancy could not be resolved without the additional onboard survey data. These onboard survey data were collected in the spring of 2006 and are being used to update the mode choice model now.
- The resources for the peak-spreading model were limited in the original project, and, as a result, a peak-spreading model was transferred from the MTC rather than estimated for San Francisco. This transfer did not produce reliable results and was not used in any planning applications. Subsequently, the FHWA funded a

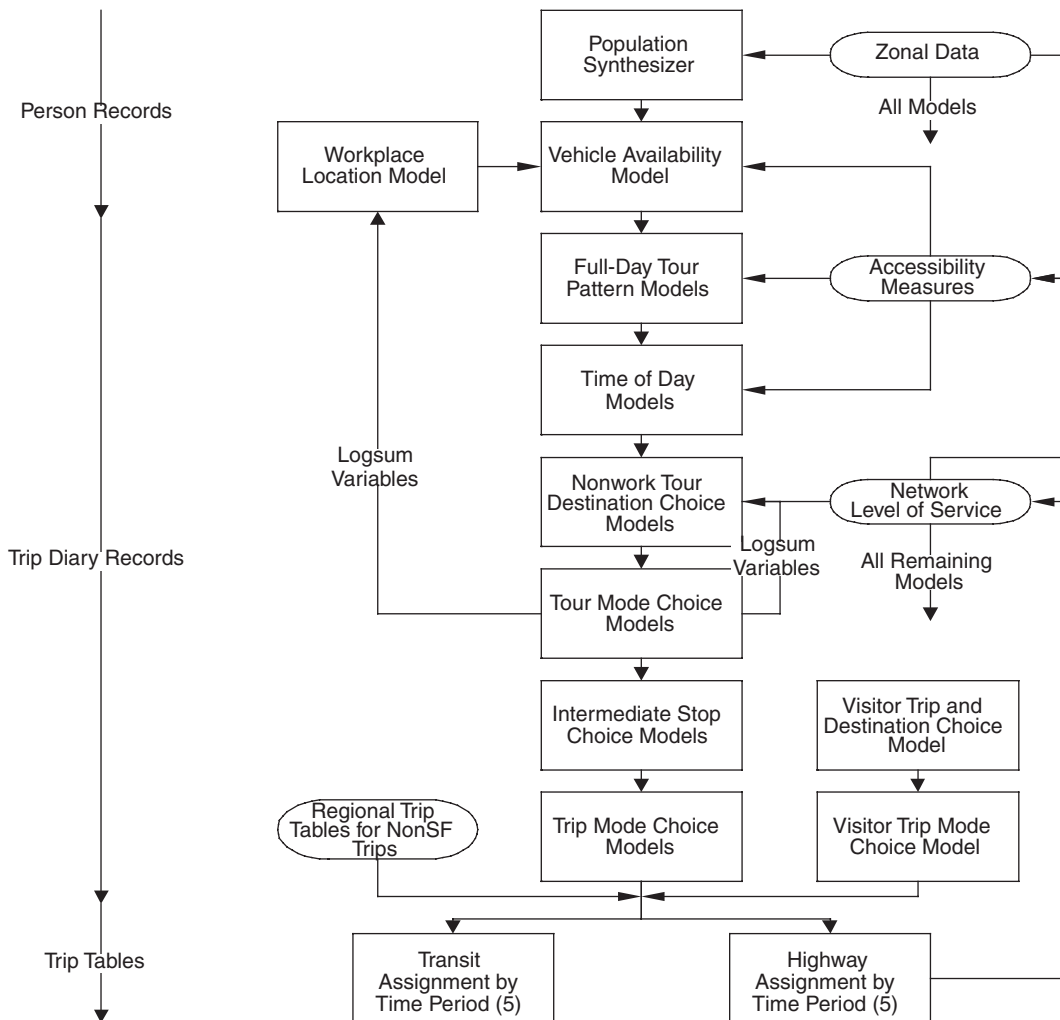


FIGURE 1 Model components.

research project on time-of-day models that included a case study of a new time-of-day model (including peak spreading) for SF-CHAMP. Plans call for this new time-of-day model to be incorporated into the model.

- The approach to trip assignment included a traditional aggregate assignment because there were too few resources in the project to implement a microsimulation assignment methodology. This approach has been used in all other tour-based model applications in the United States to date (except Transims). Nonetheless, it introduces aggregation bias and fails to take advantage of the disaggregate information on each traveler during route choice.

- SF-CHAMP combines trip tables from the MTC regional trip-based model with trips generated from the San Francisco tour-based model. As a result, only San Francisco residents are represented by the tour-based model and its advantages.

These limitations were known at the outset and accepted as lesser priorities than the core objective of building a tour-based model. In some cases, these limitations are already undergoing change in the update of the SF-CHAMP model.

There was one additional innovative aspect of the mode choice model: the inclusion of reliability and crowding as explicit variables in the transit utility functions; this aspect was tested and then not included in the final models. These variables were included in a stated-preference telephone survey of 407 transit users in San Francisco. Logit analysis was used to estimate trade-offs between in-vehicle time, frequency of service, reliability (defined as the percentage of days that the vehicle arrives five or more minutes late), and crowding (low = plenty of seats available; medium = few seats available, but plenty of room to stand; high = no seats available and standing room is crowded). It was estimated that improving the percentage of vehicles arriving on time by 10% (e.g., once every 2 weeks) is equivalent to reducing the typical wait time (half the headway) by 4 min for commuters or 3 min for noncommuters. It was also estimated that improving the level of crowding from high to low is equivalent to reducing the typical wait time by 5 min for commuters and 9 min for noncommuters. Thus, relative to commuters, noncommuters are, on average, less sensitive to delay but more sensitive to crowding. In application, the reliability and crowding was coded in the transit network by means of observed system data collected by SFCTA. The trade-offs estimated between these variables and wait time were applied in performing transit assignment and found not to be coincident with the observed boardings. As a result, these variables were not used in model application.

MODEL VALIDATION

Travel behavior was validated by comparing travel data in a household travel survey to related travel data in the travel demand forecasting model. For the validation of the current 1998 SFCTA regional travel demand forecasting model, the trip data in the 1990 Census and the 1990 MTC household survey data were compared with the same data in the model (2).

The model components were calibrated individually by using various observed data sources. This effort involved calibrating each model separately and then reviewing highway and transit assignment results for each of the five periods to make additional adjustments in the model components. The adjustments were all made to constants within the models; there were no adjustments to model coefficients. Highlights of results of the calibration are summarized below for each model component.

- **Vehicle Availability:** The vehicle availability model was calibrated primarily on two key variables—number of workers per household and superdistrict—by using the 1990 Census as the primary source of observed data. A second validation test was used to evaluate the total number of vehicles estimated by the vehicle availability model compared with Department of Motor Vehicles estimates of auto registrations. These data were different by 5%. Unfortunately, the 1990 MTC survey, which was used to estimate the model, contained different results for vehicle availability than the 1990 Census. Because the 1990 Census has a much larger sample size, these data were used to calibrate the vehicle availability model. The results, therefore, have indirect effects on the market segmentation of automobiles and workers that was carried out in the mode split model.

- **Full-Day Pattern Tour Models:** The full-day pattern tour models were calibrated by converting tours to trips and comparing these to the 1996 MTC survey expanded to match the 1998 population. The 1996 MTC survey was used because the number of trips within San Francisco County was very low in the 1990 MTC survey due to underreporting of trips. The underreporting of trips is not consistent across time periods or across trip purposes, conditions which may have influenced model estimation that was based on the 1990 MTC survey. The differences between trips by period were confirmed with initial assignments by periods with the uncalibrated San Francisco model revealing that the off-peak time periods were significantly underestimated compared with traffic counts. The vast majority of underreporting of trips in the 1990 MTC survey was in other tours.

- **Destination (Primary-and-Intermediate Stop) Choice Models:** The destination choice models were cal-

ibrated against the 1990 MTC survey data for primary destinations by purpose and distribution of trip length frequencies. The results reflect reasonable allocation of destinations among four areas of the city and those destinations located outside the city. The estimate of employment that results from the work location model compared with actual employment by neighborhood showed that results were reasonable when compared with estimated values by neighborhood. The biggest differences were the two neighborhoods in the core business district, which were underestimating employment, but calibration results also showed that the destinations in the core were within 3% for each tour type and were actually overestimated in these results. The destination choice model was also calibrated by comparing trip length and duration frequency distributions. These results showed reasonable average trip lengths and durations for all tour types. The validation of the intermediate stop choice model was challenging because similar models of destination choice had not included separate validation of the intermediate stop choice component for comparison. The results of this validation test were that both work and other tours were overestimated slightly by the model, while work-based tours were underestimated. Additional calibration adjustments to try to reconcile these differences were not pursued because further adjustments would have negatively affected the results of the highway assignments by time period.

- **Mode Choice (Tour-and-Trip) Models:** The tour-and-trip mode choice models were calibrated by tour purpose. The calibration results for tour and trip modes showed a close match between estimated and adjusted observed tours and trips by mode and purpose. Initially, estimated transit boardings were discovered to be much higher than observed boardings, particularly for local bus and Muni Metro transits; it was concluded that either the transit calibration target values generated from the household survey were too high or the observed transit boardings were low. Because the transit boardings were calculated annually by Muni, they were held constant, and both the observed and estimated transit shares were adjusted to match boardings better.

- **Trip Assignment:** There were two major modes for assignment validation: highway and transit. These were validated separately by using observed volumes of vehicles and passengers on the highway and transit systems, respectively. Assignment validation at the county level was completed by means of aggregated volumes by corridor (identified by screen lines), type of service (facility type, mode, or operator), size (volume group), and period. Speeds and travel times were also used in highway and transit validations to ensure that these were accurately represented in the models. The highway assignment results were compared for five periods and

the average daily results. All targets of highway assignment validation were met except for two screen lines and one neighborhood. For transit assignment, all modes were within 5% of the observed transit boardings. However, there were some distinct differences by time of day, with estimated bus boardings significantly greater than observed boardings in the a.m. peak period. Matching the number of a.m. bus boardings within 5% would require a 30% reduction in work transit tours compared with the observed data from the 1990 MTC household survey. An independent estimate of U.S. Census journey-to-work data indicates that the observed transit share of work tours (35%) is reasonable. Therefore, the observed work walk-transit share was held constant, causing an overestimation of a.m. period local bus trips.

COMPARISONS WITH TRIP-BASED MODEL

The comparisons of the San Francisco tour-based model with the MTC regional trip-based model showed expected differences in the base year model and some interesting differences in the forecast year model. Because the base year models were both validated to observed data sets, the authors did not see as many differences in those as in data for the future, when impacts of various forecasts showed different effects in the modeling systems.

Base Year 1998

SF-CHAMP predicted tours by type rather than trips, so a direct comparison of the home-based work trips was difficult (3). The 1996 MTC survey was used for calibration because the number of trips within San Francisco County was very low in the 1990 MTC survey (used to calibrate the MTC trip-based model) due to underreporting of trips that occurred in that survey. The underreporting of trips was not consistent across periods or across trip purposes, which may have influenced model estimation that was based on the 1990 MTC survey. Off-peak periods and work-based and other tours were all underestimated as a result.

Trip rates per household were compared by trip purpose and showed that trip rates overall were similar, but the trips per household by trip purpose were quite different. For example, the model underestimates work and school trips compared with the MTC survey, but this discrepancy can be attributed to the survey's definition of a trip to work or home as containing all trips to and from work or school. The San Francisco model differentiates between trips to work or school with an intermediate stop from those without an intermediate stop and thus

has fewer trips identified as work or school trips and many more identified as non-home-based trips.

A relative comparison for trip distribution was the summary of employment attracted to each zone as part of the work tour primary-destination choice model. This comparison required the estimation of non-San Francisco residents who work in San Francisco by zone, which, to some degree, may have biased the comparison results. Another comparison was the trip table at the district-to-district level for intracounty trips; this table showed a strong correlation in percentage distribution of trips by district between the San Francisco and MTC models but a difference in total trips due to the underestimation of trips discussed in trip generation.

Trips by mode and superdistrict showed a strong similarity between the results of the mode shares by superdistrict, which resulted from the fact that both mode choice models were developed from the same 1990 MTC travel survey data. A comparison of the vehicle trips showed there is a significant difference between the trip-based and the tour-based auto mode shares. Drive-alone trips are slightly overestimated in SF-CHAMP, and carpool trips are underestimated compared with the MTC model. A comparison with the Census Transportation Planning Package (CTPP) for trips within San Francisco showed that drive-alone trips were 89% of total vehicle trips and shared ride trips were 11% of total vehicle trips, which bore a strong correlation to the San Francisco model results.

Forecast Year 2030

MTC produced Year 2030 forecasts for its regional transportation plan. The SF-CHAMP model used the same land use projections, road improvements, and regional transit improvements as the MTC model. This consistency allowed for convenient comparison of results from the mode choice steps of each model.

The overall trip rates per household remained similar in the 2030 forecasts for both models: about 9.2 trips per household. As in the base case, for the two models, the distribution across the various trip purposes was different, due again to the impact of intermediate stops; the MTC model predicts more home-based trips, particularly work trips, and fewer non-home-based trips than the SF model. This accounting issue is well understood.

Examination of the geographic distribution of trips revealed more differences. In the base year, the San Francisco and MTC models predicted similar overall levels of trip-making among the four quadrants (defined by MTC as “superdistricts”) of San Francisco; comparison of the trip distribution patterns for the San Francisco and MTC models showed that all movements between all superdistricts varied by less than 3% on relative terms. Again, the

absolute trip-making rates were different due to trip generation issues described earlier.

When the 2030 distributions of the two models were compared, larger differences emerged. Compared with its base year forecast, SF-CHAMP showed a small reduction in intradistrict movements for all quadrants except the Sunset, the lowest-density and most suburban car-oriented part of the city. The Sunset district was the only quadrant that increased its share of trip making to and from all other quadrants, by up to four percentage points. No district-to-district movement changed by more than four percentage points when the base was compared with the 2030 forecast with SF-CHAMP.

The MTC model showed larger swings in trip distribution in a somewhat similar pattern. Again, the Sunset district showed growth, but the MTC model also predicted a relative increase in trips to downtown and an increase in intradowntown trips. These data contradicted the SF-CHAMP’s 2% reduction in trips to downtown. This finding echoed other studies that have found the gravity model used in trip-based distribution models to be quite sensitive to changes in travel time.

From the perspective of mode split, the two models behaved in similar manners in the base and future years. In both the base year and 2030, the SF-CHAMP model predicted more walk trips, fewer transit trips, and more drive trips than did MTC. The relative size and direction of these differences was about the same in both base and future years, except for walk trips.

MODEL APPLICATIONS

Equity Analysis

SFCTA developed an application of the San Francisco tour-based model to estimate impacts on mobility and accessibility for different populations so as to support development of a countywide transportation plan (4). Equity analyses based on traditional travel demand forecast models were compromised by aggregation biases and data availability limitations. Use of the disaggregate (individual person-level) San Francisco microsimulation model made it possible to estimate benefits and impacts to different communities of concern on the basis of individual characteristics such as gender, income, auto availability, and household structure.

Tenderloin Residents

A recent study of the predominantly low-income Tenderloin neighborhood took advantage of disaggregate model outputs to explore the differences between travel patterns of Tenderloin residents and other trip makers in

the neighborhood. The model suggested two interesting findings. The first was that anyone who makes trips to or from the Tenderloin, for any reason, chose walking, transit, and bicycling at greater rates than the average San Franciscan. Trips to and from the Tenderloin were about half as likely to be made by car as the average San Francisco trip.

The other interesting finding was that when non-Tenderloin residents' trips were included in the totals, car use increased. This indicated that non-Tenderloin residents who make a trip to the Tenderloin—for work, social activities, or any reason—were one-third more likely to use a car than a Tenderloin resident. This finding suggested that about one-third of the cars destined for the Tenderloin were from outside the neighborhood. The greater use of cars by non-Tenderloin residents was even greater when only work trips were analyzed. Employees who work in the Tenderloin, but live elsewhere, were more likely to drive into the Tenderloin for work. The auto mode share for all San Francisco residents with origins in the Tenderloin (35.4% for work trips) was double the automobile mode share of trips made only by Tenderloin residents (17.7%). This difference can be explained by a large number of Tenderloin workers who commuted from outlying neighborhoods by private automobile. The specific characteristics of residents versus nonresidents making trips in the neighborhood were easy to analyze because of the disaggregate nature of the SF-CHAMP outputs, which thus provided a new way of using model results to support planning project work.

New Starts

SFCTA developed an application of the San Francisco model to the proposed New Central Subway project in downtown San Francisco (5). This is the first application of a tour-based travel demand model in the United States to a major infrastructure project in support of a submission to the FTA for project funding through the New Starts program. To enable the submittal of a New Starts request, software was developed to collapse the microsimulation output of the models for tour and trip mode choice into a format compatible with the FTA SUMMIT program. SUMMIT was then successfully used to summarize and analyze user benefits accruing to the project and to prepare an acceptable New Starts submittal.

Parallel Processing

The initial implementation of the SF-CHAMP model took 36 h to run, which became a major impediment to both further model development and application. The bulk of this time was not in core microsimulation steps

but rather in the road and transit skim-building and assignment procedures. The desire to decrease random microsimulation variation (by running multiple iterations), combined with the highly granular nature of the skim-building and path-building steps, made obvious the need for a parallel structure instead of the existing top-down model process.

SFCTA devised a job control system to allow a model job to be submitted as a transaction, which would then be processed by all available machines as quickly as possible, in parallel. The most difficult aspect of this process was analyzing the dependency tree of model steps to determine which ones could be made parallel and which could not; some steps obviously required that earlier actions be complete before the steps could be made parallel. Job files were rewritten to unlink the pieces that did not depend on each other. The revised job files were passed to a new dispatcher utility program that could allocate each step to available computers and keep track of the model run progress.

The extraordinary time saving of this method was limited only by the amount of hardware available and the granularity of the model steps. In practice, full runs shortened from 36 to 9 h. The goal of an overnight run thus attained, staff added five additional core iterations to reduce error due to microsimulation variability. The model now runs in just under 12 h.

REFERENCES

1. Cambridge Systematics, Inc. *San Francisco Travel Model Development Executive Summary*. San Francisco County Transportation Authority, San Francisco, Calif., June 30, 2001.
2. Cambridge Systematics, Inc. *San Francisco Travel Model Development Report on Validation of 1998 Models*. San Francisco County Transportation Authority, San Francisco, Calif., May 7, 2001.
3. Cambridge Systematics, Inc. *San Francisco Travel Model Development Report on MTC Consistency*. San Francisco County Transportation Authority, San Francisco, Calif., May 15, 2001.
4. Castiglione, J., R. Hiatt, T. Chang, and B. Charlton. Application of Travel Demand Microsimulation Model for Equity Analysis. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1977, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 35–42.
5. Freedman, J., J. Castiglione, and B. Charlton. Analysis of New Starts Project by Using Tour-Based Model of San Francisco, California, In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1981, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 24–33.

Development of Mid-Ohio Regional Planning Commission Tour-Based Model

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In 2002, the Mid-Ohio Regional Planning Commission (MORPC) contracted with PB Consult to develop a new regional travel forecasting model. The new model is an activity and tour-based model applied with microsimulation. The development of the model was based on the 1999 Household Interview Survey, which was supplemented by the 1993 Central Ohio Transportation Authority On-Board Survey and an external cordon survey conducted in 1995. The new model system was completed in 2004.

The MORPC model incorporates most of the positive features of the other activity- and tour-based models as well as the growing body of research on activity-based modeling and microsimulation. In particular, the structure and application experience of the San Francisco County Transportation Authority model and New York Metropolitan Transportation Council model had been carefully studied before the decisions about the MORPC structure was made. When compared with its predecessors, the MORPC structure represents two significant steps toward a better and more realistic description of travel behavior:

- Explicit modeling of intrahousehold interactions and joint travel that is of crucial importance for realistic modeling of the individual decisions made in the household framework and in particular for choice of the high-occupancy vehicle as travel mode. The original concept of a full individual daily pattern that constituted a core of the previously proposed activity-based model systems has been extended in the MORPC system to incorporate various intrahousehold impacts of different household members on each other, joint participation in activities

and travel, and intrahousehold allocation mechanisms for maintenance activities.

- Enhanced temporal resolution of 1 h, with explicit tracking of available time windows for generation and scheduling of tours instead of the four or five broad time-of-day (TOD) periods applied in most of the conventional and activity-based models previously developed. The time-of-day choice model adopted for MORPC is essentially a continuous duration model transformed into a discrete choice form. The enhanced temporal resolution opens a way to control explicitly the person-time windows left after scheduling of each tour and to use the residual time window as an important explanatory variable for generation and scheduling of the subsequent tours.

At the first step, the model system generates a synthesized list of all households and population for the entire area, consistent with the household and workforce variables in the zonal data. The output from this population synthesis model is a file with a record for every person in the area (currently about 1.5 million), containing various attributes for each synthesized person. Attributes include the household to which the person belongs; whether it is a high-, medium-, or low-income household; and the type of worker or person (e.g., part-time worker, school child, university student, etc). To gain more information about a household and household composition, a record is sampled from the Public Use Microdata Sample.

Then the core set of choice models is applied for each household and person (Figure 1). It includes eight main linked-choice models. The numbering of Models 1

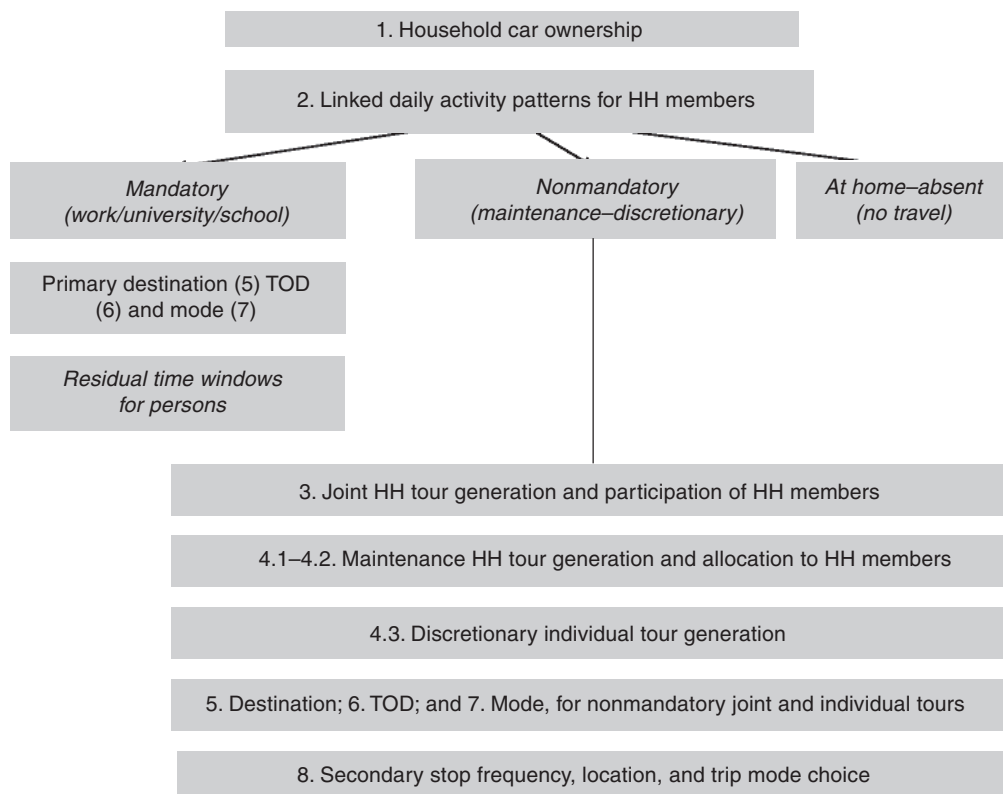


FIGURE 1 Structure of core set of MORPC models (Columbus, Ohio).

through 8 is not strictly sequential but corresponds to the meaningful blocks of which the model stream is built. Some of the models (for example, Model 6, the TOD choice model) are called twice in the procedure, first for mandatory tours (after Model 2) and second for nonmandatory tours (after Model 4). Models 5, 6, and 7 are also closely connected by sharing mode-choice log sums; thus, they are implemented together for technical convenience and computer time savings.

Model 1 is the automobile ownership model, which determines the exact number of vehicles available for each household on the basis of the household attributes and the transit accessibility level of the residence. Model 2 determines the daily activity pattern for each person. A person can either have a mandatory activity pattern, such as work or school; only nonmandatory activities, such as shopping; or no travel activity for the day. This model also determines the number of mandatory tours each person with a mandatory activity pattern makes during the day. After a mandatory tour is scheduled, the available time left for other travel opportunities is updated.

Model 3 is unique to the MORPC set of models and determines joint travel among household members. This model allows two or more members of a household to travel jointly for a shared activity, for example, eating out. Given the high propensity of household members to travel together, this model is important in that it more

accurately accounts for the characteristics of this travel, particularly in relation to mode choice. In virtually all other models in the United States, this phenomenon is not accounted for directly. Again, after joint tours are determined, the available time left for additional travel is updated for each synthesized person. Model 4 generates all individual nonmandatory tours, such as shopping, eating out, and recreation. Each tour can be scheduled only within the residual time window remaining after the scheduling of all previous tours. If no time exists for additional tours, then additional tours cannot be scheduled.

The next three models are applied together and include tour destination choice (Model 5), TOD choice (Model 6), and tour mode choice (Model 7). The destination and mode choice models are both logit based, and the destination choice step uses the log sum composite impedance measure from the mode choice model. The TOD model is based on the time windows concept, accounting for the use of a person's time budget over the day. It includes the mode choice log sum for various TOD periods, making it sensitive to congestion. These models are applied at the tour level, yielding the primary destination, TOD, and mode choice for the entire tour, and consider both outbound and inbound portions of the tour.

Model 8 covers stops and trip mode choice. This model determines whether any stops are made on either the outbound (from home), or inbound leg of the tour and the location of those stops. Furthermore, given the overall tour mode previously determined, the exact mode the traveler uses for each segment or trip on the tour is determined on the basis of a set of rules. Each of these trips is connected, and all stops are based upon the previous choices. Therefore, if the main tour mode is transit, then a person will not be able to choose to drive alone for a lunch trip made at work. Furthermore, if the primary mode of a tour is by automobile, then a person would be allowed to drop off a child at school and then drive to work. The final trips are then aggregated by zones and assigned as conventional trip tables to the highway and transit networks.

The core choice models (Models 1 through 8 as described above) are applied in a disaggregate manner. Instead of using aggregate fractional probabilities to estimate the number of trips, the new model is applied by microsimulation of each individual household, person, or tour, mostly using Monte Carlo realization of each

possibility estimated by the models, with use of a random number series to determine which possibility is chosen for that record. Both the population synthesizer and the automobile ownership models, however, perform the microsimulation through a deterministic discretizing procedure that avoids Monte Carlo variability. The new model is applied with an implementation of three global feedback loops for consistency between highway travel times that are both used as inputs to, and as forecast outputs of, the model.

The new model is being used by MORPC for conformity analysis, transit alternative analysis, and highway-related management information systems projects in the Columbus region. It is being used to generate forecasts for the North Corridor Transit Project (NCTP), currently in the draft environmental impact statement stage, with a potential New Starts submittal within the next few years. The NCTP is analyzing various travel modes along a 13-mi corridor that includes three major employment centers—the Central Business District, Ohio State University, and the Crosswoods–Polaris area—interspersed with large residential areas.

Application of a Microsimulation Model for User Benefit Calculation in Transit Projects

Peter Vovsha, *PB Consult, Parsons Brinckerhoff Inc.*

FTA has requirements for a travel demand model that is used to estimate user benefits (UBs) of transit projects. These requirements are based on the general methodology of UBs as the difference between total composite utilities calculated before and after project introduction. The current FTA approach limits the corresponding scope of choices over which the composite utility is calculated to mode and route choices. Thus, the total trip table is assumed fixed, and the mode and route choice attributes that are necessary for calculation of the composite mode choice utility are reported. The FTA approach and developed software SUMMIT have been primarily designed for four-step models characterized by an easy disintegration of the trip-distribution and mode-choice stages as well as the aggregate zone-to-zone structure of the model output. The new generation of activity- and tour-based microsimulation models, of which the Mid-Ohio Regional Planning Commission (MORPC) model is one representative, requires a certain reconsideration of the UB calculations in view of the more complicated structure in which trip distribution and mode choice stages are closely intertwined—as well as because of the fully disaggregate (individual-record) structure of the output.

In theoretical terms, the behaviorally realistic and detailed output of the new models offers numerous additional possibilities for quantifying UBs of transit projects compared with the composite mode choice utility. However, taking advantage of the activity-based approach for the UB calculation is a long-term issue for which numerous methodological and technical details should still be developed. Furthermore, extending the UB methodology for activity-based models (though highly desirable) may

create a certain bias in the comparison between regions because some metropolitan planning organizations have already developed activity-based models, while the majority are still using conventional four-step models. Under these circumstances and primarily for practical purposes, a constructive way is proposed to adjust the activity-based model output to the requirements of the conventional UB calculation procedure.

The general structure of the MORPC model system and the most important and relevant components are shown in Figure 1. A set of day-level models that corresponds to coordinated daily activity patterns for all household members appears as a single upper-level stage with no details because this paper is devoted to mode choice issues.

The subset of tour-level models includes the following components:

- Primary tour destination model that defines which of 1,805 zones and which of three subzones (with no access to transit, long walk to transit of 0.5 to 3.0 mi, or short walk to transit less than 0.5 mi) are chosen for each tour;
- Time-of-day model that defines departure-from-home and arrival-back-home combinations of hours from 5:00 a.m. (or earlier) to 23:00 p.m. (or later). Departure-from-home hour is associated with the outbound half-tour timing, and arrival-back-home hour is associated with the inbound half-tour timing;
- Entire-tour mode-best transit submode model that defines which one of six principal entire-tour modes is chosen for each tour (1, single-occupancy vehicle; 2,

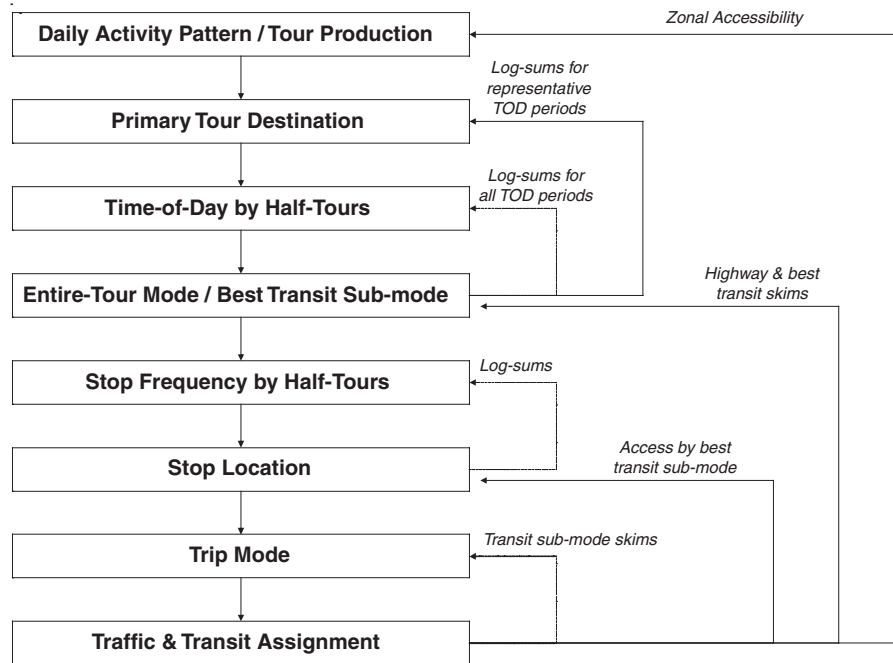


FIGURE 1 General structure of the MORPC model system.

high-occupancy vehicle; 3, walk to transit; 4, drive to transit; 5, nonmotorized; or 6, school bus), and which one of five transit submodes is chosen for each half tour for walk-to-transit and drive-to-transit tours [1, local bus; 2, express bus; 3, bus rapid transit; 4, light rail transit (LRT); or 5, commuter rail]; and

- Stop-frequency model that defines whether there is an intermediate stop at each half-tour. Because only one potential stop on each half tour is considered, the model at the tour level has only four explicitly modeled alternatives: 1, no stops; 2, outbound stop; 3, inbound stop; and 4, stops on both half tours.

Two subsequent models relate to the following trip-level choices, which are conditional upon the previously made tour-level decisions:

- Stop-location model that defines a location for each stop at the same level of spatial resolution as primary destination (1,805 zones and three transit-access subzones for each zone). Stop location availability is strongly conditional on availability of the chosen tour mode and transit sub-mode to access the location; and

- Trip-mode model that defines mode and transit submode for each trip on the tour. If there is no stop on a half tour, the entire half tour is considered one trip and the chosen mode and transit submode are preserved. If there is a stop, the half tour is broken into two successive trips (to and from the stop).

After processing through all tour-level and trip-level stages, trip tables are constructed for all modes and transit submodes. These tables are assigned to the corresponding highway and transit subnetworks. Loaded networks are skimmed to produce level-of-service attributes necessary for the models. The model system is designed to process through several global iterations, including all (or a chosen subset of) models and network assignments until an equilibrium is reached.

Furthermore, several important upward linkages of the choice models through log sums from the lower-level choices used in upper-level choices are incorporated:

- Entire-tour bidirectional mode choice log sums for the representative time-of-day periods (for example, a.m.–p.m. combination for work tours and a.m.–midday combination for school tours) are used as variables in the primary tour destination choice models; the reason that only representative mode choice log sums are used in the destination choice is that this choice dimension has $1,805 \times 3 = 5,415$ alternatives and is extremely computationally intensive.

- Entire-tour bidirectional mode choice log sums for all time-of-day periods are used as variables in time-of-day choice; because the time-of-day choice model is applied conditionally upon the chosen destination, it is significantly less intensive computationally than destination choice, and it is possible to explicitly consider mode choice log sums for all possible time-of-day combinations.

- Stop-location log sums (behaviorally interpreted as density of stop attractions on the way to and from the primary destination) are used as variables in the stop-frequency model; these log sums are calculated for each half tour and take into account stop-location access by the chosen tour mode and transit submode.

The tour-based structure imposes some problems in the way that model outputs can be compared for the base and build scenarios. The core complication is that both trip distribution and mode choice stages are closely intertwined and cannot be fully separated. Indeed, the former single-trip distribution stage is divided into primary-tour destination choice and stop-frequency–location choice. The former mode choice stage is divided into entire-tour mode choice and trip mode choice. These choices are sequenced in a way that pure trip distribution and mode choice stages cannot be recombined in a simple trip format. Consequently, the basic requirement of a fixed trip table cannot be met without some enforcement in the model chain. However, there are three possible constructive ways to meet the FTA requirements, at least on a partial basis, and to provide meaningful inputs for UB calculation that can be processed by SUMMIT. These three options are outlined in Table 1.

Currently, the first (simplest) option has been adopted for the MORPC model and implemented programmatically. According to this approach, a full microsimulation model (with several global iterations that include all steps) is run for the base scenario. Then, all tours are fixed with

their primary destinations, and the build scenario is run for several iterations, with the inclusion of only mode, stop frequency, and stop location choices, as well as assignments.

The model output directly used for the UB calculation relates to the tour-level mode choice statistics only. Technically, it is similar to the conventional model output in which trip units are replaced with tour units. The impact of other choices (stop frequency, stop location, trip mode choice) is taken into account implicitly through the overall iterative equilibration of travel times and cost and upward log sums included into the tour-level mode choice utilities.

The individual-record format can be converted into the quasi-aggregate format that corresponds exactly to the conventional SUMMIT input. The conversion is based on the following rules:

- All tour records with identical production zone, attraction zone, socioeconomic market segment, travel purpose, and time of day are collapsed into a single (aggregate) record with the corresponding values for these fields.
- The other fields for the aggregate record are processed in the following way:
 - Person trips are totaled across the aggregated records.
 - Fractions of trips that have a walk-to-transit path and drive-to-transit-only, as well as walk-to-transit and drive-to-transit-only shares, are averaged across the aggregated records (which makes their values fractional).

TABLE 1 Three Options for Comparison of Transit Alternatives

Model Stage–Feature	Option 1	Option 2	Option 3
Tour generation	Fixed	Fixed	Fixed
Tour primary destination	Fixed	Fixed	Fixed
Tour time of day	Fixed	Fixed	Fixed
Tour mode	Variable	Variable	Variable
Stop frequency	Variable	Fixed	Fixed
Stop location	Variable	Variable	Fixed
Trip mode choice	Variable	Variable	Variable
Tour OD tables by TOD periods	Fixed	Fixed	Fixed
Trip OD tables by TOD periods	Variable	Variable but totals are fixed	Fixed
Report to SUMMIT	Simplified tour-level mode choice log sum w/o intermediate stops	Simplified tour-level mode choice log sum w/o intermediate stops	Full tour-level mode choice log sum with LOS variables reflecting frequency and location of intermediate stops
Included components	Differences in mode utilities w/o stops	Differences in mode utilities w/o stops	Full differences in entire-tour mode utilities including LOS variables associated with making stops
Ignored components	Additional LOS components associated with making stops; a certain incomparability of LOS variables for alternatives with different number of trips on the tour and different stop locations	Additional LOS components associated with making stops; a certain (but less significant) incomparability of LOS variables for alternatives with the same number of trips on the tour but different stop locations	

The only nontrivial transformation that requires explanation is the aggregation of non-transit-exponentiated utility, for which the following notation is introduced:

- $i = 1, 2, \dots, I =$ choice alternatives;
- $n = 1, 2, \dots, N =$ individual records to be aggregated within the group;
- V_{in} = known individual utilities;
- $P_n(i)$ = known individual probabilities;
- W_n = person trips (1, for individual tours; party size, for joint tours);
- V_i = unknown aggregate utilities; and
- W = total person trips for the group.

The purpose of utility aggregation is to find a utility expression that will exactly replicate (a) aggregate mode shares and (b) total composite utility across all individual records and consequently replicate a UB calculation. The aggregate mode shares for the group of records can be readily calculated as follows:

$$P(i) = \frac{\sum_{n=1}^N W_n \times P_n(i)}{W} \quad (1)$$

The first condition (replication of aggregate shares) leads to the following expression:

$$V_i = \ln[P(i)] + C \quad (2)$$

where C denotes a utility scale constant that has to be determined.

The second condition (replication of the composite utility) leads to the following expression (for simplicity it is assumed that the choice model is a simple multinomial logit model and the composite utility is calculated as a simple one-level log sum):

$$W \times \ln \left[\sum_{i=1}^I \exp(V_i) \right] = \sum_{n=1}^N W_n \times \ln \left[\sum_{i=1}^I \exp(V_{in}) \right] \quad (3)$$

Equation 4 results from an equivalent transformation of Equation 3:

$$\begin{aligned} \sum_{i=1}^I \exp(V_i) &= \exp \left\{ \sum_{n=1}^N \frac{W_n}{W} \times \ln \left[\sum_{i=1}^I \exp(V_{in}) \right] \right\} \\ &= \prod_{n=1}^N \left[\sum_{i=1}^I \exp(V_{in}) \right]^{\frac{W_n}{W}} \end{aligned} \quad (4)$$

By substituting the expression for aggregate utilities from Equation 2 to Equation 4, the necessary formula for the utility scale C is obtained:

$$\begin{aligned} \sum_{i=1}^I \exp(V_i) &= \exp(C) \times \sum_{i=1}^I P(i) = \exp(C) \\ &= \prod_{n=1}^N \left[\sum_{i=1}^I \exp(V_{in}) \right]^{\frac{W_n}{W}} \end{aligned} \quad (5)$$

By combining Equations 2 and 5, it is possible to obtain the expression for aggregate exponentiated utilities that would exactly reproduce the target market shares and user benefits:

$$\begin{aligned} \exp(V_i) &= P(i) \times \exp(C) \\ &= P(i) \times \prod_{n=1}^N \left[\sum_{i=1}^I \exp(V_{in}) \right]^{\frac{W_n}{W}} \end{aligned} \quad (6)$$

Equation 6 has a simple intuitive interpretation. The aggregate exponentiated utility of each mode is proportional to a product of two factors. The first one is equal to the aggregate mode share and reflects the improvement of each mode in comparison with the other (competing) modes. The second one is equal to the weighted geometric average of the individual (exponentiated) log sums; this component is sensitive to the overall improvement of all modes.

This aggregation calculation should be implemented separately for the base scenario and the build scenario and for each group of aggregated records. In the same way that this aggregation can be applied for mode utilities, it can be applied for the composite nontransit utility as well as it can be generalized for any nested structure by using a full mode choice log sum for each record LS_n . The aggregate exponentiated nontransit utility can be calculated as follows:

$$\begin{aligned} \exp(V_{NT}) &= \left[\begin{array}{l} P(SOV) + P(HOV) \\ + P(NM) + P(SB) \end{array} \right] \\ &\quad \times \prod_{n=1}^N \left[\exp(LS_n) \right]^{\frac{W_n}{W}} \end{aligned} \quad (7)$$

where

- SOV = single-occupancy vehicle,
- HOV = high-occupancy vehicle,
- NM = nonmotorized vehicle, and
- SB = school bus.

The described methodology of UB calculation has been applied for the analysis of the recent LRT project in Columbus, Ohio, and approved by FTA. The results are provided in a companion paper.

Application of Mid-Ohio Regional Planning Commission Microsimulation Model

New Starts Review

Dave Schmitt, *AECOM Consult, Inc.*

FTA has very high standards for travel demand models used to generate ridership forecasts for its New Starts program. A model's ability to meet these standards must be assessed early on so that potential FTA concerns with the forecasts or model structure can be addressed in a timely manner. Model structure changes require long, iterative development times.

The Mid-Ohio Regional Planning Commission (MORPC) microsimulation model is being used to generate forecasts for the North Corridor Transit Project (NCTP)—currently in the stage requiring a draft environmental impact statement—with a potential New Starts submittal within the next few years. The NCTP is analyzing various travel modes along a 13-mi corridor that includes three major employment centers interspersed with large residential areas: the central business district (CBD), Ohio State University (OSU), and the Crosswoods and Polaris areas.

NCTP team members investigated many areas of the MORPC model, including its overall structure, automobile and transit travel times, path building parameters, mode choice coefficient values, and results. The analysis of the model's trip distribution and user benefit results will be discussed, as these two elements have been identified as concerns by the FTA on other New Starts projects.

The regional figures were divided into 13 districts for analysis purposes (Figure 1). Six districts are for the corridor: CBD, the OSU area, Clintonville, Worthington, Crosswoods, and Polaris. The remaining area of Franklin County is divided into four districts: northwest, northeast, southeast, and southwest. The remaining area

of Delaware County is another district, and Licking County is its own district. Portions of the surrounding counties, including Pickaway and Union, are in the final district.

TRAVEL DISTRIBUTION

Travel distribution is one of the most difficult aspects of travel demand to model effectively. FTA has identified travel distribution as a potential upstream model error that can lead to poorly calibrated mode choice models containing large, unexplainable alternative-specific constants. To explore the reliability of the work component of the distribution model, the simulated Year 2000 work tour distribution was compared with the 2000 Census Transportation Planning Package (CTPP), which captures work journeys. The first step was to compare the regionwide magnitude of modeled work trip tours to CTPP. On a regionwide basis, the model estimated 660,031 work tours compared with 630,550 CTPP records—a difference of only 4.7%. Next, district-to-district tours were compared with the CTPP (scaled so that regional CTPP records match modeled journeys). The modeled work tour distribution is shown in Table 1. The CTPP journey distribution is shown in Table 2. Table 3 displays the ratio of the modeled to the observed distribution.

Overall, the modeled trip distribution for work purposes appeared to be as good as or better than that of comparable models used elsewhere in the United States. The model was representing trips to the CBD very

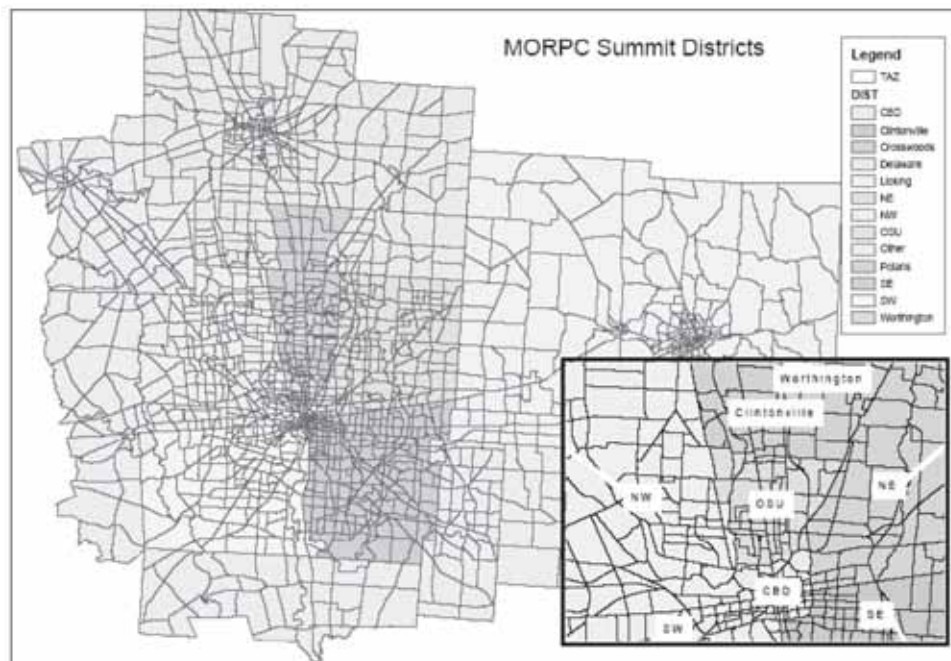


FIGURE 1 Districts used for analysis.

closely, within 1% regionally. Work trips from within the corridor to the CBD were underrepresented by 5%. Regionally, the model was overrepresenting trips to OSU by just 3%. There were specific travel markets that were weak, including a 27% underestimation of tours from the corridor to OSU. Work tour productions and attractions were well estimated by the model. Almost all markets were represented within 10% of the CTPP totals.

District-to-district tours for all purposes were compared with the CTPP and household travel survey. The CTPP results were scaled as before, but the survey records were not scaled. The modeled work tour distribution is shown in Table 4. The observed journey distribution is shown in Table 5. Table 6 displays the ratio of the modeled to the observed distribution.

TABLE 1 2000 Modeled Work Tours

District	1	2	3	4	5	6
1 - CBD	277	154	47	34	53	7
2 - OSU	3,646	3,586	1,270	1,077	1,138	200
3 - Clintonville	3,706	2,565	1,612	1,447	1,686	233
4 - Worthington	4,085	1,903	1,434	2,557	3,575	536
5 - Crosswoods	3,197	1,534	1,228	2,086	5,144	1,094
6 - Polaris	625	294	216	382	1,235	464
Corridor Total	15,536	10,036	5,807	7,583	12,831	2,534
7 - Delaware	2,820	1,241	831	1,565	4,431	1,851
8 - NW	15,631	8,178	4,407	3,957	7,360	1,467
9 - NE	11,676	5,134	2,846	4,207	6,472	1,148
10 - SE	17,249	6,414	1,972	1,981	2,496	391
11 - SW	7,265	4,542	1,182	1,025	1,230	234
12 - Licking	2,645	811	407	721	1,094	253
13 - Other	4,877	1,570	516	585	1,173	263
Noncorridor Total	62,163	27,890	12,260	14,041	24,256	5,607
Regional Total	77,699	37,926	18,067	21,624	37,087	8,141

Overall, the modeled trip distribution was very good but not as good as the work tour distribution. The production districts had some noticeable variation, including overestimating trips from Polaris, a suburban employment and retail center, by 94%. The attraction districts were generally much better. Tours attracted to the CBD and OSU, the two biggest employment centers in the region, were within 5%. The weighting and expansion factors were quite large due to the sample size of the household survey. This can lead to “lumpiness” in the observed data and make precise comparisons difficult.

USER BENEFITS

User benefit results are reasonable if they can explain the benefits of the proposed build project. For example, corridor areas should accrue the greatest number of user benefits, while areas outside of the corridor should receive minimal benefits. Major employment areas that benefit the most from the project should receive large user benefits. The district-to-district summary tables and “winners–losers” maps were reviewed for this analysis. The distribution of user benefits by travel market for home-based work (HBW) tours is shown in Table 7, and the distribution for all tours is shown in Table 8.

The tables show that the MORPC AB model produces reasonable user benefit results. The majority of user benefits occur in the corridor. For work tours, 77% of user benefits are produced in corridor districts, and 82% are destined for corridor districts. For all tours, the figures are 78% and 82%, respectively. Both tables have minimal level of benefits in intradistrict markets. The CBD has the highest level of benefits as related to attractions.

The winners–losers maps show the zones that receive the most benefit and disbenefit from the project. The maps are extremely useful in evaluating whether the user benefit results are directly related to the proposed project. Zones that receive benefits are shaded in green, with a darker color indicating higher benefits. Zones that receive disbenefits are shaded in red, with a darker color indicating more disbenefit. Figure 2 shows the production and attraction maps for HBW-peak tours.

The maps work well at explaining the benefits and disbenefits of the project. The production map shows that a majority of the benefits are accrued by people living in the corridor, especially those living near rail stations. The red zones in the Worthington region reflect the longer travel times from the proposed project compared with those for the existing bus service. The attraction map has many green zones around stations near major employment areas, especially OSU and the northern suburbs.

7	8	9	10	11	12	13	Total
8	388	167	293	170	5	12	1,565
270	5,846	3,061	2,752	1,854	48	165	24,913
418	5,346	3,281	1,966	1,181	65	144	23,650
929	5,621	5,278	1,842	983	141	213	29,097
1,597	5,883	4,940	1,498	826	178	293	29,498
830	1,478	963	285	146	42	120	7,080
4,052	24,512	17,690	8,636	5,160	479	947	115,803
12,350	7,650	5,210	1,613	865	630	1,634	42,692
3,150	49,480	8,067	6,606	8,857	212	2,895	120,267
2,423	10,431	22,156	10,979	3,146	1,444	906	82,968
705	12,093	17,788	36,222	8,876	1,485	3,228	110,900
436	20,153	4,420	9,439	14,984	113	1,923	66,946
1,202	1,781	6,342	5,713	822	46,456	1,606	69,853
1,536	7,709	4,166	10,641	3,476	2,830	11,161	50,602
21,802	109,297	68,149	81,213	41,056	53,170	23,354	544,228
25,854	133,809	85,839	89,849	46,186	53,649	24,301	660,031

TABLE 2 CTPP 2000 Journeys (Scaled to Modeled Work Tours)

District	1	2	3	4	5	6
1 - CBD	535	243	33	33	47	7
2 - OSU	4,006	6,094	833	1,030	1,023	127
3 - Clintonville	3,609	3,001	2,256	1,127	1,517	311
4 - Worthington	3,761	2,509	1,380	3,745	3,499	505
5 - Crosswoods	3,730	1,633	1,051	1,733	6,194	1,192
6 - Polaris	698	321	240	312	995	995
Corridor Total	16,341	13,801	5,793	7,982	13,275	3,137
7 - Delaware	3,318	1,524	844	1,012	3,887	2,948
8 - NW	16,883	9,268	3,567	2,517	6,983	1,469
9 - NE	11,278	3,910	1,849	3,469	6,704	1,253
10 - SE	16,179	4,264	1,495	1,948	3,585	477
11 - SW	7,675	2,338	1,104	950	2,191	315
12 - Licking	2,437	667	310	642	1,429	268
13 - Other	4,594	1,221	524	621	1,395	283
Noncorridor Total	62,364	23,192	9,693	11,159	26,174	7,012
Regional Total	78,704	36,993	15,486	19,141	39,449	10,149

TABLE 3 Ratio of Model over Scaled CTPP

District	1	2	3	4	5	6
1 - CBD	0.52	0.63	1.40	1.02	1.13	0.96
2 - OSU	0.91	0.59	1.52	1.05	1.11	1.58
3 - Clintonville	1.03	0.85	0.71	1.28	1.11	0.75
4 - Worthington	1.09	0.76	1.04	0.68	1.02	1.06
5 - Crosswoods	0.86	0.94	1.17	1.20	0.83	0.92
6 - Polaris	0.90	0.91	0.90	1.22	1.24	0.47
Corridor Total	0.95	0.73	1.00	0.95	0.97	0.81
7 - Delaware	0.85	0.81	0.96	1.55	1.14	0.63
8 - NW	0.93	0.88	1.24	1.57	1.05	1.00
9 - NE	1.04	1.31	1.54	1.21	0.97	0.92
10 - SE	1.07	1.50	1.32	1.02	0.70	0.82
11 - SW	0.95	1.94	1.07	1.08	0.56	0.74
12 - Licking	1.09	1.22	1.31	1.12	0.77	0.94
13 - Other	1.06	1.29	1.17	0.94	0.84	0.93
Noncorridor Total	1.00	1.20	1.26	1.26	0.93	0.80
Regional Total	0.99	1.03	1.17	1.13	0.94	0.80

TABLE 4 2000 Modeled Tours (All Purposes)

District	1	2	3	4	5	6
1 - CBD	11,358	4,037	911	505	343	33
2 - OSU	8,979	30,066	6,937	4,219	2,386	330
3 - Clintonville	6,692	11,397	10,899	7,733	4,024	453
4 - Worthington	6,554	7,134	7,748	19,298	12,284	1,200
5 - Crosswoods	4,485	38,835	4,175	12,245	25,199	3,793
6 - Polaris	779	545	540	1,354	4,311	3,781
Corridor Total	38,847	57,014	31,210	45,354	48,547	9,590
7 - Delaware	3,333	2,005	1,811	4,332	10,336	6,463
8 - NW	25,439	24,045	13,061	14,512	18,252	2,948
9 - NE	20,777	15,517	11,535	18,394	16,888	2,390
10 - SE	32,556	14,962	5,239	4,557	3,684	521
11 - SW	14,930	10,230	2,805	2,128	1,738	292
12 - Licking	3,106	1,058	596	1,197	1,474	311
13 - Other	6,448	2,457	959	1,041	1,672	419
Noncorridor Total	106,589	70,274	36,006	46,161	54,044	13,344
Regional Total	145,436	127,288	67,216	91,515	102,591	22,934

7	8	9	10	11	12	13	Total
15	335	182	195	88	15	24	1,752
296	4,887	2,755	1,778	926	174	104	24,036
416	4,201	2,827	1,695	816	94	99	21,969
542	5,125	4,760	2,107	963	244	182	29,322
1,083	5,255	5,280	1,792	859	210	130	30,142
934	1,340	794	350	170	16	58	7,223
3,286	21,142	16,598	7,917	3,823	753	597	114,444
13,648	6,970	5,695	1,907	789	385	860	43,788
2,256	55,319	8,268	7,483	7,429	561	1,787	123,790
1,925	10,901	29,014	9,764	2,769	1,255	530	84,620
902	14,371	19,233	35,442	7,513	1,340	1,867	108,616
390	19,977	4,790	7,996	18,272	316	1,049	67,365
722	3,111	7,698	5,144	1,010	39,761	716	63,914
574	8,767	5,521	9,164	3,425	1,539	15,868	53,494
20,417	119,416	80,219	76,901	41,207	45,157	22,677	545,587
23,703	140,558	96,817	84,817	45,029	45,910	23,274	660,031

7	8	9	10	11	12	13	Total
0.55	1.01	0.92	1.50	1.93	N/A	0.50	0.89
0.91	1.20	1.11	1.55	2.00	0.28	1.59	1.04
0.91	1.27	1.16	1.16	1.45	0.69	1.45	1.08
1.71	1.10	1.11	0.87	1.02	0.58	1.17	0.99
1.47	1.12	0.94	0.84	0.96	0.85	2.26	0.98
0.89	1.10	1.21	0.82	0.86	2.67	2.08	0.98
1.23	1.16	1.07	1.09	1.35	0.64	1.59	1.01
0.90	1.10	0.91	0.85	1.10	1.64	1.90	0.97
1.40	0.89	0.98	0.88	1.19	0.38	1.62	0.97
1.26	0.96	0.76	1.12	1.14	1.15	1.71	0.98
0.78	0.84	0.92	1.02	1.18	1.11	1.73	1.02
1.12	1.01	0.92	1.18	0.82	0.36	1.83	0.99
1.66	0.57	0.82	1.11	0.81	1.37	2.24	1.09
2.68	0.88	0.75	1.16	1.01	1.84	0.70	0.95
1.07	0.92	0.85	1.06	1.00	1.18	1.03	1.00
1.09	0.95	0.89	1.06	1.03	1.17	1.04	1.00

7	8	9	10	11	12	13	Total
45	4,803	2,984	5,690	3,605	17	74	34,405
446	16,877	10,475	9,220	5,139	67	242	95,383
789	14,224	10,865	5,016	2,462	83	179	74,816
2,123	14,011	17,879	4,047	1,787	217	312	94,594
5,261	15,260	16,069	2,769	1,290	227	421	95,029
3,579	3,021	2,590	466	202	51	153	21,372
12,243	68,196	60,862	27,208	14,485	662	1,381	415,599
64,039	17,521	15,176	2,414	1,249	1,106	2,852	132,637
8,755	200,574	16,625	14,616	31,046	239	5,448	375,560
8,527	20,072	114,245	42,893	6,721	3,036	1,913	282,908
1,029	21,378	48,440	193,418	26,120	3,619	9,964	365,487
605	48,760	8,917	27,426	91,130	134	3,374	212,469
2,141	2,132	12,748	13,921	1,051	173,182	4,590	217,507
3,402	16,179	7,180	32,040	11,901	6,436	67,320	157,454
88,498	326,616	223,331	326,728	169,218	187,752	95,461	1,744,022
100,741	394,812	286,193	353,936	183,703	188,414	96,842	2,159,621

TABLE 5 2000 Scaled CTPP + Survey Journeys and Tours

District	1	2	3	4	5	6
1 - CBD	13,383	1,619	1,071	584	137	7
2 - OSU	12,252	59,348	11,444	4,499	2,776	238
3 - Clintonville	4,674	8,899	38,017	11,486	3,474	591
4 - Worthington	6,206	4,995	7,759	27,042	13,094	755
5 - Crosswoods	6,476	2,628	2,491	14,129	23,326	2,560
6 - Polaris	698	1,455	240	312	1,818	2,023
Corridor Total	43,689	78,944	61,022	58,054	44,625	6,174
7 - Delaware	3,649	3,058	1,326	2,896	6,108	4,116
8 - NW	23,000	18,883	7,936	9,562	13,482	2,163
9 - NE	19,776	9,640	12,320	12,511	13,911	1,436
10 - SE	30,593	10,668	7,423	6,296	6,624	633
11 - SW	10,129	2,888	2,323	1,760	2,249	315
12 - Licking	3,404	1,810	1,046	1,537	1,917	322
13 - Other	4,882	1,378	524	704	1,549	283
Noncorridor Total	95,433	48,325	32,898	35,266	45,840	9,267
Regional Total	139,121	127,269	93,920	93,320	90,465	15,441

TABLE 6 Ratio of Modeled to Observed Tours

District	1	2	3	4	5	6
1 - CBD	0.85	2.49	0.85	0.86	2.50	4.50
2 - OSU	0.73	0.51	0.61	0.94	0.86	1.39
3 - Clintonville	1.43	1.28	0.29	0.67	1.16	0.77
4 - Worthington	1.06	1.43	1.00	0.71	0.94	1.59
5 - Crosswoods	0.69	1.46	1.68	0.87	1.08	1.48
6 - Polaris	1.12	0.37	2.25	4.34	2.37	1.87
Corridor Total	0.89	0.72	0.51	0.78	1.09	1.55
7 - Delaware	0.91	0.66	1.37	1.50	1.69	1.57
8 - NW	1.11	1.27	1.65	1.52	1.35	1.36
9 - NE	1.05	1.61	0.94	1.47	1.21	1.66
10 - SE	1.06	1.40	0.71	0.72	0.56	0.82
11 - SW	1.47	3.54	1.21	1.21	0.77	0.93
12 - Licking	0.91	0.58	0.57	0.78	0.77	0.97
13 - Other	1.32	1.78	1.83	1.48	1.08	1.48
Noncorridor Total	1.12	1.45	1.09	1.31	1.18	1.44
Regional Total	1.05	1.00	0.72	0.98	1.13	1.49

TABLE 7 User Benefit District Summary (HBW Tours)

District	1	2	3	4	5	6
1 - CBD	(5)	21	(1)	1	9	3
2 - OSU	305	42	—	36	111	56
3 - Clintonville	66	17	(1)	3	21	9
4 - Worthington	141	46	1	2	21	13
5 - Crosswoods	239	67	13	16	40	5
6 - Polaris	135	32	7	14	25	(2)
Corridor Total	881	225	19	72	227	84
7 - Delaware	145	24	3	4	17	(2)
8 - NW	46	21	(2)	6	42	19
9 - NE	71	27	—	3	17	5
10 - SE	(6)	44	(3)	7	28	6
11 - SW	(4)	21	(1)	2	9	2
12 - Licking	4	1	—	—	—	—
13 - Other	(3)	3	—	—	1	—
Noncorridor Total	253	141	(3)	22	114	30
Regional Total	1,134	366	16	94	341	114

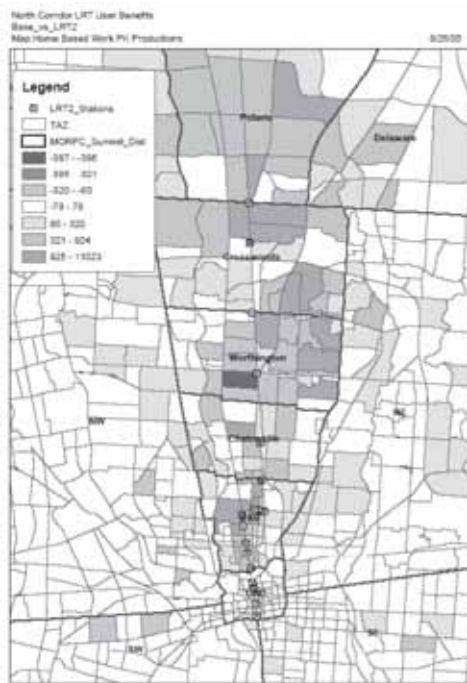
7	8	9	10	11	12	13	Total
15	1,433	733	1,372	1,253	307	24	21,938
870	23,174	15,758	5,681	2,852	1,200	104	140,197
644	13,130	7,981	2,326	892	184	101	92,479
2,027	12,639	7,668	3,010	1,236	559	707	87,697
2,417	10,297	11,303	3,055	1,855	284	130	80,951
1,527	1,340	794	350	385	16	58	11,016
7,500	62,012	44,237	15,794	8,474	2,550	1,204	434,278
48,491	19,495	14,633	2,741	857	394	1,461	109,226
6,079	208,349	13,869	11,284	16,247	631	2,509	333,994
9,314	16,403	126,005	34,800	6,028	3,106	1,908	267,157
902	28,170	54,719	233,848	14,619	5,508	3,134	403,137
1,410	33,328	6,264	11,987	71,409	405	1,181	145,650
3,515	4,446	9,986	11,088	1,491	190,467	1,180	232,209
2,285	13,504	6,066	17,013	6,169	2,714	49,320	106,389
71,996	323,695	231,542	322,762	116,820	203,225	60,694	1,597,762
79,496	385,707	275,779	338,555	125,293	205,775	61,898	2,032,040

7	8	9	10	11	12	13	Total
3.07	3.35	4.07	4.15	2.88	0.06	3.07	1.57
0.51	0.73	0.66	1.62	1.80	0.06	2.34	0.68
1.23	1.08	1.36	1.16	2.76	0.45	0.99	0.81
1.05	1.11	2.33	1.34	1.45	0.39	0.44	1.08
2.18	1.47	1.42	0.91	0.70	0.80	3.24	1.17
2.34	2.25	3.26	1.33	0.53	3.25	2.66	1.94
1.63	1.10	1.38	1.72	1.71	0.26	1.15	0.96
1.32	0.90	1.04	0.88	1.46	2.81	1.95	1.21
1.44	0.96	1.20	1.30	1.91	0.38	2.17	1.12
0.92	1.22	0.91	1.23	1.12	0.98	1.00	1.06
1.14	0.76	0.89	0.83	1.79	0.66	3.18	0.91
0.43	1.46	1.42	2.29	1.28	0.33	2.86	1.46
0.61	0.48	1.28	1.26	0.70	0.91	3.89	0.94
1.49	1.20	1.18	1.88	1.93	2.37	1.36	1.48
1.23	1.01	0.96	1.01	1.45	0.92	1.57	1.09
1.27	1.02	1.03	1.05	1.47	0.92	1.56	1.06

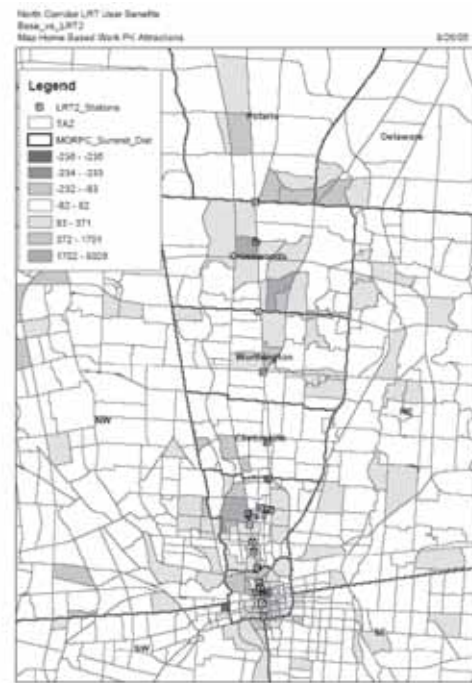
7	8	9	10	11	12	13	Total
2	(2)	1	1	—	—	—	30
33	51	75	63	38	—	—	810
6	2	3	4	3	—	—	133
9	8	3	8	5	—	—	257
7	24	13	14	7	—	—	445
—	16	23	7	5	—	—	262
57	99	118	97	58	—	—	1,937
(1)	12	11	8	5	—	—	226
11	(13)	5	2	(6)	—	—	131
6	5	(1)	4	2	—	—	139
7	(11)	(1)	(3)	(10)	—	(1)	57
2	(7)	(1)	(2)	(2)	—	—	19
—	—	—	—	—	—	—	5
—	—	—	—	—	—	—	1
25	(14)	13	9	(11)	—	(1)	578
82	85	131	106	47	—	(1)	2,515

TABLE 8 User Benefit District Summary (All Tours)

District	1	2	3	4	5	6
1 - CBD	(6)	30	—	2	12	3
2 - OSU	373	54	5	62	161	65
3 - Clintonville	151	21	(3)	3	28	10
4 - Worthington	169	59	1	2	29	16
5 - Crosswoods	257	84	18	21	52	9
6 - Polaris	140	38	9	16	29	(2)
Corridor Total	984	286	30	106	311	101
7 - Delaware	148	26	4	5	19	(2)
8 - NW	49	25	(2)	7	47	21
9 - NE	77	33	1	4	22	7
10 - SE	—	54	(1)	8	34	7
11 - SW	(1)	28	—	3	12	2
12 - Licking	4	1	—	—	—	—
13 - Other	(3)	3	—	—	1	—
Noncorridor Total	274	170	2	27	135	35
Regional Total	1,258	456	32	133	446	136



(a)



(b)

FIGURE 2 User benefit summaries: (a) row and (b) column.

7	8	9	10	11	12	13	Total
2	(2)	2	1	—	—	—	44
37	61	94	84	54	—	—	1,050
6	2	4	5	3	—	—	148
11	9	3	10	6	—	—	297
8	29	16	16	10	—	—	520
—	18	25	7	6	—	—	286
64	117	144	123	79	—	—	2,345
(1)	13	12	9	5	—	—	238
11	(13)	6	2	(7)	—	—	146
6	5	(1)	5	1	—	—	160
7	(11)	—	(4)	(12)	—	(1)	81
2	(8)	(1)	(3)	(3)	—	—	31
—	—	—	—	—	—	—	5
—	—	—	—	—	—	—	1
25	(14)	16	9	(16)	—	(1)	662
89	103	160	132	63	—	(1)	3,007

BREAKOUT SESSION

DATA AND SYNTHETIC POPULATIONS

Processing the Denver Travel Survey to Support Tour-Based Modeling Methods, Data, and Lessons Learned

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The Denver Regional Council of Governments (DRCOG) is completely restructuring its regional model. This effort began with the conduct, in the late 1990s, of the Travel Behavior Inventory (TBI) project, a suite of regional surveys, including a household travel survey. Following completion of the TBI, DRCOG began an Integrated Regional Model project, through which DRCOG is rebuilding the regional model on the basis of TBI data, in three phases:

- The refresh phase, a partial reestimation and full recalibration of DRCOG's existing trip-based model (now complete);
- The vision phase, an evaluation of advanced modeling techniques and projects throughout North America and Europe (also complete); and
- The update phase, a project to build an integrated modeling system that includes components for both tour-based travel models and disaggregate land use models (under way).

The paper is intended to aid modeling practitioners who are considering implementing advanced techniques such as tour-based models by describing the type of survey DRCOG has used in its development of tour-based models, the techniques and assumptions used to structure the survey data for that use, and trip and tour statistics that the survey produced.

SURVEY DESCRIPTION

In the mid-1990s, when DRCOG began preparing for the TBI project, attempts at advanced modeling approaches

were just beginning in practice in the nation's metropolitan planning organizations. In the early phases of the TBI, DRCOG convened a panel of modeling practitioners to assess the current and possible near-future state of modeling practice in the country so that travel surveys could be designed to support those likely approaches. Data collected in 1997 included a home-interview survey, a brief onboard transit survey, a commercial vehicle survey, and an external station survey.

The initial home-interview survey design was in an activity-based format; in this format, one record of data was collected for each activity in which the household members engaged. While Metro in Portland, Oregon, concluded that its activity-based survey was only marginally more complex than a traditional trip-based survey (1), respondents to the pilot survey in the Denver region found the format confusing. These findings led to development of a place format for the main survey that was based on a similar survey conducted in New York. The place survey asked respondents to describe the sequence of places—including the address of each, the kind of place each was (from a list of categories), and their activity at each—at which they stopped through the day. Respondents were asked to select primary and secondary activities at the place from a list of 12 possibilities (or to write in "other"). The survey included a standard sample of 4,196 households as well as 677 households recruited through the onboard transit survey.

Riders on 51 routes responded to the onboard transit survey, which collected basic information on the trip purpose and demographic characteristics of the rider. The survey was used primarily to identify transit riders who could be recruited to participate in the home-interview survey, and 677 households were recruited in

this way. The primary advantage of this method is that the full-day activity patterns of the riders and other household members could be collected rather than information only on the transit trip in question. The onboard survey itself did not collect origin and destination information in sufficient detail to be used to estimate mode choice models.

METHOD OF CODING TRIPS AND TOURS

Three traditional trip purposes were used: home-based work (HBW), home-based nonwork (HBNW), and non-home-based (NHB). These were coded on the basis of a lookup table of the 517 possible combinations of production place, production activity, attraction place, and attraction activity.

The data were then coded into a tour format. Several codes were developed to support the most common approaches to tour-based modeling:

- Tour code: Trips in the same tour must be given a common tour identification (ID) number;
- Tour mode: The primary travel model for each tour must be designated; and
- Primary destination: One of the stops on each tour must be designated as primary.

The method described here builds on the method outlined in the Integrated Regional Model Final Report (2), which in turn builds on the work of previous tour-based modeling projects in San Francisco, California (3, 4); Portland, Oregon (5, 6); New York (7); Columbus, Ohio; (8) and Atlanta, Georgia (9).

First, DRCOG developed a program to group trips into tours. Figure 1 illustrates an example of an individual's all-day activity pattern. A tour is a sequence of trips starting and ending at home, defining a single round trip. A subtour is a sequence of trips starting and ending at work, defining a single round trip. The example below includes three tours, one of which is a subtour. Trips 1, 4, and 5 compose Tour 1, Trips 2 and 3 compose Tour 2, and Trips 6 and 7 compose Tour 3. Because of the subtour, the trips in Tour 1 are not adjacent in time.

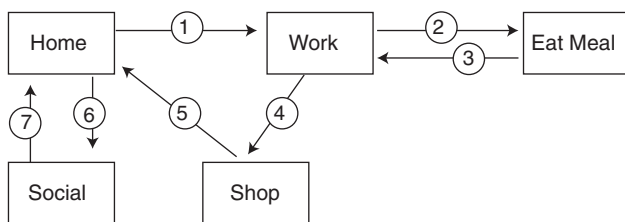


FIGURE 1 Tour pattern illustration.

To code the tours, the program passes forward through each trip, incrementing the tour ID whenever the traveler departs home. For each trip, it also keeps track of when the traveler last departed home and last departed work. For example, on Trip 5, the traveler last departed home on Trip 1 and last departed work on Trip 4.

Next, the program passes in reverse through the trips, flagging the in which the traveler departed work more recently than he or she departed home. In this pass, if a traveler arrives at work and has departed work more recently than departing home, the trip is part of a subtour. The previous trip is also part of the subtour until the trip that actually departs from work is reached.

Having flagged the subtours, the program once more passes forward through the trips, incrementing the ID of the subtour and of all subsequent tours. Most standard household trip surveys contain all the information needed to perform these steps.

The primary mode of each tour is assigned by setting a priority to the mode of each trip, in the following order: 1, school bus; 2, kiss and ride; 3, park and ride; 4, walk to transit; 5, drive alone; 6, shared ride 2; 7, shared ride 3+; 8, bicycle; 9, walk; and 10, other. For example, if any trip on the tour is on a school bus, then the primary mode of the entire tour is labeled school bus. It is not necessary that all trips in a tour have the same mode. For example, drivers switch between drive-alone and shared-ride modes when they pick up or drop off a passenger.

Finally, for each tour, one place is designated as the primary destination. The primary destination is important because standard tour-based model structures assume that the activity at that destination controls the behavior of the tour and that the other stops are scheduled around it. For example, if a traveler goes to work and stops for coffee on the way to work, the work activity is far more likely than the coffee stop to dominate that person's decisions about schedule, destination, and mode. The primary destination is set such that it is never home for any tour, and it is never the workplace for work-based subtours. However, it is possible to have work-based subtours for which the activity at the primary destination is work, such as when someone visits a print shop or another company's office.

In general, the place type, activity, and stop duration of each stop in a tour are the variables on which the designation is based. A variety of methods may be used to designate the primary destination, from assuming that one of these variables has sole priority to developing a two- or three-dimensional weighting table (for example, one that assigns higher scores as duration increases for any given stop activity and then selecting the highest-scoring stop from the table). DRCOG has adopted a simple decision tree structure, as shown in Figure 2.

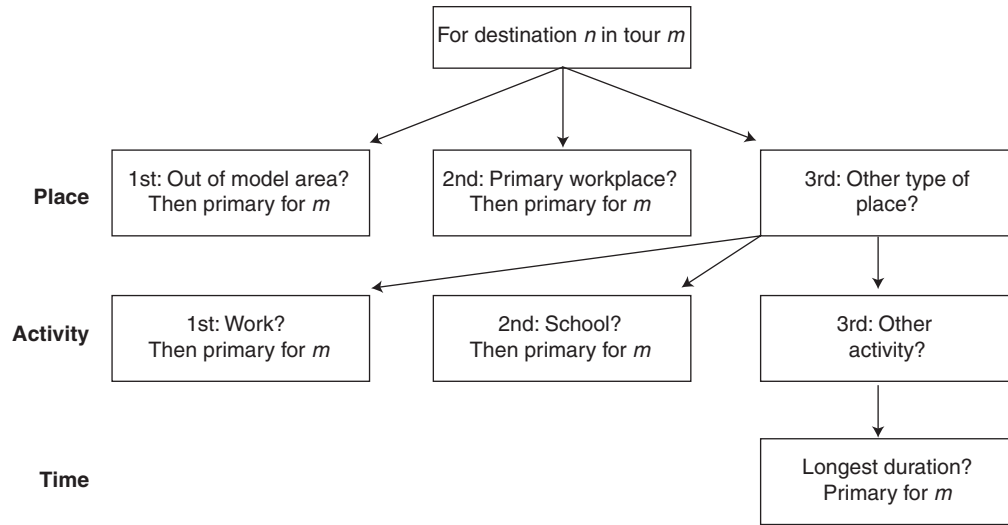


FIGURE 2 Primary destination decision tree.

DATA AND RESULTS

The data from this survey first were used in a trip-based format for the refresh phase and will again be in a tour-based format for the update phase. Of particular interest to practitioners deliberating a switch from a trip-based to a tour-based model is how the same data compare when coded in the two formats. A selection of such comparisons is included here. Table 1 shows basic statistics associated with the trip records, and Table 2 shows those same statistics associated with the tour records. Table 3 compares the trip purpose to the primary purpose of the tour for each trip record. As discussed later, these data can provide important insights into the areas of travel behavior when a trip-based model and a tour-based model might provide differing results.

As Table 1 shows, only 17% of trips are HBW trips, while in Table 2, 33% of tours are work tours. This discrepancy suggests that work remains an important driver of travel, even though the number of HBW trips is relatively small due to chaining. This observation is supported by Table 3, which shows that only half of all trips on work tours would be coded with an HBW purpose while the other half would be HBNW or NHB trips. School tours account for another 16% of all tours, and when viewed together, these two mandatory activities are central to almost half of all tours.

Useful information comes from examining the distribution of NHB trips across various tour purposes, as shown in Table 3. NHB trips account for between 15% and 39% of the trips in each tour purpose. Having a meaningful purpose associated with these NHB trips is

TABLE 1 Basic Trip Statistics

Trip Purpose	Expanded Trips	% Expanded Trips	Trips/Person	Trips/Household	% with 3+ Trips	% Shared Ride	% Transit
HBW	1,505,685	17	0.8	1.7	26	9.1	5.1
HBNW	4,444,067	51	2.2	5.1	43	53.6	1.5
NHB	2,788,283	32	1.4	3.2	88	42.2	1.3
Total	8,738,035	100	4.4	10.1	55	42.3	2.1

HBW = home-based work; HBNW = home-based nonwork; NHB = non-home-based.

TABLE 2 Basic Tour Statistics

Trip Purpose	Expanded Tours	% Expanded Tours	Tours/Person	Tours/Household	% with 3+ Trips	% Shared Ride	% Transit
Work	1,060,271	33	0.5	1.2	44	8.1	5.3
School	514,967	16	0.3	0.6	29	44.9	4.7
Shopping	386,200	12	0.2	0.4	49	42.7	0.9
Social-recreational	291,877	9	0.1	0.3	39	58.5	3.1
Drop off and pick up	268,781	8	0.1	0.3	19	32.2	0.0
Other	701,429	22	0.4	0.8	36	50.5	1.5
Total	3,223,525	100	1.6	3.7	38	33.9	3.2

TABLE 3 Comparison of Tour Purpose and Trip Purpose for Trips

Tour Purpose	Trip Purpose							
	HBW		HBNW		NHB		Total	
	Expanded Trips	Row (%)	Expanded Trips	Row (%)	Expanded Trips	Row (%)	Expanded Trips	Row (%)
Work	1,497,387	50	495,971	16	1,012,793	34	3,006,151	100
School	180	0	1,017,667	77	299,596	23	1,317,443	100
Shopping	1,591	0	689,607	62	424,438	38	1,115,635	100
Social-recreational	653	0	560,063	71	227,082	29	787,797	100
Drop off and pick up	248	0	528,673	85	90,260	15	619,180	100
Other	5,626	0	1,152,088	61	734,116	39	1,891,829	100
Total	1,505,685	17	4,444,067	51	2,788,283	32	8,738,035	100

potentially one of the biggest advantages of a tour-based model.

On average, each person in the Denver region makes 4.4 trips per day and 1.6 tours per day, for an average of 2.7 trips per day. Of all tours, 38% include three or more trips, and 55% of trips are on tours with three or more trips. These results show that a large fraction of travel includes some trip chaining, and developing a model that properly accounts for this phenomenon could have a significant influence on the model's performance.

Finally, notice the difference in mode shares between trips and tours. These differences result from the prioritization scheme used to define the primary mode of the tour. The shared-ride mode was defined as a lower priority than the drive-alone mode, such that if any trip on a driving tour is a drive-alone trip, the primary mode would be drive alone. Drive alone takes a higher priority because it requires the exclusive use of a vehicle, and the tour coding of the modes correctly captures that the driver at some point needs use of a vehicle. Conversely, transit is a high priority in defining the primary tour mode, and the transit mode share is 50% higher for tours than for trips. This result indicates a substantial level of trip chaining on transit tours, in which travelers may stop to shop at some point during their transit trip.

CONCLUSIONS

In total, the survey data present a reasonable picture of travel behavior and one that is both more interesting and more intuitive than traditional trip-based statistics. They make plain the degree of trip chaining at which the trip-based statistics hint and show primary destination-purpose statistics that make sense given most people's perception of their primary daily activities (work for older adults and school for children and young adults).

DRCOG's experience with the use of its home-interview survey in the development of tour codes strongly suggests that complex, advanced activity-based surveys are not necessary to develop reasonable tour

codes to support the development of tour-based models. The place survey conducted by DRCOG was not noticeably more complex than a traditional trip survey, and our experience with the data suggests that it would also be possible to develop tour codes by using a trip-based survey. These results suggest that many metropolitan planning organizations may already possess the data they need to develop tour-based models.

Finally, one specific lesson learned from DRCOG's experience is that there is no substitute for a robust onboard transit survey. DRCOG used a brief onboard survey to recruit transit riders to participate in its home-interview survey. While this transit oversample provided extremely useful data, the sample size was too small to provide a complete picture of the use of the transit system, and a full onboard survey would provide a nice complement to the oversample.

REFERENCES

1. Lawton, K. Activity and Time Use Data for Activity-Based Forecasting. *Proc., Activity-Based Travel Forecasting Conference: Summary, Recommendations and Compendium of Papers*, June 2–5, 1996, Texas Transportation Institute, Arlington, 1997.
2. PB Consult and Gallup Corporation. *The Integrated Regional Model Project: Vision Phase Final Report*. Denver Regional Council of Governments, Denver, Colo., March 2005.
3. Bradley, M., M. Outwater, N. Jonnalagadda, and E. Ruitter. Estimation of an Activity-Based Microsimulation Model for San Francisco. Presented at 80th Annual Meeting of the Transportation Research Board, Washington, D.C., 2001.
4. Jonnalagadda, N., J. Freedman, W. A. Davidson, and J. D. Hunt. Development of Microsimulation Activity-Based Model for San Francisco: Destination and Mode Choice Models. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1777, TRB, National Research Council, Washington, D.C., 2001, pp. 25–35.
5. Bradley, M. A., J. L. Bowman, Y. Shiftan, K. Lawton, and M. E. Ben-Akiva. *A System of Activity-Based Models for*

- Portland, Oregon*. DOT-T-99-02. U.S. Department of Transportation, 1998.
6. Bowman, J., M. Bradley, Y. Shiftan, K. Lawton, and M. Ben-Akiva. Demonstration of an Activity-Based Model System for Portland. Presented at 8th World Conference on Transport Research, Antwerp, Belgium, 1998.
 7. Vovsha, P., E. Peterson, and R. Donnelly. Microsimulation in Travel Demand Modeling: Lessons Learned from the New York Best Practice Model. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1805, Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 68–77.
 8. *The Mid-Ohio Regional Planning Commission Model: Validation and Final Report*, draft, PB Consult, New York, April 2004.
 9. PB Consult. *Progress Report for the Year 2003: Modeling Task 2—Activity/Tour-Based Models*. Regional Transportation Plan Major Update Project. Atlanta Regional Commission, Atlanta, Ga., Jan. 2004.

Validation of Atlanta, Georgia, Regional Commission Population Synthesizer

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This paper presents the results of initial base-year and back-cast validation of the new Atlanta (Georgia) Regional Commission (ARC) population synthesizer (PopSyn), which acts as the conduit of land use information to the travel demand model. It takes information from the census and the land use model and creates a detailed synthetic population consistent with land use forecasts. A travel demand model can then predict travel for this population. The synthetic population includes a record for each household in the region and a record for each person in the household, so it is well suited for use by travel demand models employing disaggregate microsimulation. Although a PopSyn constitutes a powerful tool, it should be used with caution. By design, it provides misleadingly precise details about every person in the population. Because of limitations of its inputs and its synthesizing procedures, at best only some of the person and household characteristics accurately represent the population at the regional level of geographic aggregation, and many of those characteristics can be imprecise and inaccurate for very small geographic areas such as census tracts. A fundamental goal in the development of a PopSyn therefore is to synthesize as accurately and precisely as possible, for as disaggregate geography as possible, as many variables as possible that determine travel behavior. And a fundamental requirement in the use of a PopSyn should be to rely on it only for the characteristics it accurately represents and to aggregate results to a level at which the synthetic population is precise and accurate.

From the beginning, the Atlanta (Georgia) Regional Commission (ARC) took seriously the need to use a population synthesizer (PopSyn) properly and insisted on being allowed to validate the synthetic population used for travel demand forecasts. Implicit in this insistence is the prerogative to adjust the synthesizer if the validation results are not as expected. With a flexible, adjustable PopSyn, validation can then become more of an iterative tuning procedure.

The ARC PopSyn works in the following basic steps, common to many similar PopSyns. First, it starts with an estimate of the number of households in each zone, with details (in the cells of the matrix) for each of several demographic categories. It also has population forecasts for some aggregate categories. These control totals are more accurate but less detailed than the initial estimates. An iterative proportional fitting (IPF) procedure adjusts the detailed distribution to match the control totals. Then the adjusted numbers of households of each type are drawn from the Public Use Microdata Sample (PUMS).

For the base-year population, ARC defined controls per transportation analysis zone (TAZ), with all the control values coming from census tables [Summary File 1 (SF1), SF3, and Census Transportation Planning Package]. The synthesizer's design allows flexibility in the definition of the matrix cells and control categories so that a variety of one-, two- and three-dimensional census tables can be used to supply controls, thereby enabling the capture of valuable joint distribution information available in the census tables. For families, the controls distinguish "with children" from "without." For nonfamilies, the

controls distinguish “single” from “2+” persons per household. For families with householders over 65 years of age, the distinction by presence of children is ignored.

For the forecast year, fewer controls are defined for each transportation analysis zone (TAZ). These capture ARC TAZ-level forecasts of household income and household size. However, ARC also forecasts some elements at a regional level that can be used for regional controls, such as the average number of workers within a household and the size of age cohorts.

The PopSyn creates a synthetic population for a base year and for each forecast year. There are two key differences between the base year and the forecast year. The initial distribution for the base year comes from PUMS, whereas for the forecast year it comes from the base-year distribution. The controls for the base year come from census tables, but for the forecast years they come from the land use forecasts. In both cases, the PopSyn produces a synthetic population, and it also produces a validation report that compares synthetic population characteristics with known characteristics.

To validate the synthesizer’s ability to generate a forecast population, ARC uses Year 2000 as the base year and validates a back-cast to 1990. The initial distribution comes from the base-year PopSyn. The controls then emulate a 1990 forecast data set and synthesize a 1990 population, which is then compared with 1990 census, testing the ability to generate a synthetic population with limited forecast information. In this process, it is assumed that the forecast input, though limited in amount and detail, is correct. In other words, the procedure validates the synthesizer but does not validate the land use model forecasts.

The procedure validates by calculating both aggregate characteristics of the synthetic population and the same characteristics directly from the detailed census tables. It then compares them to see how well they match. There are four levels of geographic aggregation: tract, Public Use Microdata Area (PUMA), county, and supercounty. Reports are then repeated for multiple synthetic populations to identify the variability caused by the Monte Carlo draws used in the synthesizer.

As for software, it is object-oriented Java, Version 1.5, and consists entirely of subprograms called classes. Each class consists of member objects (that is, the information it holds) and methods (functions it can accomplish). Each class can be individually coded and tested. The PopSyn has four major groups of classes tied together by PopSyn class.

DEVELOPMENT STATUS AND VALIDATION OBJECTIVES

The initial programming of the ARC PopSyn is complete. Some improvements are known to be needed, including

(a) improving the quality of the rounding procedure used after iterative proportional fitting (IPF) before drawing the households from PUMS, (b) enhancing user friendliness, and (c) adjusting the PopSyn to accommodate the recently expanded 20-county geographic scope. Enhancements would also be advisable to take advantage of enhanced inputs that may become available from the economic and land use models. Through use of the current synthesizer, base-year and back-cast synthesis have been tested, and preliminary validation results have been produced.

The ARC PopSyn allows the user to implement a variety of versions without reprogramming. For initial testing and validation, three versions were created, the simplest with 52 household demographic categories and the others with 128 and 316 categories, respectively. As more categories are used, more detail can be used from the census tables (base year) or ARC demographic and land development forecasts (forecast year) to control the synthesis procedure so that more household attributes should be synthesized precisely. However, the computation takes longer; an increase in the number of sparsely populated categories causes more rounding error; and the use of regional values and averages for the additional controls might increase the noise and introduce bias. So one of the primary purposes of the validation is to choose the best version of household categories; preliminary conclusions are reported below. The three versions are shown in Table 1, with their number of categories within each of six dimensions. They will be identified subsequently by their overall number of categories (e.g., Version 52).

Validation allows better understanding of the level of geographic detail at which the aggregate population attributes can be trusted and which household variables are synthesized well enough to be used in the travel forecasting models. Results of this analysis are reported later. Also reported is the testing of other setup parameters, including the convergence criterion for IPF and the aggregation level used in the seed distribution for the forecast year.

Validation can also be used to evaluate the level of variation in results that is caused by the stochastic nature of the simulation procedure used to generate the synthetic population. Several base-year runs have been made

TABLE 1 Three Basic PopSyn Versions

Dimension	Number of Categories		
	Simple	Middle	Complex
Overall	52	128	316
Household income	4	4	4
Household size	4	5	5
Number of workers in household	4	4	4
Family or nonfamily	1	2	2
Age of householder	1	1	2

with the same version, allowing stochastic variation. The results indicate that stochastic variation is probably not a problem, but detailed analysis of this variation has not been conducted and is therefore not reported here.

COMPUTATIONAL PERFORMANCE

The table below shows computational performance for base-year synthesis with the three versions, each synthesizing 3.6 million persons in 1.35 million households.

<i>Household categories</i>	52	128	316
Balancer IPF iterations	7	11	14
Total running time (minutes)	9.9	11.9	17.4

Computational performance for forecast-year synthesis is similar. The performance tests were run on a Pentium 4 computer with a 3-GHz processor and 2 GB of memory. Regardless of version, 3 min of overhead are required to set up for synthesis; it takes more than a minute to produce the validation statistics (if desired), and more than 2½ min are required to save the synthetic population. However, Version 316 requires much more time for other parts of the process, especially the IPF procedure so that overall run time of Version 316 is nearly twice that of Version 52.

The results in the table above come from runs in which the IPF stopped when all cells changed less than 5%. Reducing the stop criterion to 0.5% doubled the required iterations but increased the total run time by less than 5%.

VALIDATION RESULTS

This section examines the precision and accuracy of household and person variables included in the synthetic population for both the base year and the back-cast. As used here, the word “accuracy” refers to statistical bias; a variable with a nonzero mean percentage difference between the synthetic population and the census validation value is considered inaccurate. The “percentage difference” is that between synthetic value and census value for a single geographic unit (tract, PUMA, county, or supercounty). The “mean percentage difference” is the average of this difference across all geographic units in the region. “Precision” refers to statistical variance; a variable with a large variance in the difference between the synthetic population and the census validation value is considered imprecise. The order in which variables are discussed below corresponds roughly to the decreasing level of detail in which forecast controls are applied. Fig-

ure 1 provides a graphical presentation of selected variables relevant to the text discussion.

Income

Because household income is controlled at the TAZ level in four categories for the base year and the forecast year, for all three versions, it should be the most precise and accurate of all the variables, and indeed it is. Precision is slightly higher in the base year. Version 128 is oversynthesizing low-income households; this probably indicates a minor bug in the setup inputs that should be found and corrected if that version is chosen for use. The precision and accuracy of uncontrolled income subcategories are noticeably worse but could be judged as good at the PUMA level of aggregation. The back-cast results in the uncontrolled subcategories cannot be correctly evaluated because of inconsistencies in the subcategory definitions between the 1990 and 2000 census years.

The census PUMS data also include a personal variable that compares personal income with the official poverty level. The percentage of persons below the poverty level is synthesized imprecisely at the tract level but is otherwise reasonably accurate and precise in the base year. The results cannot be validated in the forecast year because of changing poverty level definitions and dollar values between census years.

Household Size

Household size is controlled at the TAZ level. In the base year, it is controlled in five categories for Versions 316 and 128 and in four categories for Version 52. Household size is controlled at the TAZ level in the forecast year, but only average household size is available. Furthermore, the base-year distribution is used to translate this into the controlled categories. In the base year, the controlled sizes are extremely precise and accurate; the uncontrolled household Size 4 in Version 52 is noticeably less precise but quite accurate. The uncontrolled size categories with very few households, such as Size 6, achieve much less accuracy and precision, although accuracy is better in the versions that control five categories. The back-cast validation procedure yields important results. First, noticeable inaccuracy arises from the use of average household size to generate the forecast control. Second, for Version 52, the precision and accuracy of the uncontrolled household Size 4 category are not noticeably worse than the four controlled sizes. Third, the precision and accuracy of Version 52 are not worse than for Versions 128 and 316. So, given that the forecasts are available only as averages, controlling five size categories instead of four yields little or no improvement in the

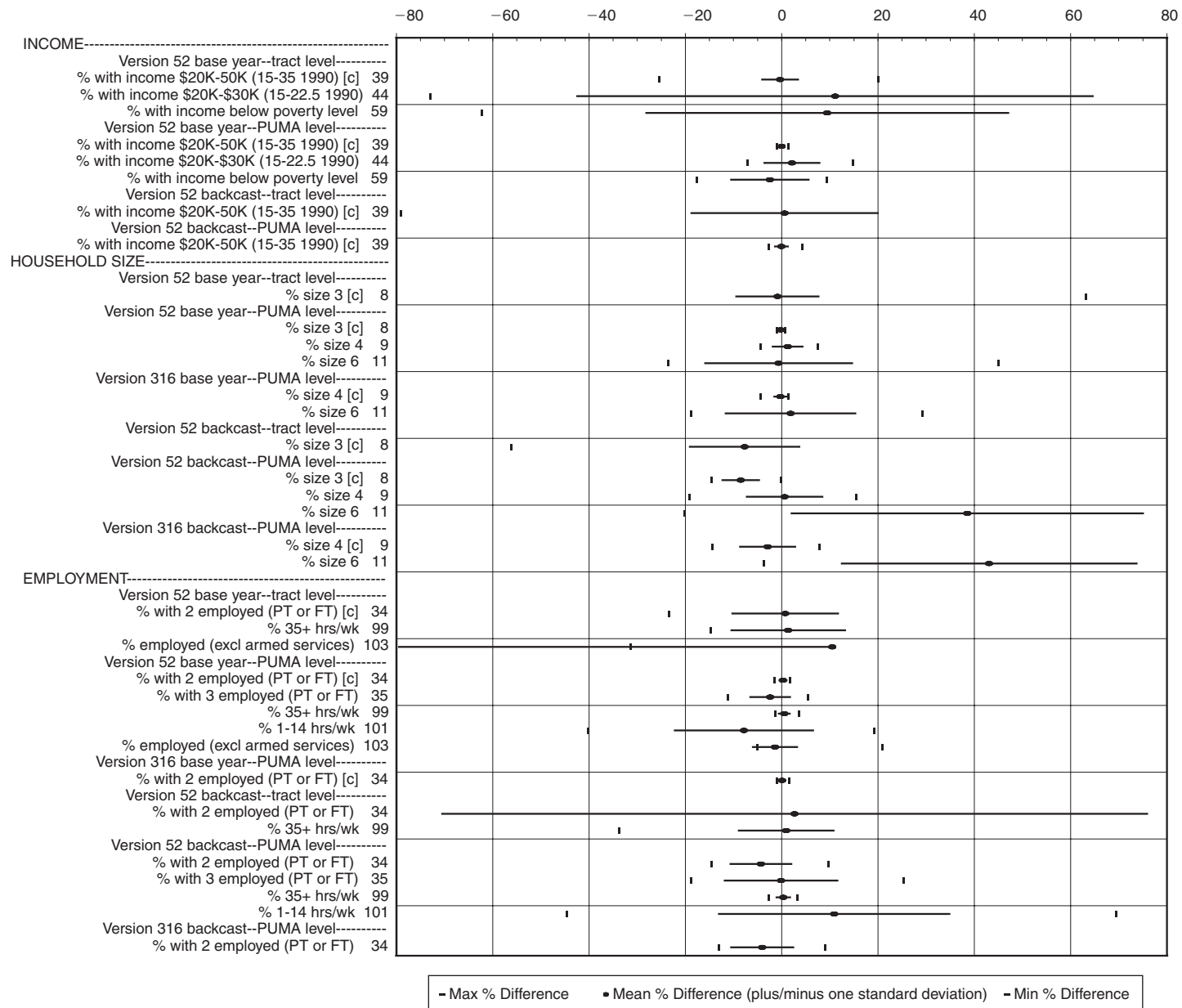


FIGURE 1 Selected validation results. ([c] indicates variable controlled at the TAZ level; numbers after label correspond to variable number in complete validation output.)

(continued)

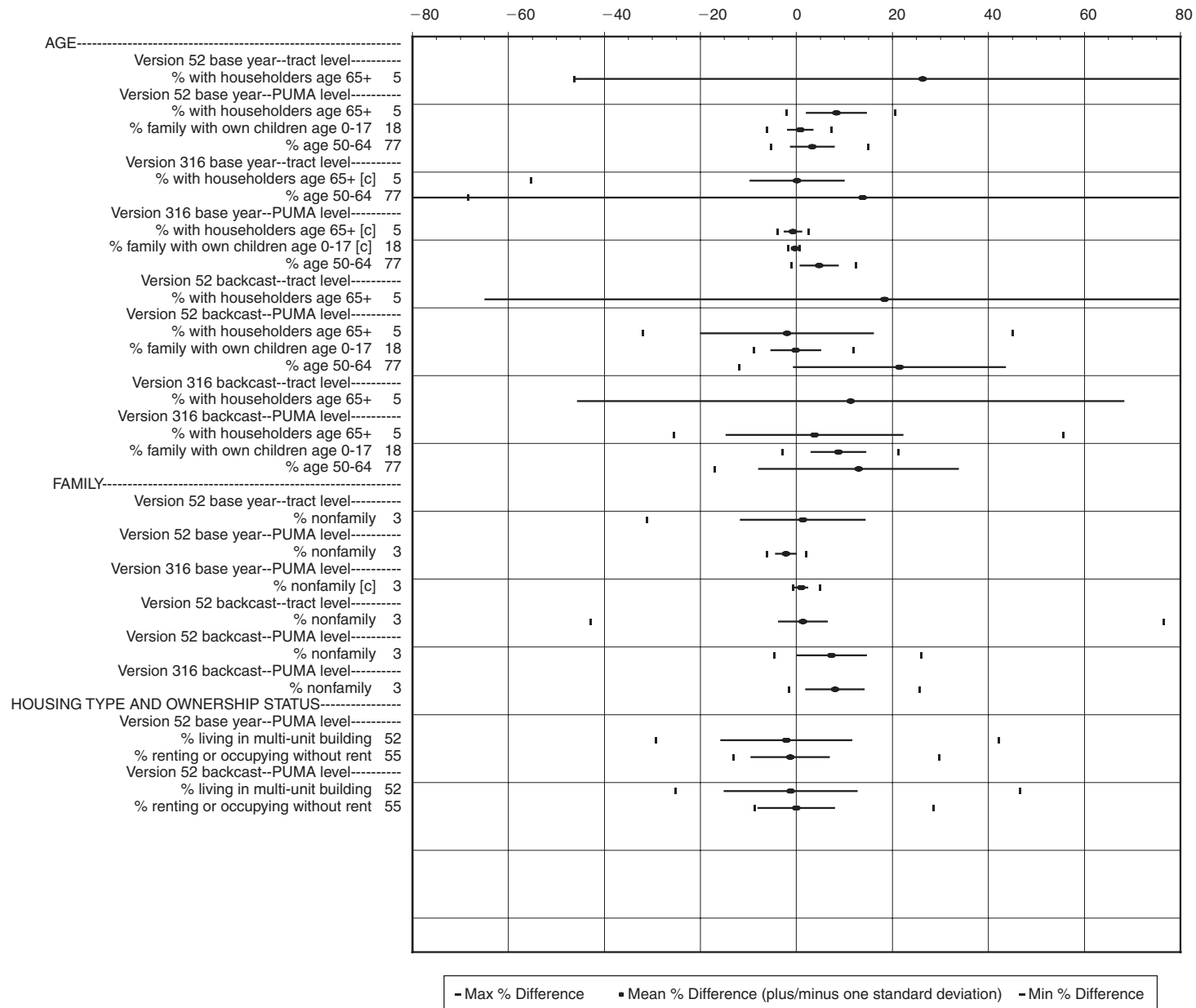


FIGURE 1 (continued) Selected validation results.

(continued)

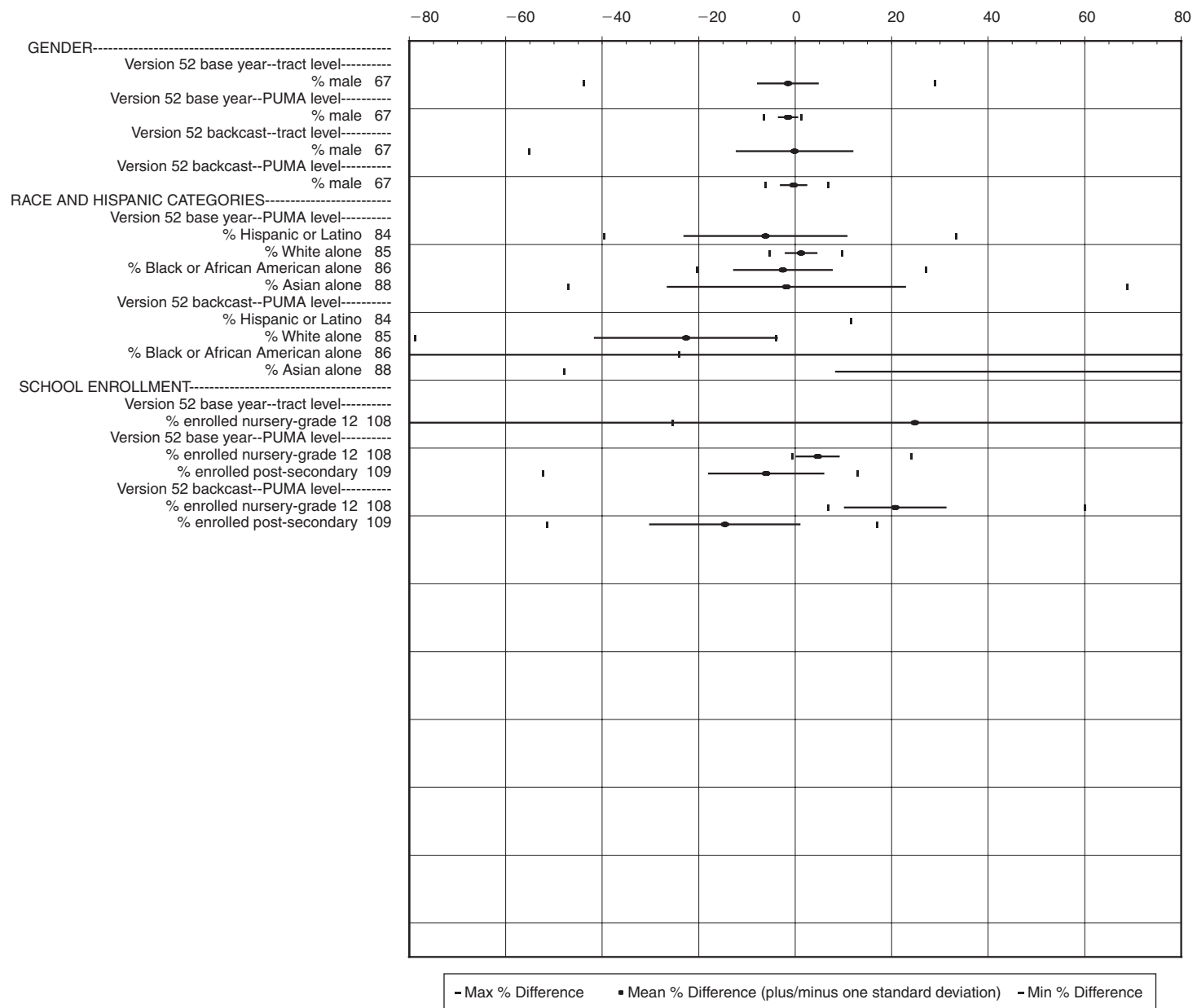


FIGURE 1 (continued) Selected validation results.

forecast year. The benefits in the forecast year of more size categories would probably be much greater if ARC could forecast a household size distribution rather than an average household size.

Employment

Employment is controlled as number of workers in a household, in four categories, with TAZ-level control in the base year. In the forecast year, the control is enforced only for the region overall, and only average number of workers per household is supplied. Therefore, the forecast-year control is really quite weak. In the base year, the controlled worker categories are extremely accurate and precise, and uncontrolled subcategories are noticeably less accurate and precise. In the back-cast, it is apparent again that inaccuracy is induced by deriving controls from averages, and the quality of the largest uncontrolled category (three workers) is not worse than the controlled categories. In addition, the use of the regional control degrades tract-level precision. There would possibly be much to gain from trying to estimate a distribution of households by number of workers rather than only an average number of workers per household, and the benefits would probably be much greater if this could be done for geographic units smaller than the region.

The employment status of each person is also in the synthetic sample. In the base year, the categories of (a) employed civilian and (b) in labor force are precise and accurate at the PUMA level, apparently because of the household-based employment controls, although they are extremely imprecise at the tract level. The back-cast validation values taken from the census are incorrect (for a yet undetermined reason), so the validity of personal employment in the back-cast cannot be determined.

For employed persons, the category hours worked per week is also recorded in the synthetic population. The category working 35 or more hours per week is extremely accurate and precise, even at the tract level, in the base year and the back-cast. For the categories of 15 to 34 h per week and 1 to 14 h per week, the results are imprecise and inaccurate at the tract level but reasonably accurate and precise at the PUMA level, in both the base year and the back-cast.

Age

Age is controlled only in Version 316, with three categories on the basis of whether a householder is over or under age 65 and, for those under 65, whether a householder's own children under the age of 18 are present. For the forecast year, the control is supplied only as the

regional sizes of the subpopulations age 65+ and less than 15. The forecast control categories are sized by using relationships in the base-year census PUMS data between the available values and the needed control categories. In the base year, the controls noticeably improve the accuracy and precision of the corresponding household categories. However, in the back-cast, Version 316 controls provide no apparent improvement in accuracy or precision over the uncontrolled Versions 52 and 128, and, for the presence of children under the age of 18, Version 316 is less accurate. Apparently, the method of transforming the population estimate into the control category induces bias in the forecast.

Examination of base-year validation statistics for age categories of persons in the synthetic population shows that controlling households by age of householder in Version 316 may provide a small improvement in the accuracy and precision of person ages for the major categories of 0 to 17, 18 to 64, and 65+. For detailed age subcategories, results are unusably inaccurate and imprecise at the tract level; at the PUMA level, precision and accuracy are more acceptable. In the forecast year, Version 316 results differ from those of the other versions but with similar accuracy and precision, and for all versions the quality degrades somewhat from the base year but not a lot.

Family

Family is controlled in Versions 128 and 316 but only in the base year. In the base year, the controls improve precision and accuracy, but without the control, precision and accuracy of Version 52 are still quite good, even at the tract level. The base-year controls appear to have little carryover effect in the forecast, in which the uncontrolled categories are no better in Versions 128 and 316 than in Version 52. Precision remains fairly high, but accuracy gets considerably worse.

Housing Type and Ownership Status

The accuracy and precision of these variables, which are completely uncontrolled in the base year and forecast, might nevertheless be considered good enough to be usable at the PUMA level of geography, except for the tiny category of mobile home dwellers. The tract-level results are too inaccurate and imprecise to be usable.

Gender

Although there are no controls related to gender, the number of males and females are fairly accurate and pre-

cise, regardless of version, in both the base year and the back-cast.

Race and Hispanic Categories

Although there are no controls related to race and Hispanic categories, in the base year, these are synthesized accurately and with reasonable precision at the PUMA level for Hispanic, white, black, and Asian categories but inaccurately and imprecisely at the tract level. For the other smaller racial categories, the results are imprecise and inaccurate at all levels. The race data definitions changed from the 1990 census to the 2000 census, making it difficult to interpret the validation results, although it appears that the accuracy and precision of the back-cast population are much worse than in the base year.

School Enrollment

School enrollment in two categories—nursery to grade 12 and postsecondary—although inaccurate and imprecise at the tract level, is reasonably accurate and precise at the PUMA level in the base year. In the back-cast, school enrollment is quite inaccurate and imprecise at all levels of geographic aggregation but perhaps usable at the PUMA level.

ADDITIONAL VALIDATION RESULTS

IPF Stopping Criterion

The preceding validation results come from test runs in which the IPF convergence criterion was set at 5%. A change in the criterion to 1% in back-cast runs causes only a slight improvement in the mean percentage difference (e.g., mean percentage difference improves from 4% to 3.9%), on average, across the usable variables at both the PUMA and tract levels of analysis.

Forecast Seed Matrix

When synthesizing a forecast-year synthetic population, PopSyn uses, as its starting matrix for IPF, the balanced matrix from the base-year synthetic population. Its starting distribution for each TAZ is a combination of the TAZ-, tract-, and PUMA-level distributions. The exact combination depends on the sizes of the TAZ and tract relative to user-assigned parameters. If the TAZ (or tract) is smaller than the user-specified minimum, then it is not trusted to provide the starting distribution; if it is larger than the user-specified maximum, then it is trusted com-

pletely. In between, its distribution is blended with those of the larger geographies. The issue at hand is whether small neighborhood peculiarities persist over time. If they do, then it would be better to use the base-year TAZ-level distribution, even for small TAZ, preserving the details supplied by the base-year census tables; if they don't, then it would be better to use the distribution from the tract or PUMA.

To test this, Version 316 back-casts were run with a variety of minimum and maximum size criteria. The quality of the validation results was then compared by averaging the absolute mean percentage difference and the standard deviation percentage difference across all usable variables and comparing them across runs. The results indicated that the back-cast population matched the back-cast validation values best when the minimum size was between 10 and 100 and the maximum size was between 100 and 500. The results were worst when the size parameters were set so high that the PUMA distributions were used exclusively. However, except for this extreme case, differences were minor compared with the levels of inaccuracy and imprecision in the best forecasts.

SUMMARY OF VALIDATION RESULTS

The following summary conclusions might be drawn from the above analysis about the preferred versions to use for base-year and forecast analysis:

In the base year, the use of census data to control for more variables in Version 316 yields a clearly superior synthetic population, especially for tract level evaluation in controlled categories. So, for base-year analysis and short-term forecasts using the base-year population, Version 316, or perhaps even a more complex version, should be used.

For the forecast year, the additional controls of Versions 128 and 316 provide little value and can potentially make the population worse. The reason for this situation lies primarily in the reliance on averages that are translated into category distributions naively from base-year distributions rather than attempting to make informed forecasts of the distributions themselves. It probably also lies in relying on regional forecasts rather than forecasts carrying information at some smaller level of geographic aggregation.

Table 2 provides a summary of the aggregate level at which various categories of variables would be reasonably precise and accurate in the synthetic population, assuming Version 316 for base-year analysis and Version 52 for forecast-year analysis.

These preliminary results demonstrate several important aspects of PopSyns. First, the accuracy of synthesized characteristics depends heavily on the control variables used for population synthesis; uncontrolled

TABLE 2 Aggregation Levels at Which Variables in Synthetic Population Have Reasonably High Accuracy and Precision

Variable	Base Year Usage (Version 316)	Forecast Year Usage (Version 52)
Household income (major control categories)	Tract	Tract
Household income (subcategories)	PUMA	PUMA
Person poverty status	PUMA	?
Household size (major control categories)	Tract	PUMA
Household size (subcategories)	Tract	PUMA
Household workers (major control categories)	PUMA	PUMA
Household workers (subcategories)	PUMA	PUMA
Person employment status	PUMA	PUMA
Person weekly work hours (35+ category)	Tract	PUMA
Person weekly work hours (other categories)	PUMA	PUMA
Household with holder age 65+	Tract	PUMA
Household presence/absence of own children age 0–17	Tract	PUMA
Person age category	PUMA	PUMA
Household family status	Tract	PUMA
Household housing type (major categories)	PUMA	PUMA
Household housing ownership (major categories)	PUMA	PUMA
Person gender	Tract	Tract
Person race and Hispanic status	PUMA	?
Person school enrollment category	PUMA	?

variables are synthesized much less accurately, even in the base year. Second, the accuracy drops when results are examined at a more detailed level of aggregation. Third, even for controlled variables, the accuracy is not perfect; in the ARC base-year case, the rounding procedures used after IPF, before the households are drawn, introduce a substantial amount of noise; in the forecast case, the use of averages (variables that do not match the IPF categories) and regional values all degrade accuracy, precision, or both. The accuracy and precision of the forecast population are less than those of the base-year population, even assuming that the forecast inputs are

accurate, because (a) the quantity of forecast controls is smaller and (b) they are more aggregate than the base-year controls. The conclusion to be drawn is that it is indeed important to implement validation procedures that provide the user of a PopSyn with the information needed to use it appropriately. It is also valuable to implement a flexible PopSyn that can be adjusted and improved in response to the validation information. With this version of the PopSyn in hand, ARC is in a good position to continue validating and improving it, even as ARC incorporates it into the demand models and uses it for analysis.

Microsimulation of Single-Family Residential Land Use for Market Equilibriums

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This paper investigates single-family residential development for housing market equilibriums by using microeconomic theory and disaggregate spatial data. A logit model and notions of price competition are used to simulate household location choices in six scenarios, with either one or multiple employment centers and with low, medium, and high value-of-travel-time assumptions. Consistent with bid-rent theory, housing market equilibrium for each scenario was reached in an iterative fashion. The spatial allocation of new households in the region of Austin, Texas, illustrated the potential shape of things to come, with endogenously determined home prices and demographic distributions.

As an essential part of urban travel behaviors, prediction of future land use patterns is of great interest to policy makers, developers, planners, transportation engineers, and others. Residential land is in the range of 60% of developed land, dominating urban areas. Moreover, the emergence of commercial, industrial, office, and civic uses is spatially correlated with residential development (e.g., Zhou and Kockelman 2005).

Numerous factors contribute to the complexity of housing location choices (e.g., Irwin and Bockstael 2004 and Bina and Kockelman 2006). Microeconomic theory tested with disaggregate spatial data offers behavioral foundations and a better understanding of such decisions. These theories of land use can be traced back to the concept of agricultural rents and travel costs around a market center proposed by Von Thünen (1826, as

reported in de la Barra 1989), which was followed by the urban examples of Wingo (1961) and Alonso (1964). These early models treat land as homogeneous and continuous and recognize only one employment center. Moreover, they neglect taste heterogeneity.

The Herbert and Stevens model (1960) determined residential prices by maximizing aggregate rents subject to constraints on (total) land availability and the number of households to be accommodated. Senior and Wilson (1974) enhanced the Herbert–Stevens model by adding an entropy term to the objective function, reflecting preference dispersion among households. Both models treat spatial elements in an aggregate manner, using an exhaustive zone-based subdivision of the region. Recent, more-advanced models (e.g., Anas and Xu 1999 and Chang and Mackett 2005) depict household distribution via general equilibrium and land use–transportation interactions. However, their complexity has greatly limited their application.

In contrast to the earlier models and methods, this investigation emphasizes parcel-level data [geographic information system (GIS) encoded] and considers taste heterogeneity of individual households via behavioral controls for demographic variables and random utility maximization. The model applied here relies on bid-rent theory, which is both theoretically meaningful and practically feasible. This work examines single-family residential land development on the basis of a microscopic equilibrium of the housing market for recent movers. Each home-seeking household is allocated to the location that offers it the highest utility, and each new home is occupied by the highest bidder. This process ensures

optimal allocation of land in the sense that each household chooses a home that most satisfies it while developers and land owners maximize profits and rents. The spatial distribution of households and the equilibrium home prices are endogenously determined as the outcome of a housing-market mechanism involving land and transport.

DATA AND METHODS

This section describes the data used to calibrate the location choice model and to reach single-family housing market equilibriums. Both procedures were coded in GAUSS matrix programming language (Aptech Systems 2003).

Location Choice Model

Bina and Kockelman (2006) undertook a survey of Austin movers in 2005. Sampling half of Travis County's recent [with "recent" meaning within the past 12 months (before the sampling date and start of the survey)] home buyers, responses were obtained from over 900 households, or roughly 12% of those buyers. The data set contains comprehensive information on household demographics, housing characteristics, reasons for relocation, and preferences when facing different housing and location choice scenarios.

Commute distance and cost have a bearing on one's residential location choice (e.g., Van Ommeren et al. 1999, Rouwendal and Meijer 2001, Clark et al. 2003, Tillema et al. 2006). The GIS-encoded addresses of homes and workplaces, accompanied by roadway network data, provide a direct measure of commute time (with commute time calculated by using Caliper's TransCAD software for shortest travel-time path under free-flow conditions) for all potential locations. Because value of travel time (VOTT) was not directly available in the data set, it was approximated as the average wage (with part-time employed persons assumed to work 1,000 h/year, while full-time employed persons were assumed to work 2,000 h/year) of each household's employed members and was assumed to be equal over the household's employed members. In addition to work access, each potential home's (Euclidean) distance to the nearest of the region's largest 18 shopping centers (DISTMALL) helps explain the impact of shopping access on location choice. Furthermore, household annual (pretax) income (HHINC), home size (SQFOOT), and housing prices per interior (built) square foot (UNITP) help explain the balance of home affordability [where price (equal to UNITP \times SQFOOT) is divided by annual income] and households' preferences for larger home sizes.

Residential location choice was modeled via a multinomial logit framework. The random utility was specified as follows:

$$U_{bi} = \beta_1 + \beta_2 \frac{\text{UNITP}_i \times \text{SQFOOT}_i}{\text{HHINC}_b} + \beta_3 \left(\frac{\text{UNITP}_i \times \text{SQFOOT}_i}{\text{HHINC}_b} \right)^2 + \beta_4 \frac{\text{SQFOOT}_i}{1,000} + \beta_5 \sum_{n=1}^{N_b} (\text{VOTT}_b \times \text{TT}_{bin}) + \beta_6 \sum_{n=1}^{N_b} (\text{DISTWORK}_{bin}) + \beta_7 \text{DISTMALL}_i + \epsilon_{bi}$$

where

- U_{bi} = random utility of household b for choosing home i ,
- $\beta_1, \beta_2, \dots, \beta_7$ = parameters to be estimated,
- N_b = number of workers in household b ,
- VOTT_b = household's approximate value of travel time,
- TT_{bin} = network commute time for worker n in household b when residing in home i ,
- DISTWORK_{bin} = corresponding Euclidean distance, and
- ϵ_{bi} = random component assumed to be independent identically distributed (IID) Gumbel, across households b and their alternatives i .

For model calibration, each household's choice set consisted of 20 alternatives: 19 randomly drawn from the pool of all homes purchased by respondents in the recent mover survey plus the chosen option. These model results are shown in Table 1. The model indicates a concave relationship between strength of preference (systematic utility) and the ratio of home price to annual income. The parameter values on the ratio and its squared term suggest that more expensive homes are preferred when the ratio is less than 1.7, becoming less attractive as the ratio of price to income exceeds this threshold.

Larger homes, of course, are more desired, with SQFOOT increasing the likelihood of a home's selection, everything else constant. The negative signs associated with commute costs and Euclidean distances to workers' workplaces support the notion that households favor homes closer to their employed workers' jobs. Major mall access, however, was not favored; perhaps the potentially high volumes of traffic and congestion in the vicinity of major shopping centers offset any possible access gains. Other forms of shopping access may be desired but require geocoding of far more smaller shopping.

TABLE 1 Results for Location Choice Model

Explanatory Variable	Coefficients	<i>t</i> -Statistics
Constant	-2.59	-15.5
Home price divided by household income	0.171	1.71
(Home price divided by household income) ²	-0.0509	-4.04
Total interior square footage (ft ²)	0.262	4.46
Euclidean commute distance (mi)	-0.0643	-7.86
Commute cost (\$)	-0.0208	-4.66
Euclidean distance to the nearest shopping mall (mi)	0.121	6.28
Log-likelihood values		
Market shares	-2293.0	
Convergence	-2437.8	
LRI	0.0594	
Number of observations	614 ^a	

^a While the original survey contains 965 records, the number of observations available for analysis here is just 614 due to missing data on workplace location (selected home attributes, such as home price, or both).

Equilibrium of Single-Family Housing Market

Microsimulation of single-family residential land development for housing-market equilibrium was applied to the City of Austin and its 2-mi extraterritorial jurisdiction, assuming a 25% growth in household numbers. (The study area accommodated about 304,800 households in Year 2000. With the projected 25% growth, the number of newly added households was around 76,000 in the whole area.) Both the supply of and demand for homes were modeled explicitly.

On the supply side, undeveloped sites with potential for residential development were located by using a Year 2000 land use parcel map obtained from the City of Austin's Neighborhood Planning and Zoning Department. Undeveloped parcels over 3,000 ft² in size (in Year 2000) were considered available for single-family residential development. Due to computational memory constraints (on a standard office PC, with 1 GB of RAM), a 10% random sample was drawn from all 16,750 developable parcels. Figure 1 depicts the study area, the undeveloped parcels, and the 10% sample. The distribution of existing single-family residential parcel sizes in Austin resembled a chi-square distribution, and large, undeveloped parcels were assumed to subdivide according to this distribution. Of course, not all subdivided parcels will be occupied by newly added households; only the chosen sites were assumed to be developed into single-family residential land after the housing market reached equilibrium. To simulate home size, a floor-area ratio (FAR) of .25 was used. (As an extension to this work, this global variable is being made more site specific and random.) The newly generated single-family residential sites—defined by home size, parcel-specific unit price per interior square foot, and distances to employment sites and shopping centers—were allocated to individual households based on rent- and utility-maximizing principles.

On the demand side, the 7,600 future households consisted of five types categorized by annual income levels (on

the basis of standard census-class weighted average): \$11,000, \$28,000, \$42,000, \$72,000, and \$170,000. The new households were assumed to be demographically distributed according to the 2002 American Community Survey. [This survey puts 19.1% in the first (lowest) income bracket, 16.0% in the second, 15.5% in the third, 30.5% in the fourth, and 18.9% in the fifth (highest) bracket.] Corresponding to a 10% random sampling of undeveloped parcels and a 25% population growth assumption, the numbers of households to be allocated (for each of the five types) were 1,500, 1,200, 1,200, 2,300, and 1,400,

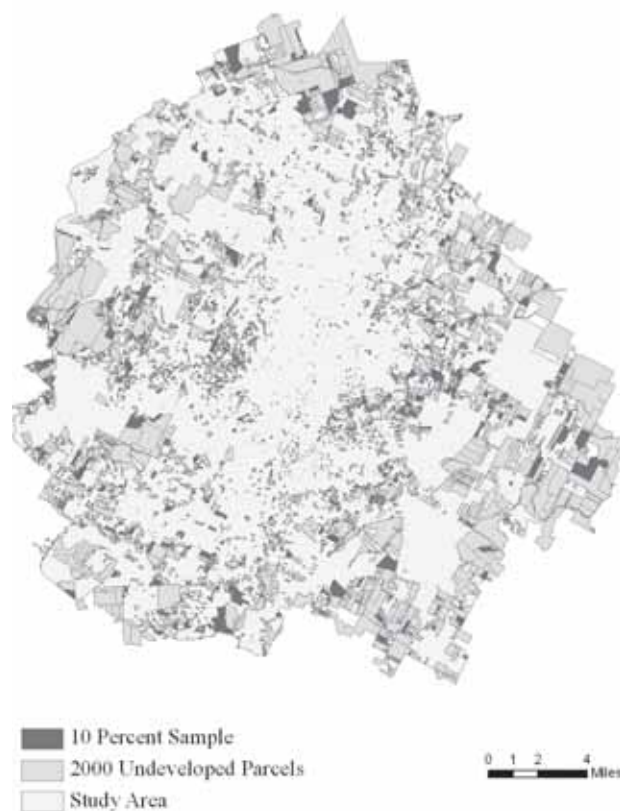


FIGURE 1 Map of study area showing all undeveloped parcels and 10% sample.

respectively. Three VOTT scenarios were designed to examine the impact of how VOTT may affect spatial allocation of residences. The low, medium, and high VOTTs for each of the five household types were assumed to be as follows: (a) low VOTTs of \$1.40/h, \$3.50/h, \$5.30/h, \$9.00/h, and \$10.60/h; (b) medium VOTTs of \$2.80/h, \$7.00/h, \$10.50/h, \$18.00/h, and \$21.30/h; and (c) high VOTTs of \$5.50/h, \$14.00/h, \$21.00/h, \$36.00/h, and \$42.50/h, respectively. [The low, medium, and high VOTTs were taken to be 25%, 50%, and 100% of employed members' wage (assuming one full-time employed person in the first four types of households and two full-time employed persons in the last type of household.)] These households compete for homes that offer them the highest utilities. Due to this competition, home prices are bid up until the market reaches equilibrium.

Essentially, individual households are assumed to evaluate all new (single-family) residential parcels as a function of their price, size, and site accessibility (in relation to travel costs, distances to employment centers and shopping malls, or both). When a home is selected as the best choice by more than one household, the imbalance in both competition and supply–demand should increase the unit price. Following such price increases, the previous best choice becomes unaffordable or at least less preferable due to the price increase, and other, relatively more preferred homes may emerge. Through this implicit price mechanism, households withdraw from competition over home sites that are experiencing high demand. Ultimately, the model presumes that land developers sell the home or home site to the highest bidder at the market equilibrium's highest price.

Equilibration Results

The market equilibrium for new home buyers (considering 10% of the presently undeveloped land in Austin) was reached in an iterative fashion. The starting home value was assumed to be low, at just \$100 per interior (built) square foot (or \$25/ft² of parcel land). Each household was assumed to consider 20 randomly selected alternative homes or home sites with specific sizes and accessibilities. IID Gumbel error terms were associated with each competing household and its set of considered alternatives. Knowing price and size, households were assumed to choose those offering the highest utilities as defined by the location choice model. Prices rose in steps of \$1/ft² when a home was desired by more than one household. When each household finally was aligned with a single, utility-maximizing home site, each occupied house was allocated to the household that tendered the highest bid. At this stage, the housing market (for new buyers–movers) is said to have reached equilibrium. In this way, Austin's single-family residential development

was simulated for each of six scenarios: the three sets of VOTTs for a study area having either a single employment center [the central business district (CBD)] or multiple employment centers (with each of 114 such centers—housing at least 500 jobs—located within the study area in Year 2000). Figure 2 illustrates the locations of these employment centers, the CBD, and the locations of the 18 shopping centers as well. The new households' working members were assumed to be allocated job sites according to the scenario (i.e., either all worked at the CBD or at sites nearest to their chosen homes).

In each simulation, the average equilibrium unit price for each (large or subdivided) parcel was computed by averaging the unit prices of the occupied pieces that were subdivided from the parcel, and average occupant income was calculated as the average annual income of households that chose to reside on the parcel. Figure 3 plots the average equilibrium unit price against the distance to the CBD or to the nearest employment center, depending on the scenario setup. As expected, the resulting plots illuminated how undeveloped parcels located near employment sites enjoyed higher average equilibrium unit prices. When VOTTs were low, there was no clear relationship between the average equilibrium unit price and the distance or travel time to employment sites. As VOTTs increased, the

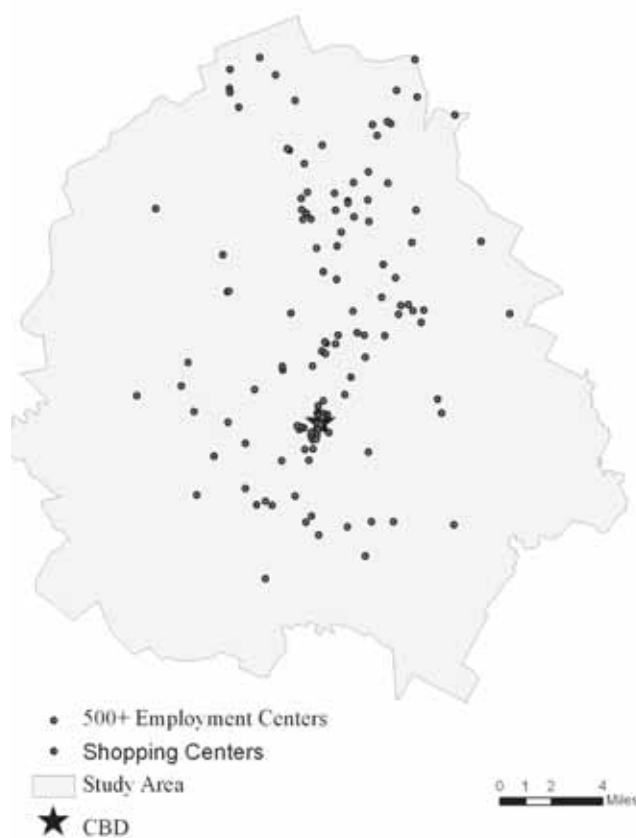


FIGURE 2 Locations of Austin's employment centers, central business district, and shopping centers.

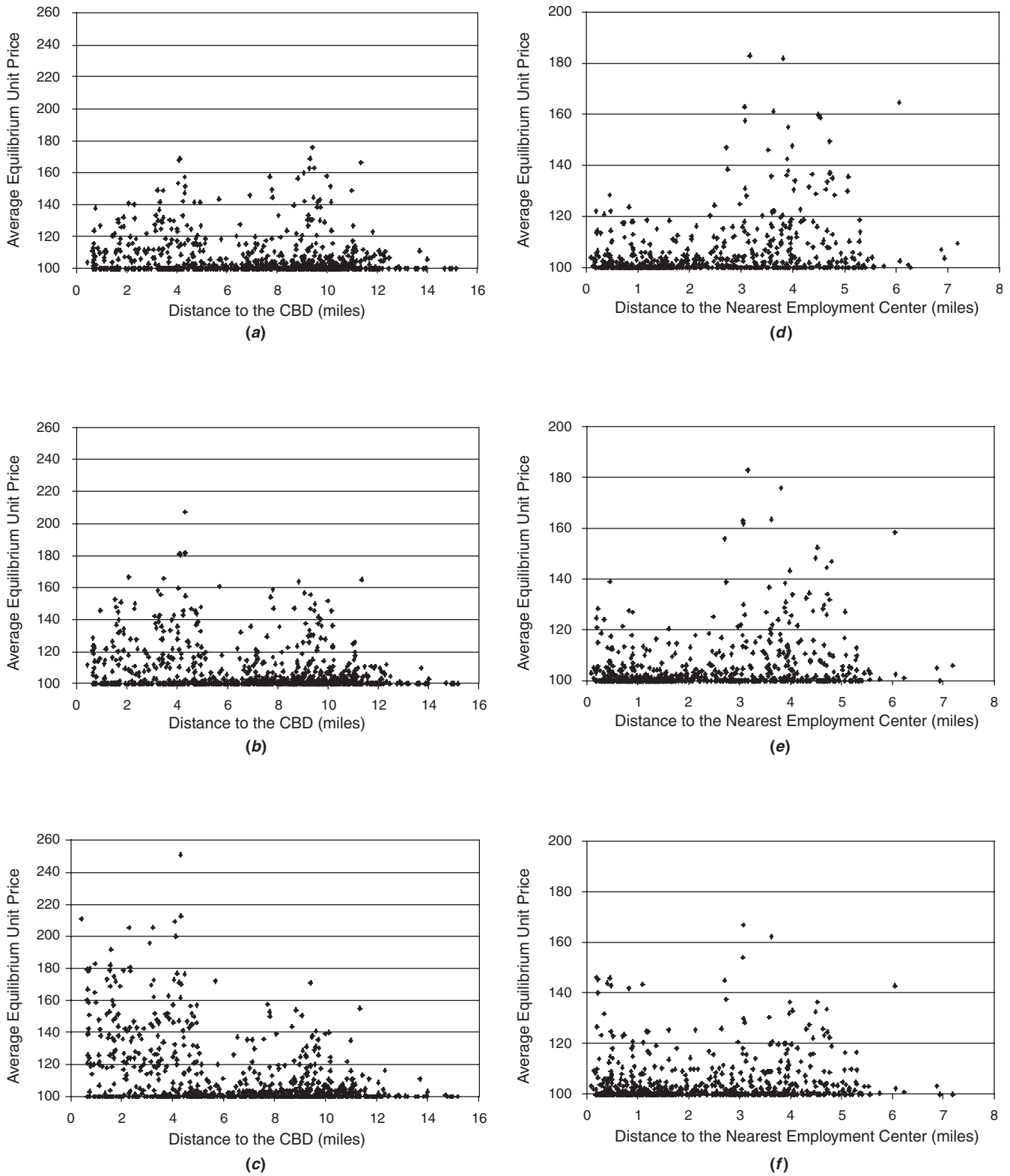


FIGURE 3 Equilibration results: (a) single employment center and low VOTT, (b) single employment center and medium VOTT, (c) single employment center and high VOTT, (d) multiple employment centers and low VOTT, (e) multiple employment centers and medium VOTT, and (f) multiple employment centers and high VOTT.

average equilibrium unit prices near employment sites rose, and the average equilibrium unit prices far away from employment sites declined. This tendency was more significant for sites with single-employment centers (i.e., monocentric job) scenarios than for the corresponding scenarios with multiple employment sites. Moreover, for the six scenarios, Moran's I-statistics [calculated on the basis of an inverse Euclidean-distance matrix (e.g., Lee and Wong 2000)] indicated that average equilibrium unit prices for residentially developed parcels had positive spatial autocorrelation over the entire region, confirming the visual information conveyed by the plots. By using Moran's statistics, a clustering of households of similar income was observed, as expected.

CONCLUSIONS

This paper developed a model for distributing new households and tracking home price fluctuations on the basis of microeconomic theories and microsimulation. Disaggregate spatial data facilitated model calibration and application for Austin, Texas, a medium-sized urban region. The results were reasonable and tangible. Perhaps most importantly, they suggested that microsimulation of an entire region's land market was viable. The model used here can be improved through more realistic developer tendencies of parcels (rather than, for example, a single-valued FAR or solely single-family residential parcels) and consideration of additional policy tools (such as roadway pricing and land regulation effects). Such approaches herald a new wave of land use modeling opportunities.

REFERENCES

- Alonso, W. 1964. *Location and Land Use*. Harvard University Press, Cambridge, Mass.
- Anas, A., and R. Xu. 1999. Congestion, Land Use, and Job Dispersion: A General Equilibrium Model. *Journal of Urban Economics*, Vol. 45, pp. 451–473.
- Aptech Systems. 2003. *GAUSS Mathematical and Statistical System 6.0*. Aptech Systems, Inc., Maple Valley, Wash.
- Bina, M., and K. Kockelman. 2006. Location Choice vis-à-vis Transportation: The Case of Recent Home buyers. Presented at 11th Conference of the International Association of Travel Behavior Research, Kyoto, Japan.
- Chang, J., and R. Mackett. 2005. A Bi-Level Model of the Relationship Between Transport and Residential Location. *Transportation Research B*, Vol. 40, pp. 123–146.
- Clark, W. A. V., Y. Huang, and S. Withers. 2003. Does Commuting Distance Matter? Commuting Tolerance and Residential Change. *Regional Science and Urban Economics*, Vol. 33, pp. 199–221.
- de la Barra, T. 1989. *Integrated Land Use and Transport Modelling: Decision Chains and Hierarchies*. Cambridge University Press, New York.
- Herbert, J., and B. Stevens. 1960. A Model of the Distribution of Residential Activity in Urban Areas. *Journal of Regional Science*, Vol. 2, pp. 21–36.
- Irwin, E., and N. Bockstael. 2004. Land Use Externalities, Open Space Preservation, and Urban Sprawl. *Regional Science and Urban Economics*, Vol. 34, pp. 705–725.
- Lee, J., and D. Wong. 2000. *Statistical Analysis with Arcview GIS*. John Wiley & Sons, Inc., New York.
- Rouwendal, J., and E. Meijer. 2001. Preferences for Housing, Jobs, and Commuting: A Mixed Logit Analysis. *Journal of Regional Science*, Vol. 41, pp. 475–505.
- Senior, M., and A. Wilson. 1974. Explorations and Syntheses of Linear Programming and Spatial Interaction Models of Residential Location. *Geographical Analysis*, Vol. 6, pp. 209–238.
- Tillema, T., D. Ettema, and B. van Wee. 2006. Road Pricing and (Re)Location Decisions of Households. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Van Ommeren, J., P. Rietveld, and P. Nijkamp. 1999. Job Moving, Residential Moving, and Commuting: A Search Perspective. *Journal of Urban Economics*, Vol. 46, pp. 230–253.
- Von Thünen, J. H. 1826. *Der Isolierte Staat in Beziehung auf Landwirtschaft und Nationaleconomie*. Hamburg, Germany.
- Wingo, L. 1961. *Transportation and Urban Land Use*. Johns Hopkins University Press, Baltimore, Md.
- Zhou, B., and K. Kockelman. 2005. Neighborhood Impacts on Land Use Change: A Multinomial Logit Model of Spatial Relationships. Presented at 52nd Annual North American Meeting of Regional Science Association International, Las Vegas, Nev.

ADDITIONAL RESOURCE

- Berechman, J., and K. Small. 1988. Modeling Land Use and Transportation: An Interpretive Review for Growth Areas. *Environment and Planning A*, Vol. 20, pp. 1285–1309.

BREAKOUT SESSION

ACTIVITY-BASED MODELS

Modeling Short-Term Dynamics in Activity-Travel Patterns

From Aurora to Feathers

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Most operational models of activity-travel demand, including nested logit models (e.g., Vovsha et al. 2004), CEMDAP (Bhat et al. 2004), FAMOS (Pendyala et al. 2005) and Albatross (Arentze and Timmermans 2000, 2005a) have been developed to predict activity-travel patterns. The main contribution of these models is to offer an alternative to the four-step models of travel demand, better focusing on the consistency of the submodels and proving increased sensitivity to a wider range of policy issues. These models are most valuable for predicting the impact of land use and transportation policies on typical activity-travel patterns, allowing policy makers to assess the likely impact of such policies in relation to changing travel demand and a set of accessibility, mobility, and environmental performance indicators.

For short-term dynamics in activity-travel patterns, these activity-based models at their current state of development have much less to offer. For example, route choice and the aggregate impact of individual-level route choice decisions on activity generation and rescheduling behavior is not included in these models. Short-term dynamics are really not addressed at all, and issues such as uncertainty, learning, and nonstationary environments are also not considered. Of course, there is a wide variety of traffic assignment, route, and departure choice models, but at their current state of development, it is fair to say that the behavioral contents of these models from an activity-based perspective are still relatively weak and that comprehensive dynamic models are still lacking. Especially in the context of day-to-day management of traffic flows, such activity-based models of

short-term dynamics in activity-travel patterns would serve their purpose.

To complement the Albatross system, the Urban Group therefore started the development of Aurora, a model focusing on the rescheduling of activity-travel patterns. The foundations of this model appear in Timmermans et al. (2001) and Joh et al. (2003, 2004), focusing on the formulation of a comprehensive theory and model of activity rescheduling and reprogramming decisions as a function of time pressure. Apart from duration adjustment processes, the Aurora model also incorporated other potential dynamics, such as change of destination, transport mode, and other facets of activity-travel patterns. Later, this model was extended to deal with uncertainty (Arentze and Timmermans 2004), various types of learning (Arentze and Timmermans 2005b, 2006), and responses to information provision (Arentze et al. 2005; Sun et al. 2005). Finally, a framework to implement this model as a multiagent simulation system has been developed and explored (Arentze et al. 2005). In 2005, a research program coordinated by IMOB (Transportation Research Institute) was funded by IWT (Institute for the Promotion of Innovation by Science and Technology in Flanders), Belgium. The goal of this program, in addition to exploring the potential use of new technology on collecting travel data, is to develop a prototype, activity-based model of transport demand for Flanders, Belgium. The basis of this model, which has been given the acronym Feathers, will be the extended version of Aurora, complemented with some additional concepts.

This paper reports the current development of this agent-based microsimulator that allows one to simulate

activity-travel scheduling decisions, within-day rescheduling, and learning processes in high resolutions of space and time. It summarizes some concepts and discusses a series of projects and activities that will be conducted to further the operational effectiveness of the models for Flanders.

AURORA

Key Characteristics

Aurora is an agent-based microsimulation system in which each individual of the population is represented as an agent. It is also an activity-based model in the sense that the model simulates the full pattern of activity and travel episodes of each agent and each day of the simulated period. At the start of the day, the agent generates a schedule from scratch, and, during the day, the agent executes the schedule in space and time. It is also dynamic in that (a) perceived utilities of scheduling options depend on the state of the agent, and implementing a schedule changes this state; (b) each time after having implemented a schedule, an agent updates his or her knowledge about the transportation and land use system and develops habits for implementing activities, and (c) each time an agent arrives at a node of the network or has completed an activity during execution of a schedule, the agent may reconsider scheduling decisions for the remaining time of the day. This may happen because an agent's expectations may differ from reality. This may result from imperfect knowledge, but it may also be due to the nonstationarity of the environment. As a result of the decisions of all other agents, congestion may cause an increase in travel times on links or transaction times at activity locations. Furthermore, random events may cause a discrepancy between schedule and reality.

BASIC CONCEPTS

Utility Function

The model is based on a set of utility functions, in which the utility of a schedule is defined as the sum of utilities across the sequence of travel and activity episodes it contains. Formally,

$$U = \sum_{a=1}^A U_a + \sum_{j=1}^J U_j \quad (1)$$

where

U_i = utility of episode i ,

A = number of activity episodes, and

J = number of travel episodes in the schedule.

The functional form of utilities differs between activity and travel episodes. For activity episodes, utility is defined as a continuous, S-shaped function of the duration of the activity. This form reflects the notion that with increasing values duration is at first a limiting factor in "producing" utility and after some point other factors become limiting. In particular:

$$U_a = \frac{U_a^{\max}}{1 + (\gamma_a \exp[\beta_a(\alpha_a - v_a)])^{1/\gamma_a}} \quad (2)$$

where

v_a = duration of episode a ,

U_a^{\max} = asymptotic maximum of the utility the individual can derive from the activity, and

α_a , β_a , and γ_a = activity-specific parameters.

The α , β , and γ parameters determine the duration, slope, and degree of symmetry at the inflection point, respectively. In turn, the asymptotic maximum is defined as a function of schedule context, attributes, and history of the activity, as

$$U_a^{\max} = f(t_a) * f(l_a) * f(q_a) * \left[\frac{U_{x_a}}{1 + \exp[\beta_{x_a}(\alpha_{x_a} - T_a)]} \right] \quad (3)$$

where

t_a , l_a , and q_a = start time, location, and position in the sequence of activity a , respectively,

$0 \leq f(x) \leq 1$ = factors representing the impact of activity attributes on the maximum utility,

U_{x_a} = base level of the maximum utility, and

$T_a^{x_a}$ = time elapsed since the last implementation of activity a .

The position variable, q_a , takes into account possible carryover effects between activities leading to preferences about combinations or sequences of activities (e.g., shopping after a social activity). For this function, the same functional form (an S-shape) is assumed as for the duration function (Equation 2). Thus, it can be assumed that the urgency of an activity increases with an increasing rate in the low range and a decreasing rate in the high range of elapsed time (T).

The start-time factor of the maximum utility is a function of attributes of the activity:

$$f(t_a) = \begin{cases} \frac{t_a - t_a^1}{t_a^2 - t_a^1} & \text{if } t_a \geq t_a^1 \wedge t_a < t_a^2 \\ 0 & \text{if } t_a \geq t_a^2 \wedge t_a < t_a^3 \\ \frac{t_a^3 - t_a}{t_a^3 - t_a^4} & \text{if } t_a \geq t_a^3 \wedge t_a < t_a^4 \\ 1 & \text{otherwise} \end{cases} \quad (4)$$

where $t_a^1 \leq t_a^2 \leq t_a^3 \leq t_a^4$ are the cutoff points dividing the day into four intervals. The intervals define start times at which the activity would not generate any utility (the first and last intervals), the utility is at a maximum (the third interval), and the utility is some fraction of the maximum.

Traveling involves effort and sometimes monetary costs, depending on the transport mode used. If it is assumed that travel time is not intrinsically rewarding, the utility of a travel episode is modeled as a negative function of duration.

Scheduling Method

The model assumes that individuals' abilities and priorities to optimize a schedule are limited by cognitive constraints and the amount of mental effort that they are willing to make. To find reasonable solutions within the constraints, the model uses a heuristic scheduling method. The heuristic assumes an existing schedule (which may be empty) as given. The schedule should be consistent, and the result of the heuristic is again a consistent schedule with a higher or equal utility value. The heuristic searches for and implements improvements by considering one operation at a time. In the order in which they are considered, these include (i) inserting activities, (ii) substituting activities, (iii) repositioning activities, (iv) deleting activities, (v) changing locations, (vi) changing trip-chaining choices, and (vii) changing transport modes. A single operation is repeated until no more improvement has been made. If the schedule has changed in any one of these steps, the process is repeated. Each step in this procedure is in itself an iterative process that can be written as

1. For all options of <Operation>,
 - a. Implement the option,
 - b. Make the schedule consistent,
 - c. Optimize durations,
 - d. Optimize start times,
 - e. Evaluate the schedule's utility, and
 - f. Restore the schedule (i.e., undo Substep a).
2. If <Best Option> improves the schedule, then
 - a. Implement <Best Option> and
 - b. Repeat from Step 1.

where <Operation> denotes a specific operation considered in Steps i through vii. As implied by this procedure, operations are always evaluated under conditions of consistency and optimal duration and timing decisions. The heuristic nature of this method is emphasized. In none of the steps is the evaluation of options exhaustive. By iteratively applying the search procedure, the method may still find good solutions. Some pairs of operations, such as mode and location choices, may interact strongly. It is

possible to extend the heuristic with a limited number of simultaneous choices so as to reduce the risk of getting trapped in a local optimum.

Travel episodes are scheduled as part of activity episodes. The trip to the location and the trip to home after having conducted the activity are considered attributes of an activity. The return-home trip is empty if the agent decides to travel to the next activity location directly without first returning home (referred to as trip chaining). Default settings are used for each activity attribute when it is inserted in the schedule by an insertion or a substitution operation.

Making the schedule consistent (Step 1b) is a subroutine that implements minimal adaptations needed to make a schedule consistent with constraints, such as that the individual should return home at the end of the day, start from home at the beginning of the day, use the same transport mode (if vehicle based) for trips that are chained, and so on. Travel times are initially set to defaults and updated each time the destination location, origin location, or transport mode changes.

Schedule Implementation

It is assumed that an activity schedule is implemented sequentially during the day. To allow for possible rescheduling behavior, it is assumed that agents decide whether to reschedule their activities at every node of the transportation network and after completing each activity. Travel times on links are estimated as a function of the number of agents using the link simultaneously for a given time step by means of the following well-known method:

$$t_i = t_i^f [1 + \alpha(v_i / c_i)^\beta] \quad (5)$$

where

- t_i = updated travel time on link i ,
- t_i^f = free-floating travel time,
- v_i = traffic intensity,
- c_i = capacity of the link, and
- α and β = parameters.

The estimates are used to determine actual travel times in that time step. Unexpected travel times and unforeseen events are two possible causes for a mismatch between a scheduled and actual end time of an episode. A time-surplus or time-lack situation at the moment of completing an episode triggers rescheduling.

Learning

After having executed the schedule, an agent updates his knowledge about choice sets, default settings of activi-

ties, and expected values of attributes of the transportation and land use system.

The location choice set consists of all locations known by the individual. “Known” in this context means that the agent knows not only the physical location but also the attributes that are potentially relevant for evaluating utility values for all potential activities. Nevertheless, location choice sets are dynamic. Changes follow from processes of knowledge decay, reinforcement, and exploration (Arentze and Timmermans 2005b, 2006). The strength of a memory trace of a particular item in the choice set is modeled as follows:

$$W_i^{t+1} = \begin{cases} W_i^t + \gamma U_i^t & \text{if } I_i^t = 1 \\ \lambda W_i^t & \text{otherwise} \end{cases} \quad (6)$$

where

W_i^t = strength of the memory trace (awareness) of location i at time t ;

$I_i^t = 1$, if the location was chosen at time t , and $= 0$, otherwise;

U_i^t = utility attributed to location i ;

$0 \leq \gamma \leq 1$ = parameter representing a recency weight; and

$0 \leq \lambda \leq 1$ = parameter representing the retention rate.

The coefficients γ and λ determine the size of reinforcement and memory retention, respectively, and are parameters of the system.

Exploration, in contrast, is a process by which new elements can enter the choice set. The probability that a certain location i is added to the choice set in a given time step is modeled as

$$P(H_i^t) = P(G^t)P(H_i^t | G^t) \quad (7)$$

where $P(G^t)$ is the probability that the individual decides to explore and $P(H_i^t | G^t)$ is the probability that location i is discovered during exploration and tried on a next choice occasion. Whereas the former probability is a parameter of the system to be set by the modeler, the latter probability is modeled as a function of attractiveness of the location based on the Boltzman model (Sutton and Barton 1998):

$$P(H_i^t | G^t) = \frac{\exp(V_i^t / \tau)}{\sum_i \exp(V_i^t / \tau)} \quad (8)$$

where V_i^t is the utility of location i according to some measure and τ is a parameter determining the degree of randomness in the selection of new locations but which can also be interpreted as the degree of agent uncertainty (Han and Timmermans 2006). The higher the τ parameter is, the more evenly probabilities are distrib-

uted across alternatives and, hence, the higher the randomness and vice versa. More than one location may be added to the choice set in a given time step. A new location has priority over known locations in location choice and cannot be removed from the choice set before it has been tried once. Once tried, the new location receives a memory-trace strength and is subject to the same reinforcement and decay processes that hold for memory traces in general. As a consequence of these mechanisms, higher-utility locations have a higher probability of being chosen, for three reasons: (a) they have a higher probability of being discovered; (b) if discovered, they have a higher probability of being chosen, and (c) if chosen, they are more strongly reinforced. At the same time, they are not guaranteed of staying in the choice set because of two other mechanisms: (a) if the utility decreases due to nonstationarity in the system (e.g., the locations do not longer fit in changed schedules), the decay process will ensure that they vanish from the choice set, and (b) if more attractive locations are discovered, the original locations will be outperformed and, therefore, will decay.

Finally, learning involves updating default settings of activities, such as duration, starting time, transport mode, and location. For this updating, each agent keeps a record of the probability distribution across each choice set. For start time and duration, which are continuous variables, a reasonable subrange is identified and subdivided into n rounded values. For each choice facet, the following Bayesian method of updating is used:

$$P_i^{t+1} = \begin{cases} \frac{P_i^t M^t + 1}{M^t + 1} & \text{if } I_i^t = 1 \\ \frac{P_i^t M^t}{M^t + 1} & \text{otherwise} \end{cases} \quad (9)$$

$$M^{t+1} = \alpha M^t + 1 \quad (10)$$

where

P_i^t = probability of choice i at time t ,

M = weighted count of the number of times the choice has been made in the past,

I_i^t = indication of whether i was chosen at time t , and

$0 \leq \alpha \leq 1$ = retention rate of past cases.

As implied by Equation 9, more recent cases have a higher weight in the update (if $\alpha < 1$), to account for possible nonstationarity in the agent's choice behavior. With the probability distribution of each choice facet at the current time step defined, the default is simply identified as the option having the highest probability across the choice set.

FEATHERS

Scope

This model is part of a wider research program that involves a number of other Belgian research institutes. This program aims at examining a series of issues pertinent in the development of an activity-based model of travel demand for Flanders, Belgium. For example, new technology for collecting vehicle data will be explored as well as the application of combined GPS–personal digital assistant (PDA) technology for collecting activity-travel data [PARROTS (PDA System for Activity Registration and Recording of Travel Scheduling), see Bellemans et al. 2005, Kochan et al. 2006]. Feathers (Forecasting Evolutionary Activity-Travel of Households and Their Environmental Repercussions) is the acronym given to the model, which will be based on the current status of the extended Aurora model, as explained earlier. However, because Aurora to date is largely based on theory only and on some numerical experiments to assess the face validity of the model, further empirical testing and operational improvement will be required. It is to be expected therefore that certain elements will be refined and that other new elements will be added. The remainder of this section briefly addresses some of these issues.

Utility Functions

The core of the models is the S-shaped utility functions (Equations 2 and 3). To date, this shape, which is quite different from that of other models of activity-time allocation, is derived from theory. No specific data to test the shape of the functions and assess its relevance have been collected to date. Therefore, one of the subprojects is concerned with collecting data on how individuals change their activity-travel patterns and testing whether the assumed S-shaped utility functions represent such change, or if not, the alternative functional forms that are required. This project will also examine and estimate the effect of context variables that influence the maximum utility (Equation 3) that can be derived. The results will be critical in that, unlike for other models, it is assumed for this model that utility functions are context dependent. Finally, also to be tested is whether the assumed addition of activity and context-specific utility functions to represent the overall utility of a daily activity-travel schedule can be corroborated or, if not, whether more complex forms are required.

Learning

It follows from the foregoing that an agent's beliefs about the system with which he or she interacts play a role in

scheduling and are updated each time a schedule is implemented. Learning may involve many mechanisms. First, it is assumed that, as explained earlier, when their activity schedules are implemented, agents will learn about the attributes or states of their environment (e.g., travel times) from experiences, which, with respect to the state of a variable, will change the subjective probabilities and hence the agents' beliefs. If the actual situation is consistent with outcomes perceived as most probable, uncertainty in beliefs will be reduced, and the individuals will be more confident in predicting outcomes on future occasions. In contrast, if outcomes are contrary to expectations, uncertainty will increase and therefore so will difficulty of prediction and perceived value of information of future events. Second, in addition to this attribute learning, it is assumed that agents have an inherent desire to make sense of the world around them. One of the mechanisms involved is identification of the conditions that allow them to explain away differences in attributes of the environment (condition learning). For example, differences in travel times can be explained in relation to day of the week, departure time, weather conditions, an accident, and the like. The condition set is not necessarily constant over time but may grow or shrink. These two forms of learning imply that, only after many personal experiences, agents will have gained sufficient knowledge about their environment. Reality suggests otherwise, and therefore it is assumed that agents also are capable of analogue learning and reasoning: they draw inferences about attributes of certain objects by analogy with other similar objects. Finally, in addition to these personal styles of learning, it is assumed that agents learn from being part of a social network: they learn by word of mouth from members of their social network.

Similar Bayesian updating equations (see Arentze and Timmermans 2006) will be used to estimate these learning processes. This is the topic of another project.

Impact of Life Trajectory Events

Above it has been assumed that the household context is stationary. However, in reality, the household context changes over time as a function of life trajectory events, such as a new child, another job, and the like, and this change may bring about changes in one or more facets of the activity agenda and preferences for choice alternatives. The potential relevance and impact of such events in an activity framework has been explored by van der Waerden et al. (2003a, 2003b) and has led to the formulation of a Bayesian decision network model applied to transport mode choice decisions (Verhoeven et al. 2005a, 2005b). The approach will be further evaluated and extended to multiple facets of activity-travel patterns in the context of Feathers. It constitutes another project in the program.

CONCLUSIONS AND DISCUSSION

This paper has reported progress and plans in the development, testing, and implementation of a multiagent activity-based model of (re)scheduling behavior called Aurora. An operational and extended version of this model will be developed specifically for Flanders, Belgium, under the acronym Feathers. Data collection for estimating the various components is on its way. Plans are to report the first empirical results in the near future.

Unlike the activity-based models mentioned in the paper's introduction, this model has the potential value to simulate short-term dynamics. As such, it should be primarily relevant to simulate dynamics in day-to-day traffic flows and their environmental impacts. Its development into a model that can be used for longer-term assessment would require additional components. Such projects are on their way as well but not part of Feathers at this stage. The future will then tell whether the greater complexity implied by these and other extensions will be feasible, not only from a modeling and computational standpoint but also in relation to acceptance by practitioners and policy makers.

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REFERENCES

- Arentze, T. A., C. Pelizaro, and H. J. P. Timmermans. 2005. Implementation of a Model of Dynamic Activity-Travel Rescheduling Decisions: An Agent-Based Micro-Simulation Framework. *Proc., Computers in Urban Planning and Urban Management Conference (CD-ROM)*, London.
- Arentze, T. A., and H. J. P. Timmermans. 2000. *Albatross: A Learning-Based Transportation Oriented Simulation System*. European Institute of Retailing and Services Studies, Eindhoven, Netherlands.
- Arentze, T. A., and H. J. P. Timmermans. 2004. A Theoretical Framework for Modeling Activity-Travel Scheduling Decisions in Non-Stationary Environments Under Conditions of Uncertainty and Learning. *Proc., International Conference on Activity-Based Analysis (CD-ROM)*, Maastricht, Netherlands.
- Arentze, T. A., and H. J. P. Timmermans. 2005a. *Albatross 2: A Learning-Based Transportation Oriented Simulation System*. European Institute of Retailing and Services Studies, Eindhoven, Netherlands.
- Arentze, T. A., and H. J. P. Timmermans. 2005b. Representing Mental Maps and Cognitive Learning in Micro-Simulation Models of Activity-Travel Choice Dynamics. *Transportation*, Vol. 32, pp. 321–340.
- Arentze, T. A., and H. J. P. Timmermans. 2006. Multi-Agent Models of Spatial Cognition, Learning, and Complex Choice Behavior in Urban Environments. In *Complex Artificial Environments* (J. Portugal, ed.), Springer Verlag, Berlin, pp. 181–200.
- Bellemans, T., B. Kochan, D. Janssens, and G. Wets. 2005. Collecting Activity-Travel Diary Data by Means of a GPS-Enabled Personal Digital Assistant. *Colloquium Vervoersplanologisch Speurwerk*, Vol. 32, Nov. 24–25, pp. 2111–2131.
- Bhat, C. R., J. Y. Guo, S. Srinivasan, and A. Sivakumar. 2004. A Comprehensive Micro-Simulator for Daily Activity-Travel Patterns. *Proc., Conference on Progress in Activity-Based Models (CD-ROM)*, Maastricht, Netherlands, May 28–31.
- Han, Q., and H. J. P. Timmermans. 2006. Interacting Learning in Transportation Networks Under Conditions of with Uncertainty, Bounded Rationality, And Strategic Choice Behavior: Quantal Response Model. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1964, Transportation Research Board of the National Academies, Washington, D.C., pp. 27–34.
- Joh, C.-H., T. A. Arentze, and H. J. P. Timmermans. 2003. Understanding Activity Scheduling and Rescheduling Behaviour: Theory and Numerical Simulation. In *Modeling Geographical Systems* (B. N. Boots, A. Okabe, and R. Thomas, eds.), Kluwer Academic Publishers, Dordrecht, Netherlands, pp. 73–95.
- Joh, C.-H., T. A. Arentze, and H. J. P. Timmermans. 2004. Activity-Travel Rescheduling Decisions: Empirical Estimation of the Aurora Model. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1898, Transportation Research Board of the National Academies, Washington, D.C., pp. 10–18.
- Kochan, B., T. Bellemans, D. Janssens, and G. Wets. 2006. Dynamic Activity-Travel Diary Data Collection: Using a GPS-Enabled Personal Digital Assistant. In *Conference Proceedings 42: Innovations in Travel Modeling Conference*, Transportation Research Board of the National Academies, Washington, D.C., pp. 94–97.
- Pendyala, R. M., R. Kitamura, A. Kikuchi, T. Yamamoto, and S. Fujii. 2005. Florida Activity Mobility Simulator: Overview and Preliminary Validation Results. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1921, Transportation Research Board of the National Academies, Washington, D.C., pp. 123–130.
- Sun, Z., T. A. Arentze, and H. J. P. Timmermans. 2005. Modeling the Impact of Travel Information on Activity-Travel Rescheduling Decisions Under Conditions of Travel Time Uncertainty. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1926, Transportation Research Board of the National Academies, Washington, D.C., pp. 79–87.

- Sutton, R. S., and A. G. Barton. 1998. *Reinforcement Learning: An Introduction*. London: Massachusetts Institute of Technology Press.
- Timmermans, H. J. P., T. A. Arentze, and C.-H. Joh. 2001. Modeling Effects of Anticipated Time Pressure on Execution of Activity Programs. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1752, TRB, National Research Council, Washington, D.C., pp. 8–15.
- van der Waerden, P. J. H. J., A. W. J. Borgers, and H. J. P. Timmermans. 2003a. Key Events and Critical Incidents Influencing Transport Mode Choice Switching Behavior: An Exploratory Study. *Proc., 82nd Annual Meeting of the Transportation Research Board (CD-ROM)*, Washington, D.C.
- van der Waerden, P. J. H. J., A. W. J. Borgers, and H. J. P. Timmermans. 2003b. The Influence of Key Events and Critical Incidents on Transport Mode Choice Switching Behaviour: A Descriptive Analysis. *Proc., IATBR Conference (CD-ROM)*, Lucerne, Switzerland, Aug. 10–16.
- Verhoeven, M., T. Arentze, H. J. P. Timmermans, and P. van der Waerden. 2005a. Modeling the Impact of Key Events on Long-Term Transport Mode Choice Decisions: Decision Network Approach Using Event History Data. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1926, Transportation Research Board of the National Academies, Washington, D.C., pp. 106–114.
- Verhoeven, M., T. A. Arentze, H. J. P. Timmermans, and P. J. H. J. van der Waerden. 2005b. Examining Temporal Effects of Life Cycle Events on Transport Mode Choice Decisions. *Proc., Computers in Urban Planning and Urban Management Conference (CD-ROM)*, London.
- Vovsha, P., M. Bradley, and J. L. Bowman. 2004. Activity-Based Travel Forecasting in the United States: Progress Since 1995 and Prospects for the Future. *Proc., Conference on Progress in Activity-Based Models (CD-ROM)*, Maastricht, Netherlands, May 28–31.

ADDITIONAL RESOURCES

- Arentze, T. A., and H. J. P. Timmermans. 2003. Modeling Learning and Adaptation Processes in Activity-Travel Choice: A Framework and Numerical Experiments. *Transportation*, Vol. 30, pp. 37–62.
- Arentze, T. A., and H. J. P. Timmermans. 2005c. Information Gain, Novelty Seeking and Travel: A Model of Dynamic Activity-Travel Behavior Under Conditions of Uncertainty. *Transportation Research A*, Vol. 39, pp. 125–145.
- Arentze, T. A., and H. J. P. Timmermans. 2005d. A Cognitive Agent-Based Simulation Framework for Dynamic Activity-Travel Scheduling Decisions. *Proc. Knowledge, Planning, and Integrated Spatial Analysis*. Library Information Science Technology Abstracts.
- Janssens, D., G. Wets, T. Brij, K. Vanhoof, T. A. Arentze, and H. J. P. Timmermans. 2006. Integrating Bayesian Networks and Decision Trees in a Sequential Rule-Based Transportation Model. *European Journal of Operations Research*, Vol. 175, No. 1, pp. 16–34.

Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns

Recent Developments and Sensitivity Testing Results

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The Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) is continuous-time activity-travel prediction software currently being evaluated through application to the Dallas–Fort Worth, Texas, metropolitan area. This paper describes the state of the overall work in progress and the tasks planned for refinement and testing of the software system. (All CEMDAP documents are available at www.ce.utexas.edu/prof/bhat/FULL_CEMDAP.htm.) The paper is organized as follows: First is a description of the latest version (Version 0.3) of CEMDAP, specifically an overview of the econometric modeling framework incorporated within Version 0.3 and a focus on software development efforts. Presented next is the sensitivity testing undertaken with Version 0.2 of the software. Last is a summary that includes identification of the areas of ongoing work and tasks planned for the immediate future.

The Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) is based on a system of econometric models. Each model corresponds to the determination of one or more activity-travel attributes. These models are applied in a systematic sequence to generate the daily activity and travel patterns of all members (both adults and children) in each household in the study area. The overall prediction procedure for a household is subdivided into two major sequential steps: first, the prediction of activity generation and allocation decisions and, second, the prediction of activity scheduling decisions.

The first step predicts the decisions of household members to pursue various activities during the day. This step, in turn, comprises the following three sequential steps (each of which may comprise one or more models):

1. Work and school activity participation and timing decisions,
2. Generation of children’s travel needs (such as school and leisure) and allocation of escort responsibilities to parents, and
3. Generation of independent activities (such as shopping, recreation, and personal business) for personal and household needs.

The second step predicts the sequencing of the activities generated in the previous step, accommodating the space–time constraints imposed by work, school, and escort-of-children activities. This major step broadly comprises the following sequential scheduling steps (each of which may comprise one or more models):

1. Commutes for each worker in the household (mode; number of stops; and, for each stop, the activity type, activity duration, travel time, and location);
2. Drop-off tour for the nonworker escorting children to school;
3. Pick-up tour for the nonworker escorting children from school;
4. Commutes for school-going children (mode and duration);

5. Joint tour for the adult pursuing discretionary activity jointly with children (departure time, activity duration, travel duration, and location);

6. Independent home-based tours and work-based tours for each worker in the household (number of tours; home-stay duration before tours; tour mode; number of stops in each tour; and for each stop, activity type, activity duration, travel time, and location);

7. Independent home-based tours for each non-worker in the household (number of tours; home-stay duration before tours; tour mode; number of stops in each tour; and for each stop, activity type, activity duration, travel time, and location); and

8. Discretionary activity tours for each child in the household (departure time, activity duration, travel duration, and location).

This new modeling system enhances the previous system embedded in CEMDAP Version 0.2 in several ways. First, the new system is developed at a finer spatial resolution and applied to a 4,874-zone system for the Dallas–Fort Worth area in Texas. Second, the activity-travel patterns of children (persons under 16 years of age) are now explicitly modeled and forecast. Third, the interdependencies between the travel patterns of children and their parents (such as escort to and from school and joint participation in discretionary activities) are explicitly accommodated. Finally, for estimation of the models, the raw survey data obtained for the Dallas–Fort Worth area were reprocessed to create a larger sample, and all the model components (over 50 in all) were reestimated. Detailed descriptions of the modeling framework, the econometric structure of each model component, and the sequential prediction procedure are available in Guo et al. (2005).

SOFTWARE IMPLEMENTATION

The goal of the CEMDAP software development process is to provide a microsimulation platform that can be easily configured for different study areas, for which the level of data availability and, consequently, the degree of modeling system complexity often vary. The software design philosophy is to create a generic library of routines that form the building blocks of an activity-based travel demand modeling system so that variants of modeling systems can be rapidly implemented. These building blocks include a number of modeling modules that are routines developed for applying different types of econometric models. The modeling modules can then be reused and reconfigured to simulate the choice outcome of various behavioral dimensions. Configuration of the modules is achieved through Windows-based user inter-

face components that support the saving and loading of model parameters. Another type of system building block is the simulation coordinator, which controls the logic and sequence in which the modeling modules are executed to generate the activity and travel patterns for a given household. The modules are plugged into the coordinators in such a way that any module can be modified, can have its parameters changed, and can be entirely replaced by a different module without introducing changes to the rest of the system. Details on the implementation of CEMDAP Version 0.2 are available in Bhat et al. (2003).

CEMDAP Version 0.3 is significantly improved over Version 0.2 in the following ways:

1. To accommodate the increased input database size resulting from the more detailed zoning system, CEMDAP now uses Postgres, rather than Microsoft Access, to run queries about the input database. Postgres is known to be stable under large data loads and is an open-source database software released under a Berkley Software Distribution license.

2. The system has built-in data caching routines to store frequently accessed data items in RAM so as to reduce the number of queries and disk accesses.

3. A new model module is added to the system for jointly simulating work start and end times.

4. Separate simulation coordinators are implemented to control the simulation sequence for different household types (households with or without children, individuals who go to work, or individuals who go to school).

5. The system's computational efficiency is enhanced by running the simulation over multiple threads.

PRELIMINARY SENSITIVITY TESTING

This section discusses preliminary sensitivity testing undertaken with a recent but older version of CEMDAP. Specifically, aggregate changes to the predicted activity-travel patterns under the following scenarios were examined: 10% and 25% increases in in-vehicle travel times (IVTT) and 10% and 25% decreases in IVTT. The intent of this exercise was to examine the reasonableness of predictions. Similar (but more exhaustive) tests using the newer version of CEMDAP are planned. Further, part of this planned exercise will compare the outputs from CEMDAP with the outputs from the four-step modeling system currently employed by the North Central Texas Council of Governments (NCTCOG).

The activity-travel patterns were predicted for the entire synthetic population (3,452,751 adults from 1,754,674 households) for the base case and each of the

above four scenarios (percentage increases and decreases in IVTT) and compared. The impacts of changes in IVTT on the aggregate activity travel patterns were examined by using several measures, including (a) trip frequency, (b) person-miles of travel (PMT) and vehicle-miles of travel (VMT), and (c) person-hours of travel (PHT).

Changes to Trip Frequency

A 10% increase in IVTT decreases the total number of trips by 1%, and a 25% IVTT increase decreases the total number of trips by 2.4% (Table 1). A 10% decrease in IVTT increases the total trips by 1.16%, and a 25% IVTT decrease increases the number of trips by 3.1%. In addition, the frequency of home-based work trips is least sensitive to IVTT changes.

Further disaggregating the trip by destination activity purpose shows that the frequency of trips for social–recreation, shopping, and personal business is the most sensitive to changes in IVTT. (IVTT affects generation of activities for these purposes via the accessibility measure.)

Changes to PMT and VMT

An increase in IVTT decreases the overall PMT (Table 2) and VMT (Table 3), whereas a decrease in IVTT increases the overall PMT and VMT. As would be expected, the PMT and VMT for home-based work trips show the least sensitivity to changes in IVTT. In contrast, the distances traveled for nonwork purposes (especially shopping, social–recreation, and personal business) are affected by transportation level of service. These changes are consistent with intuitive expectations, as the home and work locations are fixed in the short term.

Changes to PHT

The impacts of changes in IVTT on total PHT are presented in Table 4. An increase in IVTT increases the PHT for work and decreases the PHT for nonwork purposes (especially shopping and social–recreation), resulting in an overall increase in PHT. A decrease in IVTT reduces work PHT and increases nonwork PHT, resulting in an overall decrease in PHT.

TABLE 1 Impact of IVTT on Trip Frequency

	Home-Based Work		Home-Based Other		Non-Home-Based		Overall	
	No. of Trips*	% Diff.	No. of Trips*	% Diff.	No. of Trips*	% Diff.	No. of Trips*	% Diff.
Base case	3.70	—	5.58	—	2.35	—	11.62	—
10% increase	3.70	0.08	5.51	−1.27	2.29	−2.30	11.50	−1.05
25% increase	3.71	0.24	5.41	−3.05	2.23	−5.08	11.34	−2.42
10% decrease	3.69	−0.22	5.66	1.49	2.41	2.52	11.76	1.16
25% decrease	3.68	−0.59	5.80	4.06	2.51	6.83	11.99	3.14

*Number of trips is in millions.

TABLE 2 Impact of IVTT on PMT

	Home-Based Work		Home-Based Other		Non-Home-Based		Overall	
	PMT*	% Diff.	PMT*	% Diff.	PMT*	% Diff.	PMT*	% Diff.
Base case	54.03	—	83.34	—	27.53	—	164.91	—
10% increase	54.03	−0.01	77.21	−7.35	24.76	−10.05	156.01	−5.40
25% increase	54.03	0.00	69.21	−16.95	21.56	−21.69	144.81	−12.19
10% decrease	53.96	−0.13	90.65	8.77	30.91	12.26	175.52	6.43
25% decrease	53.80	−0.44	104.02	24.81	37.53	36.30	195.34	18.46

*PMT is in millions of miles.

TABLE 3 Impact of IVTT on VMT

	Home-Based Work		Home-Based Other		Non-Home-Based		Overall	
	VMT*	% Diff.	VMT*	% Diff.	VMT*	% Diff.	VMT*	% Diff.
Base case	44.84	—	58.45	—	22.00	—	125.30	—
10% increase	44.85	0.02	54.07	−7.50	19.80	−10.03	118.71	−5.26
25% increase	44.83	−0.02	48.40	−17.19	17.24	−21.64	110.48	−11.83
10% decrease	44.81	−0.08	63.65	8.88	24.70	12.25	133.15	6.27
25% decrease	44.65	−0.43	73.25	25.32	30.04	36.53	147.95	18.07

*VMT is in millions of miles.

TABLE 4 Impact of IVTT on PHT

	Home-Based Work		Home-Based Other		Non-Home-Based		Overall	
	PHT*	% Diff.	PHT*	% Diff.	PHT*	% Diff.	PHT*	% Diff.
Base case	1.68	—	3.12	—	0.79	—	5.59	—
10% increase	1.77	5.53	3.10	-0.73	0.78	-0.74	5.66	1.15
25% increase	1.91	13.89	3.06	-1.89	0.78	-1.34	5.76	2.93
10% decrease	1.58	-5.73	3.15	0.94	0.80	0.84	5.53	-1.08
25% decrease	1.44	-14.13	3.21	2.64	0.81	2.67	5.46	-2.39

*PHT is in millions of hours.

SUMMARY

The CEMDAP project represents a significant effort in the development and implementation of an activity-based travel forecasting system. The recent efforts by the researchers have been focused on incorporating several enhancements (such as modeling the travel patterns of children and incorporating children-parent interactions) to the overall modeling framework and applying the framework to an expanded 4,874 zone system in the Dallas-Fort Worth area. All the models have been reestimated for this new zoning system with household travel survey and disaggregate land use and interzonal level-of-service data from the Dallas-Fort Worth area.

The researchers are now engaged in the implementation and integration testing of the software for the expanded and enhanced software version. Simultaneously, data inputs are being assembled for evaluation and sensitivity testing of the software outputs.

The tasks planned for the immediate future include the following: (a) comparison of the travel patterns predicted for the estimation sample against the observed patterns in the activity-travel survey, (b) complete software run for the entire baseline population (synthetically generated for Year 2000), (c) evaluation of sampling strategies, (d) comparisons of CEMDAP outputs with those from four-step models currently employed by NCTCOG, (e) validations against ground counts and other measures, (f) sensitivity tests and comparisons of

CEMDAP and NCTCOG results, and (g) predictions for a future year and corresponding comparisons with NCTCOG model results.

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REFERENCES

- Bhat, C. R., J. Guo, S. Srinivasan, and A. Sivakumar. *Activity-Based Travel Demand Modeling for Metropolitan Areas in Texas: Software-Related Processes and Mechanisms for the Activity-Travel Pattern Generation Micro-Simulator*. Report 4080-5, Center for Transportation Research, University of Texas at Austin, Oct. 2003.
- Guo, J. Y., S. Srinivasan, N. Eluru, A. Pinjari, R. Copperman, and C.R. Bhat. *Activity-Based Travel-Demand Analysis for Metropolitan Areas in Texas: CEMSELTS Model Estimations and Prediction Procedures, 4,874 Zone System CEMDAP Model Estimations and Procedures, and the SPG Software Details*. Report 4080-7. Center for Transportation Research, University of Texas at Austin, Oct. 2005.

BREAKOUT SESSION
SURVEY METHODS

Directions for Coordinated Improvement of Travel Surveys and Models

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A number of recent studies have pointed out the gap between academic interest in activity-based models and the relative scarcity of activity-based models implemented for regional and statewide planning agencies. The issues that hinder the adoption of activity-based models range from the difficulty in obtaining both resources to reestimate existing models and staff to run more complicated models to theoretical concerns over the variability involved in microsimulation. This paper focuses on the data requirements to support the estimation of an activity-based model and will present the minimum requirements and the desirable features to be included in future household surveys. The underlying message of this paper should reassure planning directors that the basic surveys required to build an activity-based modeling application are similar to those required to update and revalidate a conventional model, although certain extensions are desirable. A focus on more limited improvements to conventional surveys does not represent a digression from a move toward activity-based models but rather offers a useful intermediate stop on the way and takes practical advantage of what can be already done today or in near future. For modelers wishing to explore the cutting edge of activity-based modeling, the paper also examines two promising areas of research: attitudinal and stated-preference (SP) extensions to conventional surveys. The paper concludes with a survey of existing household surveys from large metropolitan regions in North America and Europe and examines their suitability for supporting activity-based models.

For a long time, the structure of travel surveys was limited by the considerations of supporting the development of conventional four-step models. One of the major

deficiencies of such models was the matrix structure of the trip distribution and modal-split submodels that severely limited the model segmentation and the number of explanatory variables that could be used. The surveys were actually much richer than the models, and it was not clear why travel surveys should be made even more complicated (and more expensive to collect). Shifting to the microsimulation modeling paradigm has lifted this technical limitation from model segmentation, allowing for richer, more-complex models, and, in turn, fueling the desire for better data.

There are several directions in which travel demand models and corresponding surveys can be significantly improved:

1. Widening the range of explanatory variables used in models and collected in surveys,
2. Improving the understanding and modeling of causal linkages across various dimensions of travel behavior, and
3. Adding attitudinal and SP extensions to conventional revealed-preference (RP) surveys.

Each of these points is described below in detail. These three directions are not independent and actually are closely intertwined. Furthermore, model improvement can proceed in incremental steps rather than requiring dramatic improvements in all three areas simultaneously. In a resource-constrained environment, the most practical approach may be to conduct a survey for a conventional model, but the authors strongly recommend that the standard surveys be enhanced with some

of the additional variables described in the following section, to allow for more advanced model improvements in the future.

EXPLANATORY VARIABLES

Conventional travel demand modeling has developed in an environment that stressed economizing on explanatory variables as much as possible to avoid extensive model segmentation. This emphasis led to a standard approach that was expressed in a limited set of variables like household size, number of workers, car ownership, income group, and the like that are indeed important for travel behavior but are not nearly exhaustive.

Zonal “attractiveness” was measured by a limited number of employment variables stratified into three or four major categories like industrial employment, office employment, and commercial employment. In a similar way, level-of-service variables by different travel modes were limited to average time and cost components that could be skimmed by existing network simulation procedures.

New modeling frameworks open a constructive way to add variables and explanatory power to travel models. The authors believe that considerable improvements can be made within a conventional decision-making framework by adding explanatory variables. Of course, for these variables to be available to the modeling process, they must be present in the surveys.

Here is a list of traditionally used variables and new variables that could add significant explanatory power to such important travel models as mode and destination choice (trip distribution) taken as examples:

- Mode choice
 - Traditional variables
 1. Average travel time and cost
 2. Number of transfers
 3. Household car ownership–sufficiency
 4. Household income
 5. Person age and driver’s license possession
 6. Area-type constants
 - New variables
 1. Travel time uncertainty (probability of delays)
 2. Reliability in relation to transit schedule adherence
 3. Parking constraints, search, and conditions
 4. Individual parking cost, including free parking and discounted parking eligibility
 5. Driving conditions–road type
 6. Probability of having a seat for transit
 7. Probability of having a parking place for auto and of park and ride
- 8. Commercial and information services at transit stations and at park-and-ride lots
- 9. Frequency and location of stops on the way to and from the primary destination
- 10. Individual car availability for person and given travel tour, taking into account cars in disrepair, which reduces the household’s typical car availability measure, and renting cars, which supplements it
- 11. Joint travel arrangements with the other household members
- 12. Individual geographical information system–based walk time and pedestrian conditions for transit and nonmotorized modes
- 13. Road and personal safety, crime rate and public image associated with area of transit station–line
- 14. Person type-, gender-, age-, and income-specific time and cost perceptions [value over time (VOT)]
- 15. Nonlinear effects corresponding to marginal impacts of time, cost, and other variables as functions of trip length
- 16. Comfort and convenience in transit cars: possibility of reading or using laptop, air conditioning
- Destination choice
 - Traditional variables
 1. Mode-choice log sum or particular time, cost, and distance variables
 2. Zone attraction variable based on the employment–enrollment mix
 - New variables
 1. Bottleneck facilities (river crossings, bridges, tunnels)
 2. Statutory borders (states, counties, municipalities, school districts)
 3. Social frictions (income incompatibility, social and ethnic clusters)
 4. Special sensitivity to transit accessible destinations of nondriving population (children under 16, zero-car households)
 5. Household composition and activity patterns that limit spatial domain of activity (presence of child at home)
 6. Individual attraction characteristics and special trip generators that take into account size and profile of the individual attraction (going into more and more detail on the household–person side but still having terrible aggregate zonal-attraction variables that are based on three or four crude employment variables)
 7. Cognitive maps based on the spatial domain of the household and person with the pivot points corresponding to most frequently visited usual locations (residential, work, school).

The variables listed above have already been examined in various research and modeling frameworks and contexts. These are measures that can be quantified and added to a survey instrument. What is needed is to move these research achievements into practice for travel surveys and models. In particular, widening the range of explanatory variables should eventually allow for the removal of flat mode-choice constants and distribution *K*-factors that dominate the current models and “explain” most of the observed variability.

An important but underresearched area is the examination of long-term trends in travel behavior. Travel behavior obviously undergoes a significant evolution that is not captured by static travel demand models. There have been only several attempts to capture long-term trends in VOT estimates with the corresponding consequence for the choice model coefficients.

CAUSAL LINKAGES

In the authors’ view, focusing on causality represents a constructive intermediate stage between a fairly standard outcome-based approach and the new process-based approach. The difference between outcome-based, cause-based, and process-based approaches can be illustrated by the following example of location choice for shopping.

The conventional outcome-based approach would try to explain the chosen location by means of the location characteristics (size, distance from home, accessibility by different modes) and person–household characteristics (person type, gender, age, car ownership, presence of children, etc.) in a single-choice framework in which all location, person, and household attributes would be blended in the utility function and all other locations (zones) would be considered as available alternatives.

The cause-based approach would be focused on formation of the available choice set under the given conditions of the person that are considered as earlier in the causal chain and prove that these conditions indeed were fixed in the decision making at the time of making the modeled decision (available time window, car availability, usual spatial “domain” of the person) and then formulation of a choice model that would take maximum advantage of the causal–conditional variables and the conventional variables. The cause-based approach is oriented to proper sequencing and conditioning of decision-making steps in an overall static environment.

The decision process–based approach would be focused on both causal and chronological aspects of the decision making associated with the modeled event. Ideally, this would include a historical sequence of preliminary decisions about the time and location for the modeled shopping activity, probably including numerous

corrections and adjustments until the final decision was made and the corresponding activity was implemented.

The three approaches described here are not actually alternatives: they are sequentially inclusive. All factors, variables, and observed statistics pertinent to the conventional outcome-based approach are still relevant for the cause-based approach, and causality is still a part of the decision-making screening. However, in addition to what happens as a result of the combination of explanatory variables, the cause-based approach offers insights into the why sequence of decisions and events that led to the modeled what. The decision process–based approach takes an additional step in mapping the whole how chronology of the decision making that built up around the modeled event. The modeling complexity and amount of information needed for these approaches grows exponentially from what to why and then to how.

Chronological peculiarities of individual decision making are less important for large-scale models and frequently lead to complicated multistage procedures with numerous feedbacks that are difficult to convert into operational models. Understanding of causal linkages is a simpler task although it is a limited view of travel behavior. It may significantly improve the structure of the travel model system and sequencing of the modeled choices and associated decision-making steps.

The cause-based approach to surveys pragmatically serves the existing static structure of choice models and helps in improving it. It is not a substitute for a full-fledged process-based approach; it is a simplification that is practically helpful in the short term. It may also be helpful in the longer term as well, however, because the knowledge and understanding acquired in causal analysis may be of great value for the subsequent process-based analysis.

Introducing causality and proper sequencing in a static framework requires adding to the household surveys specific questions that would refer to the order and conditionality of decisions as well as to the formation of the choice set. In particular, for each visited activity location and the corresponding choice of destination, mode, and time of day (TOD), the following set of questions can be added to either RP or SP surveys:

- Was this activity-preliminary scheduled or undertaken as a result of occasionally saved time in the course of the day?
- Were the destination, mode, and TOD choices made simultaneously or was there a certain order to conditional choices? Which of these choices are usual and stable over time and which are subject to change?
- If the actually chosen alternative was not available, what would be the second-best choice?
- Is there any predetermined area from which the locations choice was made (like shopping on the same

shopping street in the town or visiting the closest movie theater) or was the choice of location based on some unique properties of the location not associated with any nearby area (like visiting Madison Square Garden or Carnegie Hall in New York)?

Introducing casualty into the modeling framework should naturally reduce the tendency for using simplified models of compensatory utility maximization and work in favor of more elaborate decision-making chains with partially noncompensatory rules (eliminations).

ATTITUDINAL AND SP EXTENSIONS TO CONVENTIONAL RP SURVEYS

For the foreseeable future, the standard RP household survey will remain the major source of information for travel demand model estimation. The most satisfactory surveys are those that essentially form travel diaries with a full accounting of all daily activity-travel patterns for all household members. This type of survey constitutes an ideal basis for additional attitudinal and SP-type questions to reflect each traveler's actual situation and is much better than a standalone SP survey in which normally one of the trips or activities is taken out of the daily pattern context and then different questions about hypothetical alternatives are pivoted off the observed choice.

However, the addition of attitudinal and SP questions to the household survey represents a practical problem because existing household surveys are generally already at the upper limits of length and complexity that can be tolerated by interviewees. Thus, it is important to make these extensions as easy, natural, and short as possible.

These extensions are not intended to replace SP surveys with extensive SP games; they are mostly intended to better the understanding of the observed choices, their sequencing, and the way in which choice sets were formed.

There are several examples of extensions of this sort that could be added to conventional household surveys:

- For mode and location choices, there can be a question asking whether the mode–location was usual or occasional;
- For mode and location choices, there can be guided questions on the reasons behind the choice of a specific mode or destination;
- For departure and arrival time choices, there can be a prepared set of answers on questions about how the schedule was actually built, such as “planned in advance” or “occurred in the course of the day out of necessity.” A different set of questions might be asked at the end of the survey about the schedule priority of all activities and whether any schedule adjustment took place to accommodate some other activities in the schedule.

While the authors recognize that not all agencies will have the budget to support such extensive surveying, it is also the case that activity-based models can make the biggest advances in the exploration of the sequencing and scheduling of activities at both the individual and household levels. Yet making these advances requires data that have not conventionally been collected in the context of travel demand surveys and may require new innovations in data collection technology. It might well be worth treating these SP extensions as a pilot study or only collecting the additional data on a subset of the households.

Using Global Positioning System Data to Inform Travel Survey Methods

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While the transportation community continues to work toward the long-term goal of using Global Positioning System (GPS) technology to produce higher-quality trip files, the reality is that the current method of random samples, telephone surveys, and travel logs continues to be used. Thus, for any given regional travel survey, trip underreporting will occur at some level. The research question that forms the focus of this paper is whether an analysis of GPS data collected as part of a regional travel survey can be used to minimize trip underreporting through improved survey methods. The focus is on demographic characteristics, travel behavior characteristics, and indicators of adherence to survey protocol that potentially impact trip underreporting. The results suggest that, while more research into this subject is warranted, there are specific, low-cost changes to the survey materials as well as to the interviewing process that can be made immediately to reduce trip underreporting.

Ten years ago, the transportation community began in earnest an investigation into the application of Global Positioning System (GPS) technology to the collection efforts for travel survey data. The immediate focus of this technology application has been to improve the quality of travel survey data, with a long-term goal of eventually replacing respondent-reported data with travel details collected passively through GPS devices. The main application of GPS in regional travel surveys to date has been for auditing trip reporting, to determine the level of trip underreporting by vehicle drivers, and to develop appropriate correction factors for the data. Specifically,

GPS has been used in 12 regional travel surveys: Lexington, Kentucky (1996); Austin, Texas (1997); California (2001); Los Angeles, California (2001); Pittsburgh, Pennsylvania (2001); St. Louis, Missouri (2002); Ohio (2002); Laredo, Texas (2002); Tyler–Longview, Texas (2003); Kansas City, Missouri (2004); Reno, Nevada (2005); and in a pilot test for the upcoming Oregon statewide travel survey (2005). In addition, other GPS studies not directly linked to regional travel surveys have employed GPS for speed studies and in testing the development of trip tables solely from GPS data. For purposes of this paper, references to GPS studies refer to those conducted as part of regional travel surveys only. In the conduct of these studies, several important have been gleaned:

- Respondents who self-select to participate in GPS travel studies are different from those who do not elect to participate. As documented in several travel survey reports, GPS participants tend to report higher incomes and own their own homes compared with those who elect not to participate (see, for example, NuStats). Thus, most of the findings to date and conclusions about trip underreporting are based on a select group of respondents and not general populations of entire regions.
- The methods to process the GPS data streams vary across the GPS studies conducted to date and influence the degree of trip reporting detected. Some studies, such as the Los Angeles study, used in-vehicle devices to capture trip details for both drivers and passengers, while others focused only on drivers. In addition, as shown in an early analysis of the Austin data, the time thresholds used in vehicle movement detection can cause the trip

underreporting rate to vary greatly (in Austin the rate was 12% or 31%, depending on the time threshold).

- The actual data collection methods and instructions to respondents can also influence the calculation of trip underreporting rates. In most studies, respondents are instructed not to report trips out of the geographically defined study area and trips for commercial purposes. However, most early trip-detection algorithms did not distinguish between these types of trips and those reported by respondents, resulting in overreported trip-underreporting rates. In addition, as determined in the Laredo study, the survey process does not directly collect information about trips made by nonhousehold members driving the GPS-equipped vehicles.

On the basis of a review of literature on trip underreporting in regional household travel surveys and the development of associated correction factors, most trip underreporting is associated with households that own three or more vehicles, households with incomes of less than \$50,000, and respondents under the age of 25. From a travel behavior perspective, respondents who travel substantially make several short trips (less than 5 min) and make trips of a discretionary nature are most likely to “forget” to record this travel (as has been suggested on parallel literature about trip chaining).

The studies to date have clearly aided in identifying factors associated with trip underreporting in regional travel surveys. In this paper, the authors contribute to this existing literature and continuing discussion about GPS technology in travel surveys in several ways. First, in the current study (and unlike earlier studies), both the presence of trip underreporting by an individual and the level of trip underreporting by the individual are modeled. The separation of the presence of trip underreporting from the level of trip underreporting recognizes that different explanatory variables may affect these outcomes, that the same explanatory variable may affect these outcomes differently, or both. Second, the joint model also recognizes that the likelihood of trip underreporting and the level of trip underreporting may be related to one another. For example, it is conceivable (if not likely) that individuals who are, by nature, less likely to be responsive to surveys are the ones who underreport and underreport substantially. Similarly, individuals who are, by nature, interested in the survey would be the ones less likely to underreport at all, and even if they did underreport, would do so only marginally. Third, in addition to jointly modeling trip underreporting and the level of trip underreporting, the empirical analysis in the current study considers a comprehensive set of variables related to driver demographics, driver travel characteristics, and driver adherence to survey protocol. Finally, this work translates the empirical analysis results to recommendations about household travel survey proce-

dures to reduce the magnitude of trip underreporting in future travel surveys.

GPS AND TRAVEL SURVEY DATA

The empirical analysis in the current paper uses data extracted from the Kansas City Regional Household Travel Survey conducted in spring 2004 under the sponsorship of the Mid-America Regional Council and the Kansas and Missouri Departments of Transportation. As part of the Kansas City survey, complete demographic and travel behavior characteristics of 3,049 randomly sampled households were obtained, including details about 32,011 trips for 7,570 household members. The GPS component of the study involved equipping the vehicles of 294 households with GPS equipment to record all vehicle travel during the assigned travel period. Of the 294 households, both computer-assisted telephone interview (CATI) and GPS data are available for 228 households. All subsequent analyses in the current paper focus on these 228 households, corresponding to 377 drivers and 2,359 vehicle trips. (For more details on the characteristics of these GPS households compared with the general survey participants as a whole, see NuStats.)

Of the 377 drivers, 269 (or 71%) accurately reported all travel in their CATI survey, while 108 (or 29%) had at least one instance of a trip that was not reported. [A subtle, but important, point is that, for the underreporting analysis, the authors focused on the CATI-reported vehicle trips across all individuals in the household who drove each GPS-equipped vehicle. This focus allows a fair comparison between the CATI-reported vehicle trips and the GPS-detected vehicle trips. However, rather than confine the analysis of the determinants of underreporting to household-level characteristics, also included were person-level characteristics to accommodate person-specific tendencies to underreport. To accomplish this, the authors identified a primary driver for each GPS-equipped vehicle on the basis of information provided by respondents and used these primary-driver characteristics as explanatory variables in the analysis (along with household demographics). This approach is reasonable because each vehicle in this study was predominantly used by only one primary driver in the household (especially within a short period of time, such as a survey day). Specifically, in the sample used for our analysis, there was car sharing of some form among household members in 6% of all households.] Among the 108 respondents who underreported, 53 (49%) missed one trip, 22 (20%) missed two trips, 11 (10%) missed three trips, six (5.5%) missed four trips, and 16 (14.5%) missed five or more trips. There was a narrow, long tail in the ≥ 5 missed-trips category, with one individual underreporting 17 trips.

A comparison of the CATI-reported trips with the GPS-detected trips identified 280 GPS-detected trips that were not reported by the drivers in the CATI travel survey. [The extraction of trips from the GPS traces was based on a multilevel trip detection algorithm developed by GeoStats, with several built-in checks to avoid ghost trips (such as due to starts and stops at street lights). The full details of the GPS processing are available in the study report by NuStats.] A descriptive analysis of trip underreporting by driver demographics, driver travel characteristics, and driver adherence to survey protocols was undertaken. The results related to demographic characteristics suggested that drivers between the ages of 50 and 69 who were male, with low education levels, were not employed or were employed in sales-clerical occupations, working at locations characterized as residential, from single-adult or retired households, from one- or three-person households, and from 3+ vehicle households were the most likely to underreport trips. The driver travel characteristics indicated that drivers who made a relatively large number of total trips during the survey day, pursued long distance trips, and undertook trip chaining on the survey day were overrepresented in the pool of those who underreport. Finally, in the category of driver adherence to survey protocols, the results suggested that drivers who did not use their travel diaries for recording travel and who had their travel details reported by proxy were more likely to underreport.

These descriptive statistics provide suggestive evidence of the effect of various driver attributes on the propensity to underreport trips. However, these are unidimensional statistics in that they do not control for the influence of other variables when the impact of any single variable is being examined. For instance, the gender difference in underreporting may be a manifestation of different travel patterns of men and women. Further, the descriptive analysis does not focus on the characteristics affecting the level of trip underreporting. To obtain a comprehensive picture of the factors affecting whether an individual underreports and the level of underreporting, it is necessary to pursue a multidimensional and comprehensive analysis that examines the effects of all potential determinants of both underreporting propensity and the level of underreporting propensity. The next section presents the model structure and empirical analysis for such a methodology.

MODEL SUMMARY

The approach adopted in this study used two equations: a binary model for whether an individual underreports or not and an ordered-response model for the number of trips underreported if there is underreporting at all. The methodology accounts for the correlation in error terms

between the two equations. That is, it accounts for the potential presence of unobserved individual factors (such as, say, an overall disinclination to respond to surveys or substantial time constraints) that influences both whether an individual underreports and the level of underreporting. For a more detailed discussion of the modeling portion of this research, see Bricka and Bhat.

The fundamental hypothesis underlying our empirical analysis was that trip underreporting is largely due to three areas of influence: who the driver is (driver demographics such as household type, age, number of household vehicles, employment status, etc.), the characteristics of trips made (total number of trips, average distance of trips, and level of trip chaining), and how well the driver adhered to the survey protocol (whether driver used the travel diary to record all travel and whether driver talked directly with interviewer). All exogenous inputs to the model were classified according to these broad categories. The final variable specifications for the binary model of underreporting and the ordered-response model for level of underreporting among underreporting individuals were developed by adopting a systematic procedure of eliminating statistically insignificant variables. Of course, as indicated earlier, the entire specification effort was also informed by the results of earlier studies and intuitive considerations.

RESULTS AND IMPLICATIONS FOR SURVEY METHODS

The results from our modeling effort provide important insights about underreporting tendencies in traditional household travel surveys. First, the underlying mechanism that represents whether an individual underreports or not is different from the mechanism that determines the level of underreporting. At the same time, there are common unobserved factors that influence both the underreporting propensity and the propensity associated with the level of underreporting. Consequently, it is important to use the joint binary-unordered response framework of the current study to analyze trip underreporting and its magnitude. Second, the effect of driver demographics indicates that young adults (less than 30 years of age); men; individuals with less than high school education; unemployed individuals; individuals working in clerical and manufacturing professions; workers employed at residential, industrial, and medical land uses; and individuals in nuclear families are all more likely to underreport trips in household travel surveys than other respondents. Third, driver travel characteristics that affect the tendency to underreport include making a high number of trips on the survey day, traveling long distances per trip, and trip chaining. Fourth, drivers who do not use the travel diary to record their travel are

more likely to miss trips than those who use the travel diary, and proxy reporting leads to more missed trips.

The model results can be used to identify specific improvements in the methods to conduct future travel surveys. These improvements may include (a) the use of special survey materials for respondents who travel more than usual or who are under the age of 30 and (b) developing better probes in telephone interviews when collecting information from unemployed individuals, proxy reporters, and individuals who travel longer-than-average distances. Each of these potential improvements is discussed below.

Use of Special Survey Materials

The empirical results from this study indicate that an important predictor of trip underreporting is the extent to which a respondent travels. Those who travel more have a higher propensity to underreport trips. This empirically supports the findings of prior studies, most of which related the increased travel to heavier respondent burden (and thus suggested missed trips were the respondent's way of ending the survey interview early). While the relationship between respondent burden and trip underreporting is well accepted, there is another component to this relationship that should be considered: the design of the travel log.

The travel logs used in the Kansas City study allowed space for recording up to 10 trips and instructed respondents to record additional travel on paper. The limit of 10 trips was based on the fact that most people report an average of five person trips in a day. In addition, it allows for a portable-sized log when printed. It works well for normal or light travelers who typically have room in their travel diaries at the conclusion of the travel day. It is possible that the heavy travelers record only up to the space in the log and nothing more (while the GPS unit continues to detect trips for the remainder of the travel day). The problem may be further compounded if the data are then reported by proxy: the person reporting travel for the heavy traveler may read the 10 trips from the log, and, not knowing what other travel was made that day, end the travel day prematurely. Additional study is warranted to determine the characteristics of heavy travelers such that they can be preidentified in the recruitment interview and provided a special log with either additional pages or a special insert for recording additional trips (similar to the way special instructions about transit-trip recording are provided to zero-vehicle households). This is a relatively low-cost solution that would help to minimize trip underreporting from the heavy-traveler group of respondents.

A second important driver characteristic is age. This study reveals that the propensity to underreport travel

decreases with age. Thus the worst trip reporters are those respondents under the age of 30. The authors recommend that future travel surveys consider the funds to conduct cognitive interviews or focus groups targeted specifically toward younger drivers. The purpose of this qualitative research would be to identify specific methodological improvements to the survey instruments that would result in better capture of travel from this age group. It may be possible, for example, that this group is more impatient with the telephone interview format and more receptive to self-reporting their travel via an Internet-based retrieval tool or simply being encouraged to return their logs by mail, with telephone follow-up as needed.

Finally, most travel survey materials are designed for persons with an eighth-grade education. However, this study found that respondents with less than a high school education are very likely to underreport their travel. This finding is independent of the age effect (i.e., a continued reflection of being under age 30). While most of the respondents reporting the lowest education level were under the age of 30 and still in high school (67%), one-third reported ages from 32 to 82. Further investigation is warranted to identify improvements in survey materials so that individuals with a low education level can understand what travel to report and how to record the travel as part of the survey. Different approaches may likely be needed based on whether the respondent is still in high school or in a later stage of life.

Developing Better Probes

On the basis of the findings of the earlier GPS studies, it has become standard procedure to probe workers about potential stops made during their commutes. In addition, as a form of validation, respondents who report no travel are subjected to a series of questions to confirm the legitimacy of the reporting. The results of this study suggest that additional probes as part of the travel retrieval interview may be warranted for all travelers, not just workers or those who report no travel.

Specifically, this study indicates that there is a high propensity to underreport travel if the driver is unemployed, has his or her travel data reported by proxy, or travels long distances. The finding that unemployed drivers have a higher tendency to underreport trips is a new correlate to be considered. In the past, the modeling focus on the work trip (and how discretionary travel may be incorporated into the work commute) has led to an emphasis on collecting travel activities that occur during the lunch break or during the commute to or from the workplace. Drivers who are unemployed do not receive similar levels of scrutiny or probes but, according to the findings of this study, should.

Unlike employment status, the finding that proxy-reported travel is associated with higher propensities of underreported travel is well documented. While the most obvious solution is not to allow any proxy reporting, the cost implications of such a decision are tremendous and may introduce more bias into the survey data than that introduced by allowing proxy reporting. A second, but also costly, approach is to only allow proxy interviews if the travel log is used. The better solution here may be to strengthen the telephone interview in a manner similar to the recommendation above for strengthening the travel of unemployed persons.

In summary, this paper has examined the driver demographics, driver travel characteristics, and driver adherence to survey protocol considerations that affect the likelihood of underreporting as well as the level of trip underreporting. These results can be used to adjust for

underreporting in traditional household travel surveys, to improve travel survey data collection procedures, or both. Although the authors plan to replicate this analysis on future travel surveys with GPS components, they believe that the survey method improvements identified in this study will enhance the collection of complete trip information in any household travel survey.

REFERENCES

- Bricka, S., and C. R. Bhat. *A Comparative Analysis of GPS-Based and Travel Survey-Based Data*. University of Texas at Austin, July 2005.
- NuStats. *Kansas City Regional Household Travel Survey: GPS Study Final Report*. Mid-America Regional Council, Kansas City, Missouri, 2004.

Dynamic Activity-Travel Diary Data Collection Using a Global Positioning System–Enabled Personal Digital Assistant

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Activity-based transportation models have set the standard for modeling travel demand for the last decade. It seems common practice nowadays to collect the data to estimate these activity-based transportation models by means of activity-travel diaries. This paper presents a general functional framework of an advanced data collection application for activity-travel diaries to be deployed on a Global Positioning System–enabled personal digital assistant. The different modules, the building blocks of the application, will be reviewed as well.

In the past, four-step models were developed to predict travel demand in the long run. The predicted travel demand, as outcome of the four-step models, can be used to support different kinds of decisions such as investments in new road infrastructure. In these four-step models, travel is assumed to be the result of four subsequent decisions that are modeled separately. More recently, especially in the 1980s and early 1990s, several researchers claimed that limited insight was offered into the relationship between travel and nontravel aspects in the widely adopted four-step models. Indeed, travel has an isolated existence in these models, and the question of why people undertake trips is completely neglected. This is where activity-based transportation models come into play. The major idea behind activity-based models is that travel demand is derived from the activities that individuals and households need or wish to perform. The main difference between traditional (i.e., four-step) transportation forecasting methodologies and activity-based transportation models is that the latter

attempts to predict interdependencies between several facets of activity profiles. These facets are often identified as which activities are conducted where, when, and for how long, with whom, with which transport modes being used.

As activity-based transportation models mature, they incorporate increasing levels of detail. An evolution toward dynamic activity-based models that incorporates learning effects can be observed in the literature (Joh 2004). The dynamics of travel behavior are driven by learning over time and short-term adaptation on the basis of within-day rescheduling. In contrast to static models, dynamic models try to capture these dynamics through enhanced activity-travel data. To accommodate the growing data requirements for calibration and validation of the dynamic activity-based models, more detailed activity-travel diary data must be collected. As the collection of basic data for activity-travel diaries already puts a heavy burden on the respondents, new techniques must be developed to allow for the collection of even-more-detailed scheduling behavior data. In this paper, a general functional framework of an advanced data collection application for activity-travel diaries to be deployed on a Global Positioning System (GPS)–enabled personal digital assistant (PDA) is presented. This tool must allow for the collection of detailed activity-travel diary data while limiting the burden on the respondents.

The remainder of this paper is organized as follows: the next section gives an overview of the state of the art in relation to computerized collection tools for activity diary data. Then, the advantages and disadvantages of a

GPS-enabled PDA are discussed. Following that, the functional description of the data collection tool receives further consideration, with the final section presenting conclusions.

STATE OF THE ART IN COMPUTERIZED ACTIVITY-TRAVEL DATA COLLECTION TOOLS

CHASE (Computerized Household Activity Scheduling Elicitor) was the first computer-aided self-interview of activity scheduling behavior (Doherty and Miller 2000). The purpose was to work out a survey that was able to track down the preceding scheduling process that resulted in the definitive execution of an individual's schedule, along with the observed activity-travel patterns as the outcome. In the past, traditional survey techniques that use diaries (e.g., paper-and-pencil techniques) were limited almost exclusively to observed patterns, providing little insight into decision processes. This shortcoming was dealt with through the development of a multiday computerized scheduling interface. The users' task consisted of keeping track of their scheduling decisions by adding, modifying, and deleting activities to their schedule as they occurred during a multiday period. The application made notes of each of these scheduling decisions, along with prompting for additional information (e.g., the reasons for these decisions, the exact timing of these decisions). The prompting process was extremely complex with paper-and-pencil techniques. Initial testing results indicated that this computerized approach revealed a considerable amount of information on the scheduling process and observed patterns, while minimizing respondent burden (Doherty and Miller 2000). Many adjustments and sophistications of this method have followed the original approach, including applications on the Internet (Lee et al. 2000), development of a geographical information system (GIS) interface for location and route tracking (Kreitz and Doherty 2002), and integration of GPS in a PDA application (Doherty et al. 2001).

In contributing to this line of research, the authors suggest an application that runs on a GPS-enabled PDA. Several key development issues are desire (a) to capture the dynamic activity-travel scheduling processes, (b) to reduce respondent burden, and (c) to improve activity-travel data quality.

The application described in this paper captures the process of dynamic activity-travel scheduling by collecting first information on the activities the respondent plans to execute and then information on the activities that the respondent did execute (diary) afterwards. Next, the planning and the diary are compared, and additional information about the differences is gathered if required.

ADVANTAGES AND DISADVANTAGES OF A GPS-ENABLED PDA

In the past, desktop computer-assisted data collection tools were used for completing scheduling surveys; this process provided activity-travel diary data. However, these systems are not able to trace the actual activity-travel execution due to their mobility constraints. To solve this problem, one might think of a PDA with GPS technology for enhancing the data collection tool's mobility. The potential advantages of using a PDA with GPS to supplement travel survey data collection are numerous: (a) when using a desktop computer-assisted data collection tool, the respondents have to remember the exact locations of their start and end positions whereas, with a PDA with GPS, trip origin, destination, and route data are automatically collected without burdening the respondent; (b) as the respondent may forget to report an activity trip, another advantage exists in recovery of unreported trips, as all routes are recorded; (c) accurate trip start and end times are automatically determined, as well as trip lengths; (d) the GPS data can be used to verify reported data; (e) both the data entry cost and the cost of postprocessing the data constitute a significant share of the total data collection cost (Zhou 2003). These costs can be reduced to a minimum with computer-assisted forms of data collection.

One of the most important shortcomings of GPS technology is that the system is not always reliable during the entire trip-recording period. Indeed, civilian GPS receivers have potential position errors resulting from, for example, multipath, selective availability, and the like. However, by combining the GPS data with other data sources such as location information reported by the respondent and GIS maps, these errors can generally be overcome. Another issue associated with the use of a handheld device is the storage capacity available to save the collected data. However, with ever-decreasing storage capacity prices, PDAs can readily be fitted with sufficient memory to conduct the surveys at a reasonable price. As a PDA is powered by a battery, it has to be recharged regularly, an extra burden for the respondent. To reduce the number of times the PDA needs to be recharged, an energy-conserving battery management system was integrated into the data collection application. This way the autonomy of the data collection tool can be significantly improved.

FUNCTIONAL DESCRIPTION OF GPS-ENABLED ACTIVITY-TRAVEL DIARY DATA COLLECTION TOOL

The central theme of the data collection tool revolves around a PDA. Compared with a typical computerized

activity-travel diary data collection system (e.g., CHASE), a mobile system does not restrict the location for data collection and is easy for the survey respondents to carry for in-situation data input. Moreover, as the PDA is equipped with a GPS receiver, GPS data can be collected as well.

The system conceptually consists of two graphical user interfaces (GUIs), household survey and activity-based survey; a GPS logger; a data structure (activity diary and both household and GPS data); a data quality control module (data integrity checks); a trip identification module; a GIS module; and a communication module (Figure 1). The modular structure of the application allows for customization. The implementation of modules less important for the current research can be omitted.

The GPS logger is used to trace the physical travel paths and the travel times. If the GPS is active, it receives the GPS data from the GPS chip and stores it by using the GPS data module. The GPS logger collects data continuously, and therefore it needs to operate in the background. This automatic feature has two advantages. First, it facilitates data capturing, and, second, although the survey respondent may forget to register a new activity, the GPS logger captures the user's position during the travel period. In this way, the system can prevent the loss of activity-travel data. Indeed, once the system detects a change in location that is not reported as travel by the survey respondent, it prompts the respondent for additional information.

The GPS data, stored in the GPS data module, can also be used for trip identification. Once the performed trip is identified, it can be used to verify whether the information about activities reported by the respondent

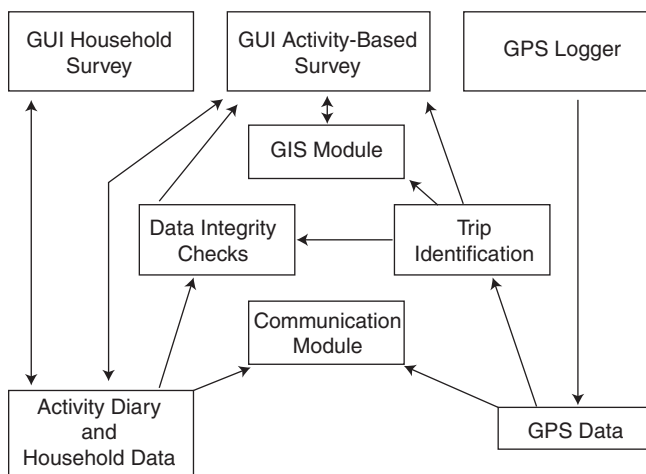


FIGURE 1 Schematic representation of functional description modules composing collection tool for activity-travel diary data.

is consistent with the actually recorded trip. If there are inconsistencies, the respondent will be prompted for clarification.

The household survey GUI inquires for personal demographic and activity-travel-related information. These data are collected at the beginning of the survey period and stored in the activity diary and household data module.

During the survey period, the respondent interacts frequently with the activity-based survey GUI, which is the major interface of the application. This GUI is used to register the activity-travel diary data during the survey period. It is used to enter, to modify, or to delete an activity or a trip, but it is also triggered if the data integrity checks module detects an inconsistency (e.g., a city name that does not exist) and the activity diary data need to be altered. The information stored in the handheld devices can be downloaded through the communication module. Depending on the implementation of the communication module and the available hardware, the data can be collected and stored on a data server either during or after the survey period.

The spatial dimension (the “where” facet) is the most difficult item to collect in traditional paper-and-pencil diaries. People often do not precisely recall the exact location or the name of the street where a particular activity occurred. Hence, traditional diaries are often restricted by limitations to the details of information collected. The computer-assisted data collection tools can make a significant contribution here by integrating a GIS module, which enables the user to either pinpoint a location on a map or to enter a location manually.

Computer-assisted data collection tools allow for data quality control. Indeed, a computer system can check for anomalies and prompt the respondent for additional information. Entries that report activities with a start hour of an activity later than the end hour, activity locations that do not exist, and many others are detected by the data integrity checks module of the PDA application.

CONCLUSION

In this paper, a data collection tool that is able to capture dynamic activity-travel scheduling behavior was presented. The detailed data collected by this tool will be used to develop a dynamic activity-based transport model.

In the functional description of the application, a modular approach toward a general data collection application was presented. Next, the importance of each of these modules was described. Currently, the presented data collection tool is deployed in a large-scale activity-travel survey in Flanders, Belgium.

REFERENCES

- Doherty, S. T., and E. J. Miller. 2000. A Computerized Household Activity Scheduling Survey. *Transportation*, Vol. 27, No. 1, pp. 75–97.
- Doherty, S. T., N. Noel, M.-L. Gosselin, C. Sirois, and M. Ueno. 2001. Moving Beyond Observed Outcomes: Integrating Global Positioning Systems and Interactive Computer-Based Travel Behavior Surveys. In *Transportation Research Circular E-C026, Personal Travel: The Long and Short of It*, TRB, National Research Council, Washington, D.C., pp. 449–466.
- Joh, C. H. 2004. *Measuring and Predicting Adaptation in Multidimensional Activity-Travel Patterns*. CIP-Data Koninklijke Bibliotheek, The Hague, Netherlands.
- Kreitz, M., and S. T. Doherty. 2002. Spatial Behavioral Data: Collection and Use in Activity Scheduling Models. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1804, Transportation Research Board of the National Academies, Washington, D.C., pp. 126–133.
- Lee, M. S., S. T. Doherty, R. Sabetiashraf, and M. G. McNally. 2000. Conducting an Interactive Survey of Household Weekly Activities via Internet: Preliminary Results from a Pilot Study. In *Proc., 9th International Association for Travel Behaviour Research Conference* (D. Hensher, ed.), Queensland, Australia, July 2–7.
- Zhou, J. 2003. Real-Time Tracking of Activity Scheduling–Schedule Execution Within Unified Data Collection Framework. Presented at 83rd Annual Meeting of the Transportation Research Board.

BREAKOUT SESSION
ASSIGNMENT ADVANCES

Dynamic Traffic Assignment Model Breakdown

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Dynamic traffic assignment (DTA) models are being implemented more frequently in practice. An entire Sunday afternoon session at the 2005 TRB Annual Meeting was devoted to presentations on practical experience with DTA models. Furthermore, commercial software vendors are making DTA products available in their traditional transportation planning packages. Several new commercial software releases occurred during the past year. Many presentations of the successes achieved in DTA implementations and demonstrations of the capabilities of DTA models will likely be forthcoming. This paper, however, examines a less successful DTA model. The emphasis will be on describing the development of methods for analyzing DTA model results, understanding the detailed interactions in the software, detecting relationships among data elements that produce various results, and synthesizing an implementation approach that tries to overcome or avoid obstacles. The goal is not only a set of network simulation results that can be compared with observational data but also evidence that the results are logical and that the model has worked as intended. This paper will discuss the use of one DTA software package, the Vista package (see www.vistatransport.com), and its application in a project in Atlanta, Georgia. First, a brief description of the project identifies the scope for which the DTA model is intended. The data requirements and manipulations for the DTA model are then outlined, and the model results are discussed. An example of the buildup of congestion on a network and its effect on traffic flow patterns is given. Potential underlying causes for the excessive congestion are addressed, which will

provide further insight into how the DTA solution algorithm functions. Next, the knowledge gained from the analyses performed is described, and an approach to overcome the problems highlighted and the impact of implementing this approach are given. Finally, the findings with regard to implementing a large-scale DTA model and the insights gained from breaking down the problems encountered and understanding those problems in the context of the algorithmic steps involved in solving the DTA are summarized.

IMPLEMENTATION DETAILS

The Georgia Department of Transportation is doing operational planning studies on sections of its freeway system to guide decisions concerning the programming of improvements. Its plan is to use focused microscopic traffic simulation models of sections of its freeway system to evaluate operational alternatives. A DTA model implementation has been identified as a means to calculate realistic time-dependent flows through areas where the DTA model uses input data from the regional travel demand modeling process and produces data required by the microscopic simulation methods. DTA models represent individual vehicle movements, and aggregate link performance characteristics gleaned to determine dynamic route choices and network equilibrium conditions. A traffic flow solution determined at such a mesoscopic scale is more appropriate for specifying time-dependent traffic flows through a focused area than a traffic flow solution defined at either a macroscopic

scale (lack of representational detail, specifically with regard to traffic queuing) or a microscopic scale (too computationally intensive to model an entire region).

DTA MODEL SPECIFICATION

The use of dynamic traffic models requires one to consider the specification of time much more carefully than is necessary in customary static network models. Time is relevant in a number of contexts in a dynamic model. First, demand is specified as the number of vehicles to load on the network during a certain time period. The Atlanta regional model demand in a 4-h period representing trips departing between 6:00 and 10:00 a.m. Analysis periods should be defined over which results of the DTA model will be compiled and compared with observed data. These periods could be a single 1-h period, several 1-h periods, several 15-min periods, and so forth.

The analysis period should almost certainly not align with the demand period. If, for example, the demand period were 6:00 to 10:00 a.m. and the period of interest were 6:00 to 7:00 a.m., the DTA model would estimate travel times on the network by simulating vehicles that were entering the network starting at 6:00 a.m. The first vehicles to load on the network would have no other vehicles to contend with, which in most urban areas is unrealistic. If it is necessary to evaluate traffic simulated at 6:00 a.m., then some estimate of demand occurring before 6:00 a.m., say from 5:00 to 6:00 a.m., should be determined and used to allow the DTA model to produce realistic traffic levels at the times the intervals of interest occur. As is discussed later, getting realistic traffic at 6:00 a.m. is easier than getting realistic flows at 8:00 and at 9:00 a.m., as the network is continually loading. The demand period for trips departing their origins before the time interval of interest is often referred to as a *warm-up period*.

The last vehicles to be loaded onto the network at the end of the demand period also have an important effect on other vehicles. For example, some number of vehicles will be loaded on the network just minutes before 10:00 a.m. It might be thought that those vehicles will only contribute to link flows after 10:00 a.m. and therefore that the simulation of vehicles need only occur between 5:00 and 10:00 a.m., giving 5 h of simulation time. However, vehicles entering the network near 10:00 a.m. will have an impact on vehicles that started their travel earlier. The vehicles entering at 10:00 a.m. may contribute to congestion on links at 10:00 a.m. or later. Had these vehicles not been simulated past 10:00 a.m., links could be represented as having less congestion than they should have, which could affect route choices made by vehicles that started their travel much earlier than 10:00 a.m.,

and that will end their travel after 10:00 a.m. The affected route choices of vehicles will then of course influence link flows in periods earlier than 10:00 a.m. The end of the simulation period, the *cool-down period*, after vehicles are no longer loaded on the network, is therefore necessary as well.

In the implementation, a 1-h warm-up period was used. Three 1-h analysis periods (6:00 to 7:00, 7:00 to 8:00, and 8:00 to 9:00 a.m.) were defined, for which flows were tabulated and compared with observed 1-h counts. Finally, a cool-down period sufficient to allow all vehicles to be simulated entirely from their origins to their destinations and therefore to exit the network was used. Depending on how well converged the dynamic user-equilibrium solution was, the cool-down period could have been from 3 to 7 h. The simulation period was therefore defined to start at time zero at 5:00 a.m. and end anywhere from noon to 5:00 p.m., depending on how well vehicles were allocated to routes. The more converged results that were used to compare with observed counts were typically based on 8 h of simulation time, with all vehicles exiting the network during those 8 h.

Besides the demand and analysis periods, the DTA assignment procedures use assignment intervals and link aggregation intervals. An assignment interval is a length of time when all vehicles traveling between a given origin and destination and departing their origin during this interval experience the same travel time at equilibrium. When this state occurs over all assignment periods, the DTA is in a state of dynamic user-equilibrium. At that point, no vehicle has an incentive to follow a different route, and the DTA solution is stable. Assignment intervals were defined with lengths of 15 min.

Link aggregation intervals are the length of time over which the simulated vehicle travel times on a link are averaged to yield a single link travel time for that aggregation period. These average link travel times by aggregation period are used in the time-dependent shortest path (TDSP) calculations that are part of the DTA's dynamic user-equilibrium solution procedure.

INPUT DATA REQUIREMENTS

The input data for Vista include the Atlanta regional highway network described as a link table and a node table, much as the network is defined for the regional demand model. The link table contains node IDs at each end of the link, length, free speed, and link capacity information. The node table contains spatial coordinates and a type to distinguish regular intersection nodes from centroid nodes. Vista also uses input tables to define the location and operational characteristics of signalized intersections in the network. Finally, Vista requires an

input table for the demand that is to be simulated for the network.

To develop the Vista network data from the Atlanta regional model data, the link and node tables were transformed directly into the format required by Vista by reordering the data fields and converting some of the units. For the demand data, the regional model demand matrices were first exported to test files using the Citilabs Cube (see citilabs.com) software with which they were created, and those text files were then manipulated to produce the required Vista demand table. The trip matrices from the regional model were developed by using typical aggregate model methodologies. The resulting matrices defined flow rates of vehicles per 4-h demand period by vehicle class (sov, hov, truck). The flow rate from an origin zone to a destination zone could in general be a noninteger number and often was some fraction of a trip. The Vista demand table required a record for every discrete vehicle, so the conversion process included converting flow rates to discrete vehicles while conserving the total number of vehicles and included assigning departure times, in seconds from the start of the simulation period. The departure time profile from the regional model, which specified the proportion of vehicles departing during each hour of the 4-h period, was used to control the departure time assignments.

DTA model requirements for network data are sometimes purer than is typical for aggregate travel demand model networks. Specifically, where an aggregate model might define the speed field to be free-flow speed as observed or as an expected value, including the influence of traffic signals, a DTA model will require posted speed for links and should be allowed to simulate the relationship among traffic, traffic control, and speed. Similarly, where an aggregate model might have network capacities defined to ensure that congestion effects are adequately represented in assigned network travel times and flows, a DTA model requires that network saturation flow rates on surface streets and service flow rates on uninterrupted flow facilities be defined so that the correct aggregate fundamental traffic flow relationships can be represented.

Because the movement of vehicles through the network is represented by a traffic simulation model to determine network characteristics for the dynamic user-equilibrium route choice procedure, it is necessary to represent the traffic control system. The traffic simulation will simply move vehicles along network links on predetermined paths over time at their free speed as long as there is room for them to move. When more vehicles want to move on a link than the link has room for, congestion will develop, and vehicles will need to progress according to some rules, usually some kind of first-in, first-out rule. In line with this general way of moving vehicles along their paths, the simulation model must

follow simple rules of the road with regard to traffic signals; a vehicle encountering a red light at a traffic signal (or the end of a queue waiting at a traffic signal) waits and moves forward after the signal changes to green (or the queue moves forward). In Vista, traffic signals are defined as simple preset signals. It is possible to include permitted, protected, and permitted-protected combination phasing. In the implementation described here, permitted left-turn phases were defined if left-turn flows warranted a separate phase, and permitted phases were defined for through and right-turn movements.

Traffic control settings for signalized intersections were determined by applying a straightforward green time allocation methodology to the approaches at signalized intersections. A custom-written program was used to read movement flows from an initial Vista model run and to calculate cycle length, number of phases, phase lengths, and order of phasing. From this information, the tables required by Vista to represent traffic control were written.

One further note about traffic control might be relevant. One might be tempted to believe that preset signal timing parameters are a limitation given that in reality many intersections have traffic-actuated traffic control. This would clearly be the case in a microscopic context where traffic patterns are more or less fixed and the microscopic model is used to evaluate the impact of details such as geometry, capacity reductions, traffic control, and traffic merging and weaving. In the mesoscopic DTA model, however, traffic is simulated to produce dynamic user-equilibrium route assignment for the vehicles in the demand table. Simulating traffic control that varies as traffic varies is problematic for the dynamic network equilibrium methodology, and the use of preset traffic control makes the problem much more tenable.

SOLVING FOR THE DYNAMIC NETWORK EQUILIBRIUM

The dynamic user-equilibrium solution procedure involves a sequence of steps that include simulating the movement of vehicles along predetermined routes, calculating those routes between origin-destination zone pairs by time interval, and allocating vehicles to one of a set of competing routes. When the routes used by vehicles between origin and destination by departing assignment interval are equal for all origins, destinations, and assignment intervals, and no additional lower travel-time routes exist, the dynamic user-equilibrium solution has been determined.

The vehicle simulation is based on the propagation of vehicles according to the cell transmission model (CTM) (1). Network links are divided into cells, and vehicles are moved from cell to cell along links and between links as

they traverse their routes. The propagation depends on the posted speed for the links, saturation flow rates, and jam density for links. The values specified for these link properties define a speed–flow–density relationship for the link to which simulated vehicles adhere. The resulting effect is that at a link level, vehicles exhibit proper traffic flow theory properties in that they form queues, and queues may spill back to other links. Link travel times therefore consist of time required to traverse a link at posted speed plus time spent delayed in queues and time delayed by traffic control devices.

Once the vehicle simulation has finished, it is possible to compute link travel times at any aggregation interval desired. A typical Vista application include a simulation time step of 6 s, meaning that the position of vehicles in cells is updated every 6 s. The travel times on links could then be computed for every link at every 6-s interval, or they could be computed at longer intervals where an average of the 6-s times would be calculated and stored.

Given time-dependent (by link aggregation interval) link travel times, a TDSP algorithm can be used to calculate routes through the network. The TDSP algorithm works much like the conventional shortest-path algorithms used in static traffic assignment methods, except that the link times have a time index. At each step in the algorithm, as a link is being considered for inclusion in the shortest path, the criteria used includes the travel time on the link at the current accumulated time along the path. In other words, for a specific assignment interval, if a link is 60 s of accumulated link time from the origin along the shortest path, the link is evaluated for inclusion in the shortest path based on the link time associated with the aggregate time interval that corresponds with 60 s past the beginning of the assignment interval. The result of the TDSP is a set of routes between every origin and destination zone starting in every assignment time interval.

With the capability to simulate traffic and compute time-dependent link travel times and TDSP, a DTA model can compute a dynamic network equilibrium solution. Typically, for planning studies, a dynamic user equilibrium is the desired outcome. For intelligent transportation system applications, one might be more interested in a dynamic system-equilibrium solution. The dynamic equilibrium is usually defined by extension of the static user-equilibrium principle that states that no used route between an origin and a destination may have a higher travel time than any unused route. By extending this principle to the time-dependent case, one arrives at a similar condition: at no time along a route from an origin to a destination can a traveler change to a different route and lower his or her travel time. In other words, the travel times for all used routes between an origin and a destination starting during the same time interval are all equal at equilibrium.

In most DTA models, the equilibrium solution is determined by first identifying a feasible or reasonable path set, then allocating flow between those paths to cause the path times to be equal as per the definition given above. In Vista, a reasonable path set is determined by solving the dynamic user-optimal equilibrium problem with the method of successive averages (MSA) procedure. This involves iteratively solving the CTM and TDSP, then averaging the time-dependent flow solution with the solutions from previous iterations. The weight of the most recently calculated flows is $1/N$, where N is the iteration number, and the weight of the previous averaged flows is $(1 - 1/N)$. The MSA solution converges very slowly toward an equilibrium solution, but each iteration provides the opportunity for new routes to be determined subject to traffic conditions established as the combined effect of the other iterations.

Once the reasonable path set is determined, an allocation mechanism can be used to achieve a more exact equilibrium solution over the fixed set of reasonable paths. Vista uses a methodology called simplicial decomposition, which, for any origin–destination–time interval set, causes flows from higher travel-time routes to be apportioned to lower travel-time routes, and conversely, lower travel-time flows shifted to higher travel-time routes. The solution procedure results in a set of time-dependent link flows and route times corresponding to the dynamic user-optimal conditions. (The solution is not a pure equilibrium solution. Routes with shorter travel times may exist that were not identified in the MSA procedure. However, the solution is probably nearly an equilibrium, and it is thought to be adequately close.)

The implementation described here involved iteratively building a reasonable route set and solving the dynamic user-equilibrium for that route set. Following each dynamic user-equilibrium solution, routes that had previously received vehicles but no longer did were pruned from the route set and new reasonable routes were determined with the approximate MSA solution procedure. This was followed by solving for the more precise dynamic user-equilibrium solution for the route set. When one of these iterations produced only a small number of new routes, the model was said to have converged sufficiently.

ANALYSIS OF VISTA RESULTS FOR ATLANTA

A DTA model of the Atlanta region is a large problem to solve. Most DTA results published to date are for much smaller problems. An attempt was made to reduce the problem size by limiting the demand loaded on the network. At first trips were simulated beginning between 6:00 and 7:00 a.m. with the intention of increasing

demand when the simulation was verified to be working properly.

The simulation results included a small number of links with travel times exceeding 1 h. One feature of Vista that facilitates postsimulation analysis is that all the input data and most of the results are stored in a database that can be evaluated by using the language of databases, SQL. It was easy, for example, to query all the link records that experienced such a high travel time and to plot their locations with a geographic information system (GIS). The first explanation that came to mind was that there must be a coding error in the network or that a centroid link must be dumping a lot of trips into these areas. Detailed inspection of the problem areas revealed no evidence that either of these explanations was correct.

With another query of the database, it was possible to collect all of the vehicle arrivals at one of the excessive time links. On the basis of the arrival time at the link and the arrival time at the downstream link, it was possible to plot a time–space diagram of the vehicles arriving at these links and derive their propagation along cells defined for the links. The next section shows an example of how congestion might develop on network links.

ILLUSTRATING CONGESTION ON LINKS IN CTM MODEL

Figure 1 shows a set of vehicle trajectories on a time–space diagram to illustrate the evolution of congestion occurring in the CTM.

In Figure 1, the horizontal axis is space, as shown by Link 1 → Link 2 → Link 3, and the vertical axis shows

time increasing from the top to the bottom of the diagram. The diagram shows that Link 1 has two cells, each with capacity for six vehicles; Link 2 has three cells, each with capacity for two vehicles; Link 3 has one cell with capacity for two vehicles. At time 0 s, vehicle *a* arrives at the first cell of Link 1. One should notice that there is a reduction in capacity from Link 1 to Link 2, and this reduction will result in congestion, as will be seen later.

At time 6 s, vehicle *a* moves to Cell 2 of Link 1 and vehicles *b* and *c* arrive at Link 1. At time 12 s, vehicle *a* moves on to Link 2; vehicles *b* and *c* move to Link 1, Cell 2; and vehicles *d*, *e*, and *f* arrive at Link 1. It is relatively easy to follow the arrival of vehicles at Link 1 with 20 total vehicles (*a–s*) arriving in 60 s (ten 6-s intervals from time 0 to time 54).

One might expect delays to occur on Links 2 and 3, given their reduced capacity and the clear excess overcapacity of the flow trying to use those links, but from the diagram it can be seen that each vehicle moves through the cells in Links 2 and 3 at constant, free-flow speed of one cell per 6 s. This is true for vehicle *a*, vehicles *b* and *c*, vehicles *d* and *e*, and so forth. There is no congestion at all in this diagram for Links 2 and 3. The congestion occurs prior to (upstream of) the capacity reduction at Link 2. In other words, the congestion, identified by time delay incurred by vehicles, appears on Link 1. Consider time 18 s at Link 1. Four vehicles arrive at Cell 1 and three vehicles move from Cell 1 to Cell 2. In the next time step, 24 s, vehicles *d*, *e*, and *f* want to move to Link 2, but there is only room for two, so only *d* and *e* move, and *f* waits for the next time step. Also in that time step, the four new vehicles at Cell 1 move to Cell 2 and join *f*. At time step 30 s, vehicle *f* finally arrives at Link 2. The

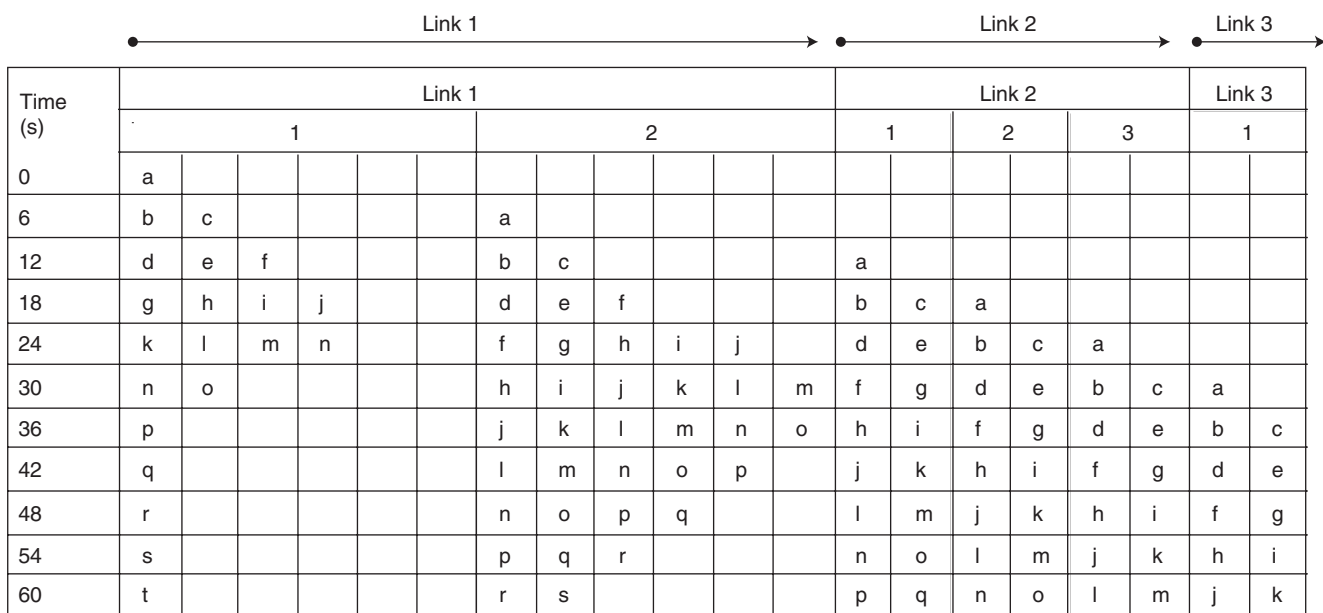


FIGURE 1 Time–space diagram of vehicles on a simple network.

time difference for vehicle f , and therefore its travel time on Link 1, is $30 - 12 = 18$ s. All the vehicles before f , $a-e$, have travel times of 12 s on Link 1, which is the free-flow travel time for Link 1. Therefore, vehicle f has 6 s of delay on Link 1. Following similar trajectories for the other vehicles indicates that the most delay occurs for vehicle n on Link 1 (30 s).

EFFECT OF CONGESTION ON ATLANTA DTA RESULTS

The above exercise illustrates clearly that with the simultaneous arrival of too many vehicles, only some could continuously move along, while others had to wait. The number allowed to move at each time step was determined by the saturation flow rate defined for the link, which determines the number of vehicles that can occupy a cell during any time step. The number of time steps that elapsed before the vehicles could completely traverse the link determined the total delay experienced on the link.

For the entire Atlanta network, once cells became saturated while vehicles continued to arrive, the cell saturation effect moved upstream. The original overcongested link caused many links upstream of it to become oversaturated. When propagation of congestion affected a freeway link, routes between origins and destinations spanning nearly the entire region became affected, and the simulation broke down. It was not possible, due to the excessive times on important links, for all the vehicles to complete their trips during the simulation period. With many vehicles having route attributes associated with incomplete trips, the dynamic user-equilibrium results and subsequent route-generation steps were suspect.

The dynamics of a traffic jam produced by the simulation results showed that the software was responding the way it was intended but did not provide any explanation for why so many arrivals occurred at these links. The next course of action was to look more carefully at the set of vehicle arrivals at this congested link, ordering them by their arrival time. Doing so revealed that some of the vehicles exiting a link in question were exiting at essentially free-flow speed while others exiting the same link at the same time but toward a different downstream link were exiting with times in the 2,000+ s range. Eventually, all vehicles regardless of their downstream link would experience huge travel times, but initially as congestion built up on this one link, there was a large variability in exiting travel times, or in other words, a large variability in movement times passing through a given link at a given time.

Routes are determined on the basis of the link time averaged over the link time aggregation period as defined

earlier. Where there is a large variability in vehicle travel times over movements through a link, the result might be that the congested link appeared to the route generator to be suitable long after it was congested due to the averaging. In such an instance, one should use movement-based times in TDSP, at least in problematic areas, to address the problem described here. Movement-based times would cause the route through the congested link pair to be considered much differently from the link pair that shares a common link but has essentially free-flow times. It is more resource intensive to do movement-based TDSP, which is why the default is to use link-based TDSP, but it is possible to identify a select number of locations for which movement-based times should be used. In general, in dynamic network models, one must be aware of problems that could be caused by highly variable movement travel times exiting links.

It was believed that high variability in exiting link times can be used to identify the locations requiring movement-based times. A query of vehicles arriving at links during the same time period but destined for different downstream links, where the vehicles have much different downstream arrival times, identified those links. By using the GIS, a spatial correlation between links with high variability in movement times and links with excessive travel times was confirmed. Only a couple dozen such locations were identified, and the changes necessary for Vista to consider movement-based times in TDSP were easily made.

SOME PRELIMINARY VISTA SUMMARY RESULTS

Calibration of the Vista DTA model of the Atlanta region is still in progress, but some preliminary results can be described. Table 1 shows the link summary statistics for the Vista model for the 6:00 to 7:00 a.m. demand period. The number of links, total observed count, and total estimated flow are listed for volume ranges, along with relative error and percent root mean square error statistics. Figure 2 shows the scatter plot of the same DTA results.

The results were determined from the DTA model run resulting from the first traffic signal setting retime following the initial Vista DTA model results.

Table 2 and Figure 3 show the DTA results after four iterations of retiming traffic control settings and running the DTA model to solve for dynamic user-equilibrium.

The results after the first iteration show a good fit with observed data. The results after the fourth iteration show an even better fit. Results from the second and third iteration, not shown here, had successively better fit, leading up to the fourth iteration results.

The iterations involved figuring traffic control settings, solving for an equilibrium-based distribution of vehicles to routes, updating the traffic control settings,

TABLE 1 Dynamic User–Equilibrium Summary Statistics After First Signal Retime

vol7Range	Volume Range	Link Counts	6–7 a.m. Count	6–7 a.m. Flow	Rel. Error	% RMSE
0	<500	91	28,544	43,276	51.6%	126.5
1	500–999	46	32,877	32,797	–0.2%	79.4
2	1,000–1,999	34	47,934	39,065	–18.5%	62.7
3	2,000–4,999	21	72,760	75,987	4.4%	43.6
4	5,000+	16	107,936	86,434	–19.9%	45.6
Total		208	290,051	277,559	–4.3%	77.6

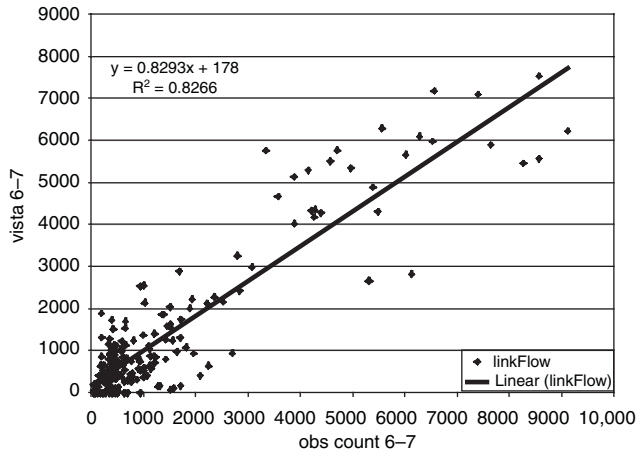


FIGURE 2 Dynamic user–equilibrium solution after first signal retime.

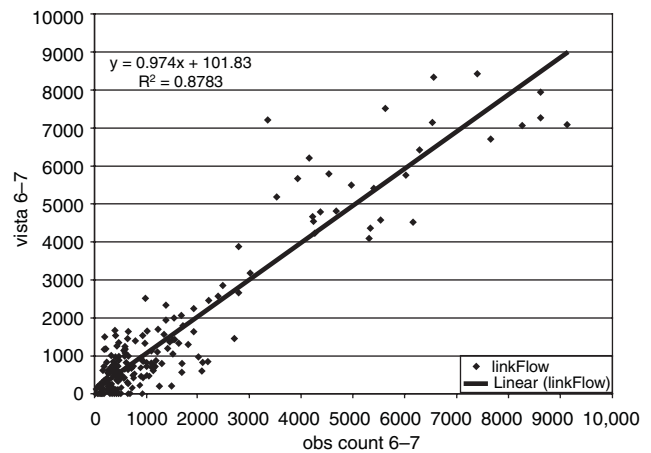


FIGURE 3 Dynamic user–equilibrium solution after fourth signal retime.

TABLE 2 Dynamic User–Equilibrium Summary Statistics After Fourth Signal Retime

vol7Range	Volume Range	Link Counts	6–7 a.m. Count	6–7 a.m. Flow	Rel. Error	% RMSE
0	<500	91	28,544	42,952	50.5%	119.0
1	500–999	46	32,877	33,295	1.3%	72.0
2	1,000–1,999	34	47,934	40,493	–15.5%	62.4
3	2,000–4,999	21	72,760	83,557	14.8%	39.2
4	5,000+	16	107,936	103,381	–4.2%	32.7
Total		208	290,051	303,678	4.7%	63.0

resolving the equilibrium settings, and so forth. The flows seemed to be converging toward the observed counts, and the traffic control settings seemed to be converging to a stable set of parameters. This outcome is exactly what would be desired in practice, yet nothing in the theory indicates that this will happen. There is no model specification for the problem of simultaneously computing traffic control settings and DTA solutions. It is a bi-level optimization problem that has no particularly useful formulation—at least none that would predict a convergent solution. Yet the experience indicates that the solution was moving toward convergence.

While these results look promising, they do not tell the whole story. These results were for a fairly low level of demand (6:00 to 7:00 a.m.); results were not shown for subsequent hours (i.e., 7:00 to 8:00 a.m. or 8:00 to 9:00 a.m.). (They have been calculated but are not sufficiently converged or calibrated at this point.) In fact, flows are generally a little more than half of what their

counts are in these later periods. The challenge is to identify the reasons for these poor DTA results and develop a strategy once the causes are understood. The potential causes are many: ill-defined demand or temporal distribution of demand, network coding problems, model calibration parameters, or even incorrectly defined counts. One must try to identify causes of the underestimation of flows by building reports and analysis procedures that will help inform other DTA models and not just try to find some settings to which the DTA is particularly sensitive and modify those to calibrate this one model.

CONCLUSIONS

This paper describes the experience of using DTA to calculate regionwide time-dependent flows for the purpose of specifying time-dependent origin–destination flows through a focused area for which detailed traffic

microsimulation techniques could be employed. The paper describes the steps that DTA models employ, some difficulties encountered with a large-scale implementation of a DTA model using Vista, and the findings of detailed analysis of these problems.

The intent is not to showcase any particular DTA package but to identify problems that are likely to be encountered in any DTA implementation and to understand why they occur. The problems addressed include excessive localized congestion, excessive variability in movement travel times by exiting vehicles, and why vehicles continue to be routed through problem areas even after congestion has developed.

The work on which this paper is based is ongoing. It is hoped that additional insight, clarification, and conclusions will be forthcoming and that there will be an opportunity to discuss them and hear of other experiences at the Innovations in Travel Modeling Conference.

REFERENCE

- Daganzo, C. F. The Cell Transmission Model: A Simple Dynamic Representation of Highway Traffic Consistent with the Hydrodynamic Theory. *Transportation Research Part B: Methodological*, Vol. 28, No. 4, 1994, pp. 269–287.

Urban Arterial Speed–Flow Equations for Travel Demand Models

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This paper describes the effort to improve the speed–flow relationships for urban arterial streets that are contained in the Southern California Association of Governments’ (SCAG) metropolitan area travel demand model. Intersection traffic counts and floating car runs were made over 4-h-long periods on 1-mi-long sections of eight different arterial streets within the city of Los Angeles. The field data were then filtered to identify which speed measurements were taken during below-capacity conditions and which measurements were made during congested conditions when demand exceeded the capacity of one or more intersections on the arterial. Because the traditional manual intersection traffic count method that was used to gather volumes did not measure queue buildup, and therefore demand, the speed data points obtained during congested conditions were not used in the fitting of speed–flow equations. Several different speed–flow relationships were evaluated against the field data for below-capacity conditions. The most promising speed–flow equations for below-capacity conditions were then evaluated for their ability to predict delays for congested conditions where one or more intersections on the arterial are above capacity. The theoretical delay due to vehicles waiting their turn to clear the bottleneck intersection on the arterial was computed by using classical deterministic queuing theory. Speed–flow equations that underpredicted the delay to clear a congested intersection were rejected. Of the speed–flow equations tested, the Akcelik equation performed the best for above-capacity situ-

ations and performed as well as other possible equations for below-capacity conditions.

The objective of the study was to develop improved field-calibrated speed–flow equations for use in travel demand models to predict the mean speed of traffic on signalized urban arterial streets.

FIELD DATA COLLECTION

Intersection movement counts and Global Positioning System–equipped floating cars were used to gather 216 hourly observations of speed and flow on 54 directional street segments (defined as a one-way link between two signalized intersections) at eight different sites in the Los Angeles basin (see Figure 1). A total of 12.8 directional miles of arterial streets were surveyed. Table 1 shows the salient characteristics of each survey site.

DATA FILTERING

The method used to collect intersection volumes measured intersection discharge rates rather than demand. When the demand is less than the discharge capacity for the intersection approach, discharge rate and demand are identical. When the demand exceeds capacity, the demand diverges from the counted discharge rate. Con-

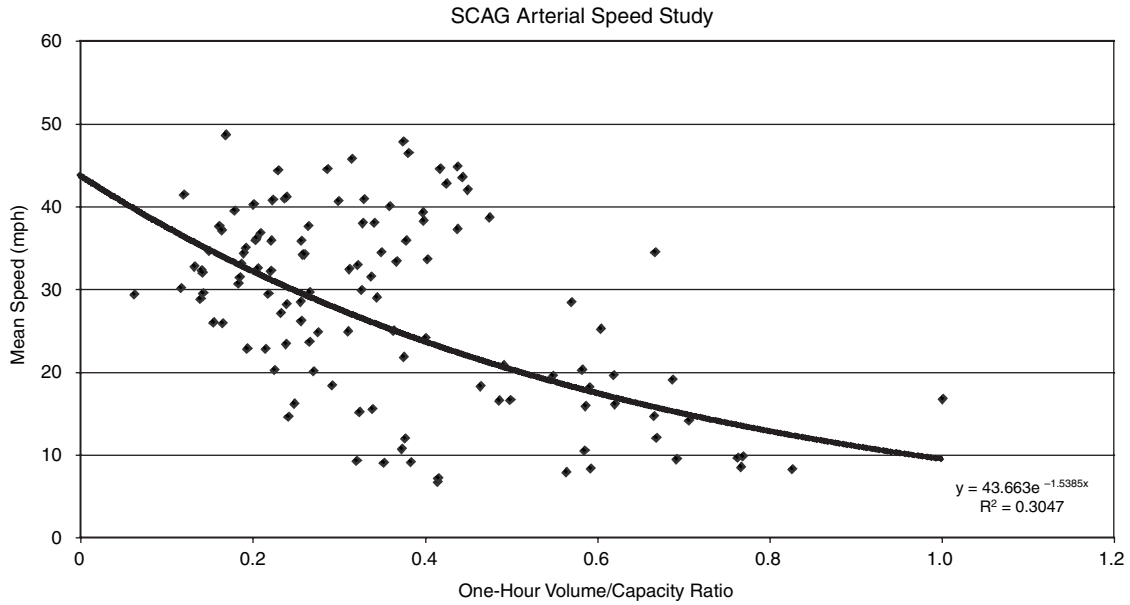


FIGURE 1 Hourly speed–flow observations.

TABLE 1 Speed Survey Site Characteristics

Street	From	To	Length (miles)	Facility Type	Area Type	Lanes (both dir.)	Signals (#)	Speed Limit (mph)	ADT (2-way)
1st St.	Ford Blvd.	Gage Ave.	0.90	3	4	4	4	35	19,300
Aviation Blvd.	W 120th St.	W 135th St.	0.99	2	4	4	4	40	33,800
Beverly Blvd.	Robertson Blvd.	La Cienega Blvd.	0.44	2	2	4	4	40	34,700
Lincoln Blvd.	Fiji Way	Venice Blvd.	1.43	2	3	6	7	35–40	54,600
San Vicent Blvd.	Curson Ave.	Hauser Blvd.	0.64	2	2	6	4	35–40	39,900
Sunset Blvd.	N La Brea Ave.	N Cherokee Ave.	0.51	2	3	6	4	40	33,200
Verdugo Rd.	Colorado Blvd.	N Shasta Circle	0.83	3	5	4	4	35–40	16,000
Western Ave.	W 111th St.	W 120th St.	0.68	2	4	4–6	4	35	21,300

Note: Facility type: 2, principal arterial; 3, minor arterial. Area type: 2, central business district; 3, urban business district; 4, urban; 5, suburban.

sequently, it was necessary to identify data points when the counted volume did not equal the demand and drop these points from the data set.

CANDIDATE SPEED–FLOW EQUATIONS

Several candidate speed–flow equations might be fitted to the observed data. Table 2 describes several candidates. The first five candidates—linear, logarithmic, exponential, power, and polynomial—are standard mathematical functions commonly used in data analysis. The last two equation forms—Bureau of Public Roads (BPR) and Akcelik—are unique to travel time and delay analysis. The BPR equation has been the traditional method for predicting vehicle speed as a function of volume–capacity (v/c) ratio in travel demand models.

$$S = \frac{S_0}{1 + a(X)^b}$$

where

- S = average link speed (mph or km/h),
- S₀ = free-flow link speed (mph or km/h),
- X = v/c ratio,
- a = 0.15, and
- b = 4.

The BPR equation was originally fitted to 1965 *Highway Capacity Manual* freeway speed–flow data (1). Since then additional research has indicated a less significant effect of v/c ratio on mean speeds until capacity is reached (see Exhibit 13-4 of the 2000 *Highway Capacity Manual*).

The Akcelik equation was derived by Akcelik from the steady state delay equation for a single-channel queuing system. He derived the following time-dependent form:

$$S = \frac{L}{L/S_0 + 0.25T \left[(x-1) + \sqrt{(x-1)^2 + \frac{8Jx}{cT}} \right]} \tag{1}$$

TABLE 2 Functional Form Candidates for Speed-Flow Curves

Functional Form	Example	Comments
Linear	$s = -ax + b$	Not acceptable. Reaches zero speed at high v/c .
Logarithmic	$s = -a \ln x + b$	Not acceptable. Has no value at $x = 0$ (the logarithm of x approaches negative infinity).
Exponential	$s = as_0 \exp(-bx)$	Has all required traits for equilibrium assignment.
Power	$s = a/x^b$	Not acceptable. It goes to infinity at $v/c = x = 0$.
Polynomial	$s = -ax^2 - bx + c$	Not acceptable. It reaches zero speed at high v/c .
BPR	$s = s_0/(1 + a(x)^b)$	Has all required traits for equilibrium assignment.
Akcelik	$s = L/\left\{L/s_0 + 0.25[(x - 1) + \sqrt{[(x - 1)^2 + ax]}\right\}$	Has all required traits for equilibrium assignment.

Note:

s = predicted speed; a, b, c = global parameters for equation; L = link length; x = volume/capacity ratio; s_0 = link free-flow speed.

where

- L = link length (mi),
- S = average link travel time (h),
- S_0 = free-flow link travel time (h),
- x = v/c ratio,
- T = duration of analysis period (h),
- c = capacity (vph), and
- J = calibration parameter.

PRELIMINARY SCREENING OF CANDIDATE SPEED-FLOW EQUATIONS

Speed-flow equations must meet several behavioral requirements to permit capacity-constrained equilibrium assignment to be performed by travel demand models. The speed-flow equations must be monotonically decreasing and continuous functions of the v/c ratio for an equilibrium assignment process to arrive at a unique

solution. As a practical matter, the speed-flow equations should never intersect the x -axis (that is, the predicted speed should never reach precisely zero), so that the computer implementing the travel demand model is never confronted with a “divide by zero” problem.

Three of the candidate functional forms meet the equilibrium assignment requirements for a speed-flow curve—exponential, BPR, and Akcelik.

MODEL SPEED-FLOW EQUATION CALIBRATION— $v/c < 1.00$

The exponential, BPR, and Akcelik equations were fitted through a least-squares error-fitting process to the observed speed-flow data. Figure 2 compares the fit of the standard BPR and the other fitted curves to the data. As can be seen, the wide scatter of the observed data allows almost any speed-flow curve to be drawn through the cloud of data. All three functional forms

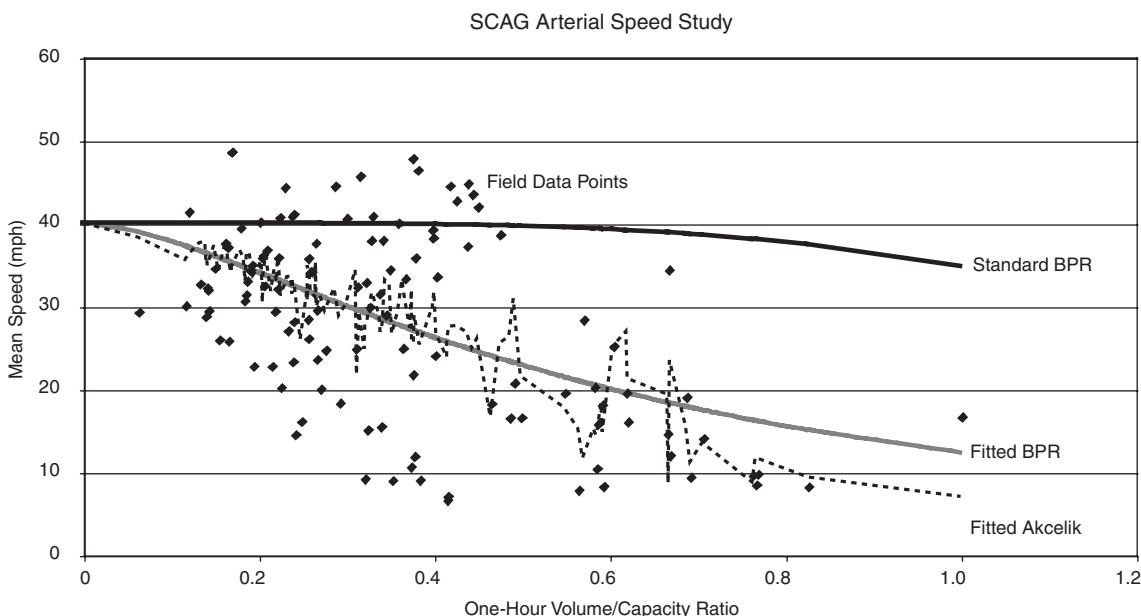


FIGURE 2 Speed-flow equations versus field data for $v/c < 1.00$.

appear to account for some of the observed variation in speeds.

The Akcelik equation is of interest because it is not a smooth curve in v/c like the others. The Akcelik equation–predicted speed is sensitive to the link length in addition to the v/c ratio. The Akcelik equation adds the same delay to a link for a given v/c ratio, regardless of the link length. (The assumption is that all the delay occurs at the downstream signal at the end of the link. No delay accrues over the length of the link.) The result is that the Akcelik curve shows a bit more scatter (similar to the observed data) than the other curves, for which the predicted speeds are not sensitive to link length.

The reader will note that a simplified version of the original Akcelik equation has been calibrated. The constant multiplier of 8 for the J calibration parameter has been subsumed within the J calibration parameter itself. The variable “capacity” from the Akcelik equation was dropped because the simplified equation fit the data better. Note also that, because the length of analysis period is 1 h, it is no longer necessary to carry the time period duration variable, T . The final equation is shown below.

$$S = \frac{L}{L/S_0 + 0.25 \left[(x-1) + \sqrt{(x-1)^2 + Jx} \right]} \quad (2)$$

where all variables are the same as defined before.

A statistical comparison of the equations is presented in Table 3. This table shows the root-mean-square error and the bias for each curve when compared against the observed data. The fitted equations (BPR, exponential, and Akcelik) naturally do better against the field data than the standard BPR equation because they have been fitted to the data. While the standard BPR equation overestimates arterial speeds by an average of 11.5 mph (bias) (18.4 km/h), the other curves overestimate arterial speeds by less than $\frac{1}{2}$ mph on average. The RMS error for the standard BPR curve is 16 mph (25.6 km/h), while the other curves have significantly lower RMS errors. The best-fitting curve, the Akcelik equation, has about a 40% better RMS error than the standard BPR equation.

TABLE 3 Quality of Fit to Observed 1-Hour Data for $v/c < 1.00$

Fitted parameters	Standard BPR	Fitted BPR	Fitted Exponential	Fitted Akcelik
S_0 (free-flow speed)	40 mph	40 mph	40 mph	40 mph
A	0.15	2.248	1.0512	0.0019
B	4.00	1.584	-1.185	
Bias (mph)	11.53	0.30	0.04	0.13
RMSE (mph)	16.00	9.83	9.84	9.40

MODEL SPEED–FLOW EQUATION CALIBRATION— $v/c > 1.00$

The field data could not be used to evaluate the speed–flow curve candidates for demands greater than capacity because the standard traffic counting procedure used could only count the served demand, not the unserved demand. Thus a theoretical evaluation was conducted of the speed–flow curves comparing their predicted delays for volumes greater than capacity against the delays predicted by queuing theory.

According to classical queuing theory, when demand is greater than capacity, vehicles must wait in line until the vehicles in front of them have had a chance to pass through the intersection. This theoretical average delay can be graphed and compared with the predictions produced by the candidate speed–flow curves.

Figure 3 illustrates this (the chart plots travel time per segment, the inverse of speed, so that the theoretical delay due to queuing can be included in the chart). Points that fall on the horizontal portion of the queuing theory line represent traffic moving at free-flow speeds with no delay. Points above this horizontal line represent speeds below free-flow speeds, with delay.

The theoretical average delay due to queuing is the thick solid line at the bottom of the chart. The line is flat until the real-world capacity of the link is reached, then the predicted travel time increases rapidly, but linearly with increasing demand.

The ideal speed–flow curve would not cross the theoretical solid line for queue delay. As can be seen, however, both the standard and fitted BPR curves cross the theoretical queuing delay line. Both of these curves underestimate the delay due to queuing when demand exceeds the real-world capacity of an intersection at the end of a link.

The fitted Akcelik curve is consistent with the queue delay line, because the Akcelik curve is derived from classical queuing theory.

CONCLUSIONS

There is a great deal of variation in the observed arterial street segment speeds that cannot be explained solely on the basis of the v/c ratio for the signalized intersection at the terminus of the segment. The v/c ratio appears to explain about 30% of the variation. Other factors, such as signal timing offsets, affect the observed mean hourly speed on a segment.

In evaluating data for demands less than the approach capacity, many equations, such as the fitted BPR, fitted exponential, and the fitted Akcelik, performed equally well. The fitted Akcelik equation performed slightly better because it adds signal delay to the segment free-flow travel time rather than treating delay as a multiplicative

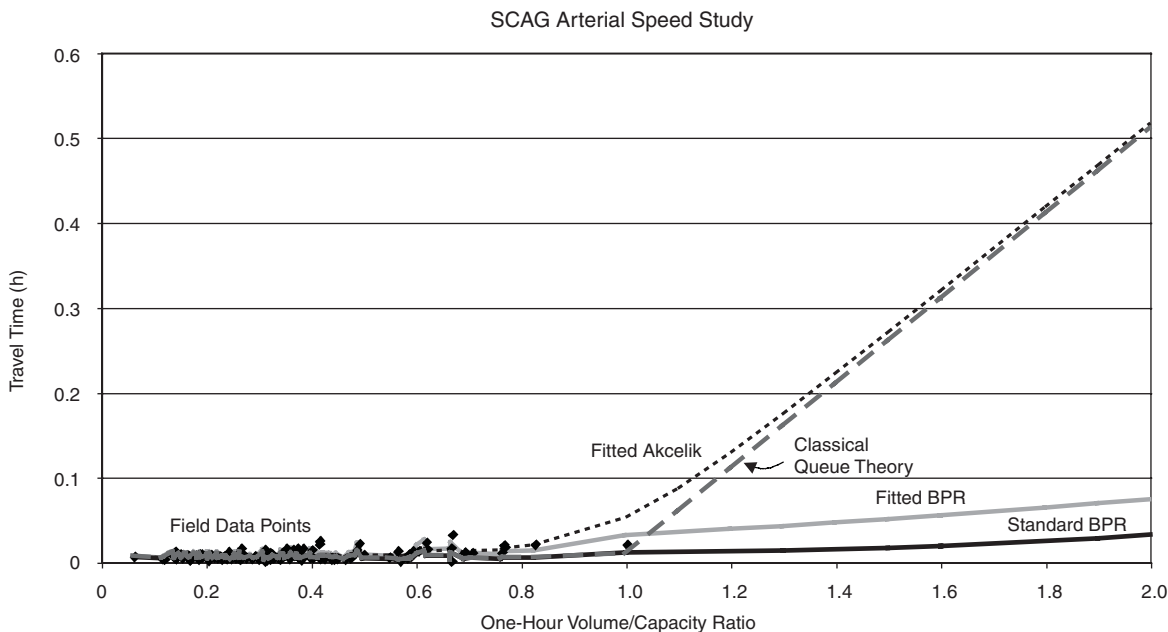


FIGURE 3 Speed-flow equations versus queuing theory.

factor of the segment length, as is done in the BPR and exponential equations.

In evaluating the speed-flow equations against theoretical delays for hourly demands that exceed hourly capacities, only the Akcelik equation produced the expected delays due to oversaturated conditions at the downstream signal on a street segment. The other equations significantly underestimated delay within the 1.00 to 2.00 v/c range, the BPR curve eventually surpasses the delay estimates produced by queuing theory and the Akcelik equation.

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REFERENCES

- Akcelik, R. 1991. Travel Time Functions for Transport Planning. *Australian Road Research*, Vol. 21, No. 3, pp. 49–59.
- Highway Capacity Manual*. 2000. TRB, National Research Council, Washington, D.C.
- Special Report 87: Highway Capacity Manual*, 2nd ed. 1965. Highway Research Board, Washington, D.C.
- Traffic Assignment Manual*. 1964. U.S. Bureau of Public Roads. Washington, D.C.

A Comparison of Static and Dynamic Traffic Assignment Under Tolls in the Dallas–Fort Worth Region

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As the number of drivers in urban areas increases, the search continues for policies to counteract congestion and for models to reliably predict the impacts of these policies. Techniques for predicting the impact of such policies have improved in recent years. Dynamic traffic assignment (DTA) models have attracted attention for their ability to account for time-varying properties of traffic flow.

A feature common to all DTA approaches is the ability to model traffic flow changes over time. A variety of formulations exists, with significant differences in how traffic flow is modeled, or in how the mathematical program is described. Simulation is sometimes used to incorporate more realistic flow in traffic models while maintaining tractability. Peeta and Ziliaskopoulos (2001) provide a comprehensive survey of DTA approaches and difficulties.

While recognizing the dynamic features of traffic is more realistic, it introduces issues that are irrelevant in static assignment, such as ensuring first-in-first-out queuing disciplines. Also, significantly more input data are required because DTA models require time-dependent travel demand, rather than the aggregate figures that suffice for static assignment.

Thus, it is not surprising that DTA formulations lead to complicated solutions that require a substantial amount of computation time when applied to large networks. It is natural to wonder, therefore, what justifies the added computational and data requirements. To this end, this work investigates the differences in results obtained from applying static and dynamic assignment to a large network under a congestion pricing scenario. The Dallas–Fort Worth (DFW) network used here con-

tains 56,574 links and 919 zonal centroids. Comparisons are made of three models: traditional static traffic assignment (STA), the TransCAD approximator (an analytical, link performance–function–based approximation to DTA), and VISTA’s simulation-based DTA approach.

An additional contribution is an algorithm that efficiently generates a time-varying demand profile from aggregate demand data (static origin–destination [O-D] trip tables) by interpolating a piecewise linear curve. This algorithm is described below, and is followed by brief descriptions of the TransCAD add-in and the VISTA model, as well as key issues that arise when attempting to compare these models with static assignment. A method to facilitate comparisons of the approximator’s results with those of static assignment is also described, as well as the DFW network results and a summary of modeling contributions and limitations.

GENERATION OF TIME-DEPENDENT DEMAND DATA

Unlike static assignment models, DTA models require specification of how demand is distributed over time. Much of the current literature focuses on estimating these data from observed traffic counts; however, in this work, an algorithm is developed to generate such time-dependent demands from existing data used for STA (such as total demand for a.m. and p.m. peak hours). This algorithm generates a piecewise linear demand curve, running more quickly than the quadratic optimization procedure applied previously.

This function represents a time rate of demand, so integrating over an interval gives the number of vehicles assigned in that interval. Because the demand function is piecewise linear, these integrals can be calculated using basic geometric formulas to compute the area under the curve. The curve itself is generated using these formulas: starting from a seed value, successive linear segments are determined to ensure that the correct number of vehicles is assigned for the major periods given as input to the algorithm, and such that the curve is everywhere non-negative. Several curves are generated using different seed values, and these are averaged to minimize the impact of artifacts unique to particular seeds.

THE VISTA MODEL AND TRANSCAD'S DTA APPROXIMATOR

This work compares the results of an STA model to two DTA implementations: VISTA and an add-in to TransCAD software.

VISTA is a network-enabled software that integrates temporal network data and models for a wide range of transport applications. In particular, VISTA can perform using a cell transmission model (CTM), a traffic flow model developed by Daganzo (1994) as a discrete version of the hydrodynamic traffic flow model. The CTM divides links into smaller cells, which can then be modeled individually at a fine resolution, on the order of 5 to 10 s.

A unique feature of the CTM is that flows cannot exceed capacity; queues form to maintain flow. As volume increases, travel time in a cell is constant until critical density is exceeded, after which point travel times increase rapidly, corresponding to free-flow and congested conditions, respectively.

The DTA approximator is an add-in to the TransCAD software package, and is based on an iterative algorithm developed by Janson and Robles (1995). Much like STA and unlike VISTA, it uses link performance functions to calculate vehicle delay. Although such functions are less computationally intensive, and the approximator runs more quickly than VISTA, they cannot model traffic flow as closely as the CTM: for instance, interaction between links (such as queues that spill into upstream links) is not modeled in the approximator, and flow on a link always increases with volume, even beyond the nominal capacity.

Parameters used by the two models are quite different, however. The link performance functions used by STA and the DTA approximator require capacity and free-flow time to be specified for each link, along with two calibration parameters. The CTM, on the other hand, requires specification of jam density and length for each cell, as well as two parameters indicating the slopes

of the flow–density curve when flow is increasing or decreasing with volume, corresponding to the cases when density is either less than or greater than the critical density, respectively.

COMPARING STATIC AND DYNAMIC TRAFFIC ASSIGNMENT

It is difficult to compare STA with DTA because typical measures of comparison, such as volumes on individual links or total system travel time (TSTT), cannot be readily applied due to fundamental differences between the modeling approaches. Moreover, the behavioral assumptions are so different that parameter assumptions are not particularly comparable, either.

Clearance intervals in the DTA approximator show shorter travel times than static assignment. Clearance intervals account for vehicles departing near the end of the model period, and thus arriving at their destinations beyond the model period: during these intervals, no additional vehicles are assigned, but vehicles remaining on the network are allowed to complete their trips. This results in some links experiencing flows for a longer time than in STA, and an effective increase in link capacities. This does not occur in STA because static methods are unable to determine when vehicles depart, and thus assume steady-state conditions.

Thus, to enable comparison, link capacities were increased commensurate with the additional clearance time needed for DTA. In essence, this extends the period of analysis in STA to correspond to the added time provided for queue clearance in the approximator, eliminating the bias that exists in a direct comparison of the two.

Comparing STA and VISTA results is even more difficult because the CTM used by VISTA is distinct. Therefore, global measures of comparison were used. Individual link flows are not comparable because of the vast differences between the assignment procedures, and measures such as volume/capacity (v/c) ratios have different meanings: in VISTA, v/c is the ratio of actual flow to capacity and cannot exceed 1; in static assignment, v/c is the ratio of link demand to capacity (which can exceed 1). This distinction makes v/c comparisons meaningless. Thus, the total travel time for each of five functional classes of roadways (freeways, arterials, and so forth) was compared, as was the total system travel time for the entire network.

RESULTS

The DFW network contains 919 zones, 15,987 nodes, and 56,574 links (92 of which are tolled in this application). A 3-h peak period (6:00 to 9:00 a.m.) was chosen for analy-

sis. For the DTA approximator, this period was broken into eighteen 10-min intervals, with three additional 10-min intervals provided for network clearance. A total of 2.56 million vehicle trips were assigned. Because TransCAD's approximator does not recognize tolls, delay-based tolls were added to the free-flow travel time for each link, using an assumed travel time value of \$10 per vehicle hour. Tables 1 and 2 summarize the results for comparing the approximator and VISTA with STA.

The most notable differences between the approximator and STA are in links that are predicted to be congested under the static analysis. For these, DTA predicts an even higher level of congestion, often significantly so. While static analysis predicts a TSTT of 1.27 million vehicle hours, the DTA approximator predicts 2.53 million vehicle hours. Unfortunately, the approximator's use of Bureau of Public Roads-type functions, which allow arbitrarily high volumes, precludes taking advantage of the queue spillback features available in other DTA implementations (such as VISTA) that can provide added realism. Additionally, it should be noted that much of this increased congestion can be found on freeways, which carry far more traffic than other functional classes.

As with the DTA approximator, TSTT is much higher under VISTA than under static assignment: VISTA predicts a TSTT of 3.09 million vehicle hours for the same 3-h application. Another, perhaps more significant, result is that static assignment tends to designate considerably more vehicles to freeways, whereas VISTA's assignment relies more on arterials and collectors. This is in contrast to the DTA approximator, in which the distribution of traffic among the roadway classes was more comparable. This arises from fundamental distinctions between the link performance function-based approach

and the strictly capacity-constrained CTM. The shift from freeways to arterials and collectors is felt to be more consistent with CTM's more detailed traffic flow model. However, actual traffic counts and speed checks would be needed to determine which model's predictions are more accurate.

CONCLUSIONS

While congestion-reduction policies and DTA each have attracted considerable interest in recent years, efforts at using the latter to evaluate the former on large-scale networks are relatively few. Several issues arise when trying to do this. A comparison of static and dynamic traffic assignment is nontrivial due to fundamental differences between the models; however, the increase in capacity induced by clearance intervals in the DTA approximator can be accounted for by an appropriate increase in the capacities used in static assignment. With models such as the CTM, which are vastly different from static assignment, it is much more difficult to compare the results on a link-by-link basis, and in this work only global measures of system performance were compared.

The CTM may produce results that are considerably different than traditional assignment, because it models traffic flow at a more detailed level. This is particularly apparent in congested networks because many assumptions in static traffic assignment about steady-state conditions and link performance functions are less realistic. In this investigation, the effects of these assumptions were amplified with the DTA approximator, which also uses link performance functions.

However, the additional computation time required to find a DTA solution, particularly with the CTM, can-

TABLE 1 Comparison Between Static Assignment and DTA Approximator

Category	N	Vehicle-miles Traveled (millions)		Average v/c (VMT-weighted)	
		Static	Dynamic	Static	Dynamic
Freeway	6,292	25.88	29.86	1.02	1.64
Principal Arterial	4,936	6.46	5.39	0.72	0.86
Minor Arterial	10,434	7.65	6.25	0.43	0.52
Collector	14,596	2.97	2.74	0.77	1.39
Frontage Road	2,783	1.56	1.44	0.60	0.96
Congested	2,995	18.35	22.61	1.26	2.08
Uncongested	25,997	28.61	25.11	0.62	0.79

TABLE 2 Comparison Between Static Assignment and VISTA

Functional class	Total travel time (h x 10 ³)		Proportion (%)	
	Static	Dynamic	Static	Dynamic
Freeway	505	325	40.6	10.5
Principal Arterial	174	543	14.0	17.6
Minor Arterial	237	715	19.1	23.2
Collector	227	738	18.2	23.9
Frontage Road	45	390	3.7	12.6
Total System	1,266	3,086	100	100

not be neglected. While the more realistic modeling may balance this additional time for long-term planning applications, the time needed to run a large number of models may be prohibitive. Nevertheless, to reduce the running time needed for DTA, the demand profiling algorithm described above can be used to generate the data more quickly.

When static and dynamic assignment models were applied to the DFW network, TSTT was significantly higher when predicted by DTA, which indicates that static assignment models can significantly underpredict congestion levels due to changes in demand over the peak period. Additionally, the distribution of trips among different classes of roadways is significantly different between the cell transmission model (used by VISTA) and the link performance function-based models (static assignment and the DTA approximator) because CTM prohibits flows from exceeding capacities. VISTA predicts significantly fewer freeway trips than static assignment or the approximator.

Further insights could be gained if the DTA approximator in TransCAD provided additional capabilities. In particular, the ability to extract path flows for each O-D pair and departure time would greatly enhance model-

ers' ability to predict policies' impacts at a more disaggregate level. Moreover, the use of link performance functions limits its ability to model queues or spillover effects between links due to congestion, which can be captured using other formulations, such as the CTM. With such improvements, investigations like this one could be extended to account for traffic dynamics under congestion management policies in greater depth.

REFERENCES

- Daganzo, C. 1994. The Cell Transmission Model: A Dynamic Representation of Highway Traffic Consistent with the Hydrodynamic Theory. *Transportation Research*, Vol. 28, No. 4, pp. 269–287.
- Janson, B. N., and J. Robles. 1995. Quasi-Continuous Dynamic Traffic Assignment Model. In *Transportation Research Record 1493*, TRB, National Research Council, Washington, D.C., pp. 199–206.
- Peeta, S., and A. K. Ziliaskopoulos. 2001. Dynamic Traffic Assignment: The Past, the Present, and the Future. *Networks and Spatial Economics*, Vol. 1, No. 3, pp. 233–265.

BREAKOUT SESSION
EDUCATION AND OUTREACH

Lifelong Education as a Necessary Foundation for Success in Travel Modeling

Rick Donnelly, *PB Consult*

Remarkable theoretical and practical advances in travel forecasting have taken place over the past two decades. An unintended consequence of this has been a widening gap between research and practice, which this conference is designed to help overcome. There are many reasons for this gulf of knowledge, one being that many practitioners have not been able to stay current with new techniques. A lifelong training program to help close that gap is proposed as an essential part of the advancement of travel modeling.

Travel demand forecasting has been an important tool for policy and investment analyses in the United States for more than 40 years. A loosely defined standard practice was established during the early years and is still in use. The principles of this practice, based upon four-step sequential models of travel demand, are well known and documented in the literature. Several universities, as well as federal and some state transportation agencies, offer courses in the subject. Most transportation planners in the United States are familiar with the process, with many possessing the experience necessary to apply, extend, and maintain such models.

There has been considerable R&D in the past decade that seeks to move the field beyond sequential models. Activity- and tour-based models have been widely discussed in the literature, and several promising implementations have been achieved. Freight has become an important issue in transportation planning, but its dynamics do not map well to the familiar four-step modeling paradigm. Work on large-scale simulation models such as Transportation Analysis and Simulation System

has also opened new frontiers in travel modeling. Planning applications of dynamic traffic assignments have sprung up within the past year, and seem to be ideal complements for activity- and tour-based models. Finally, there is a resurgence of interest in and development of integrated land use–transport models in several locations.

This new-age modeling is rapidly moving beyond limitations of the current practice in transportation planning, which has required researchers to draw from a number of disciplines not normally encountered in travel modeling. Recent advances and techniques from other large-scale simulations in meteorology, operations research, economics, natural resources modeling, and logistics are all integral parts of the current research. Moreover, software development has become an important part of R&D. The skill set needed to approach many of these new models is impressive in its breadth, as well as its departure from current practice:

- Travel choice behavior (solid foundation in discrete choice modeling concepts);
- Activity-based travel analysis;
- Traffic science, control systems, and intelligent transportation systems;
- Network dynamics and disequilibrium;
- Simulation analysis and modeling, with emphasis on microsimulation and sample enumeration;
- Object-oriented programming;
- Database systems;
- Spatial analysis tools and techniques; and
- Integrated land use–transport modeling.

These subjects require a background in mathematics, statistics, and microeconomics—the last prerequisite usually being the weakest link among most transportation engineers and planners. Transportation planners with degrees in disciplines outside of engineering usually lack an adequate foundation in all three areas.

There are few training opportunities for practitioners in any of these areas. Massachusetts Institute of Technology (MIT) and the University of Sydney offer highly acclaimed, weeklong, intensive courses in discrete choice modeling. MIT also offers a weeklong course in the modeling and simulation of transportation networks. (Information about these courses can be found at http://web.mit.edu/mitpep/pi/courses_topic.html#data_modeling and http://www.itls.usyd.edu.au/professional_development.asp, respectively.) Ken Train has also put together an excellent distance learning course on discrete choice methods with simulation. (See <http://emlab.berkeley.edu/users/train/distant.html>.) All are a step in the right direction. However, these courses are mathematically rigorous, which limits their appeal and suitability for planners and modelers without a strong quantitative background. Moreover, these courses cover only a few of the topics identified earlier. The author is not aware of any program that offers training in the broader list of new-age modeling skills.

The National Highway Institute also offers courses in travel modeling. There are undoubtedly a number of other short courses available through planning agencies, university extension services, consultants, and software vendors. Most of these courses have a nuts and bolts orientation that facilitates rapid assimilation of the concepts, in a format that does not intimidate participants lacking a strong quantitative background. The weakness of such courses is that they can only impart a broad overview of the topic. Participants often leave short courses with enough knowledge to begin participating in model development and application, but lack the deeper understanding needed to design, implement, test, and evaluate all but the simplest of travel modeling systems. This is not a criticism of such courses, as they are intended to meet the needs of entry-level planners, not mid-level and senior modelers looking to expand their skill base.

If formal training in these areas is not readily available, how will transportation planners and modelers acquire these skills? The evidence is not encouraging. Ken Cervenka has facilitated an online focus group seeking input about whether and how to move toward new-age models. Similar dialogue has progressed through the Transportation Model Improvement Program listserv. The views expressed are all over the board, but many participants are either not speaking the same language or do not feel they understand these new concepts well enough to enter the debate. Furthermore, the absence of

formal mentoring or training programs beyond those already noted speaks for itself. There are few distance learning opportunities for graduate degrees or certificates in transportation planning or engineering, and none tailored to travel modeling or simulation.

As with our new-age modeling techniques, it is helpful to turn outside of our profession to find compelling solutions. There are numerous executive MBA programs that incorporate distance learning in some or all of their coursework, and the idea of professional certificates in emerging technologies is gaining currency in many universities. Most of these programs cater to established professionals. Such students typically cannot take extended leaves of absence to participate in traditional university degree programs, so the coursework comes to them, often supplemented with brief periods of residency to gain interaction with professors and colleagues. (Many executive MBA programs only meet on campus for one 4-day weekend per month and perhaps a few weeks during the summer. The rest of the course work is done by the student at home, often with directed reading or lectures delivered by streaming video. This obviously places an additional burden on the student to keep up, since formal class meetings are further apart than with traditional lectures in residence. The success of the executive MBA programs suggests that most students have the maturity and motivation to thrive in such a program.) Such an instruction format would pay significant dividends for modelers seeking to hone their skills. They would obtain a deeper exposure to the subject material than is possible with short courses, but without the disruption of studying full time.

If one accepts that current training opportunities offer neither the content nor the depth to close the gap between researchers and practitioners, the question quickly becomes how this might be overcome. A continually evolving training program taught by the leaders in R&D of travel models can certainly play an important role. The MIT and Sydney courses are compelling success stories that can be extended to many of the other topics identified earlier. There are several obstacles to overcome in this regard:

- Universities respond to incentives. Without a strong federal commitment to such a program there is little likelihood that such a program will be developed or maintained.
- Most public agencies and individuals cannot afford the cost of tuition and travel for such courses. Establishment of a scholarship fund for public agency planners is imperative to make such a program affordable.
- Public agencies will need reasonable assurances that the staff they send to such training will remain at their agencies long enough to benefit from the investment.

- Preference should be given to practitioners working for agencies preparing to implement or in the process of implementing new-age models.

- No single university has faculty with established track records and interest in all of these topics. The simple solution would seem to be a joint program between leading universities.

Much effort is needed to launch and shepherd such a

program. However, new-age travel models cannot succeed without investments in human capital, which will not happen without active and concerted efforts by the developers and consumers of travel models. There are few models of such collaboration between the transportation profession and academics to guide us. It is a topic worthy of attention by the Transportation Research Board, its sponsors, and the profession as a whole.

Traffic Forecasting in a Visioning Workshop Setting

Don Hubbard, *Fehr & Peers Associates*

Visioning workshops have become a vital tool in regional planning. Unfortunately, traffic forecasting has played only a small role in these workshops even though traffic congestion is often viewed as a critical long-term issue. This creates the danger of a consensus forming in a workshop around a vision that traffic modelers later declare is unworkable from a traffic standpoint. A disconnect of this kind can lead to one of two undesirable outcomes: 1) the agency abandons the consensus vision, in which case the workshop participants rightly wonder whether their views are being taken seriously, or 2) the agency is stuck trying to implement the unworkable. One way to ensure that the consensus forms around a workable vision is to perform traffic forecasts during the workshop and give participants immediate feedback as to the likely consequences of their plans, allowing them to adjust their plans accordingly.

This approach was successful in visioning workshops sponsored by the Council of Governments for San Luis Obispo County, California (SLOCOG), and the Sacramento Area Council of Governments (SACOG). These are believed to be the first public workshops to forecast traffic in real time. The experiments used different models and approaches, both of which provide important lessons for agencies that may want to play a role in visioning exercises.

GENERAL REQUIREMENTS FOR WORKSHOP MODELS

Travel demand models are typically designed to be used in a private, unhurried setting with ample opportunity to

scrutinize inputs, analyze outputs, and, if necessary, perform additional model runs. Models are usually designed to accommodate detailed changes to networks or modeling parameters and to provide a rich assortment of potential outputs. In other words, their normal operating environment is completely unlike a public workshop.

A workshop model must produce sensible results within 15 min of receiving inputs from the participants—anything longer will make for unreasonably long workshops and/or loss of interest by participants. Included in that 15 min is whatever processing is needed to compute key indicators and report the results, which may take the form of printed reports or figures projected on a screen, plus time the operator needs to analyze and interpret the results. There is not enough time to rerun the model if something goes wrong, so the inputs must be prepared correctly the first time. Moreover, the model must be robust enough to produce logical results for a wide range of input values, because it is difficult to predict what sort of proposals will arise during a public workshop.

Fortunately, the outputs needed from a workshop model are much simpler than in a traditional model application. Public participants have neither the time nor the training to sort through long tables of subtle indicators; they prefer results expressed in a few easily understood numbers or figures. This greatly simplifies the modeling task because it allows a modeler to pick a few key indicators and then eliminate any model components that do not contribute to those outputs. For example, a workshop model might report the regional mode split but is unlikely to report patronage on individual transit

lines, in which case there may be no need to run the transit assignment component of the model.

THE SLOCOG AND SACOG VISIONING WORKSHOPS

The SLOCOG and SACOG workshops' goals and modeling approaches differed substantially. With SLOCOG there was a consensus on future roadway projects but not on land uses; the visioning workshops therefore focused on the type and location of future real estate developments. SLOCOG had a geographic information system (GIS) program—Planning for Community, Energy, Environmental, and Economic Sustainability (PLACE³S)—that enabled it to make quick changes in land uses, and had recently developed a TransCAD model with a fairly short run time (17 min).

SACOG, on the other hand, had already achieved a broad consensus on future land uses through its award-winning Blueprint Project. Its new round of workshops was intended to create a consensus on future road and transit projects for its 25-year Metropolitan Transportation Plan (MTP). SACOG had a regional model that operated in a mixture of MINUTP and TP+ scripts with a typical run time of more than 8 h. Table 1 compares the two modeling situations.

SLOCOG had the easier modeling task because its original TransCAD model required only a few changes to fit within the run time constraints. The smallest downtown travel analysis zones were consolidated and only a single period (daily) was run. In fact, the run time was fast enough that a team of three modelers was able to service 15 tables of participants, thus eliminating the need to bring in less-skilled staff. Moreover, editing land uses (for SLOCOG) turned out to be easier than editing links (for SACOG) and less likely to cause error.

SACOG faced the daunting task of needing to reduce its model's run time by 97%. It had hoped to achieve this through hardware and software improvements; however, the software upgrade had only a minor impact on run time. Therefore, the model had to be simplified by elim-

inating feedback to trip distribution, running fewer assignment iterations, foregoing transit assignment, and limiting roadway assignment to two periods (peak and off-peak) that were then processed in parallel.

SACOG also faced difficulties trying to edit networks in a hurry. Attempting to add each project link-by-link was not practicable within the time constraints and would almost certainly have led to coding errors. This task was simplified by preparing a master file containing the existing road and transit networks along with a large number of potential projects—far more than could be included in the MTP. A GIS interface was developed that allowed the links for each proposed project to be modified simultaneously from a drop-down menu. For example, a proposed 6-lane expressway could be converted into a 4-lane arterial or eliminated by checking the appropriate box on a menu. While the option to edit the attributes of individual links was available, it was rarely used because the participants tended to think in terms of entire projects rather than individual links.

In each case certain constraints were placed on participants to force them to face uncomfortable realities. In the SLOCOG workshops participants were required to accommodate the forecast number of new residents and jobs. The SACOG workshop participants were limited to the programmable portion of the MTP budget, with project costs based on actual estimates (if available) or on average unit costs.

Five separate software packages were used in the SLOCOG workshops. The land use data were edited in PLACE³S, which produced an output file readable in Excel. Excel macros were used to reformat the data into a file usable by TransCAD, which produced graphical outputs and tabular indicators. These were combined into a Word file for printing and distribution to the participants at the originating table and into a PowerPoint presentation for discussion by all the tables. Most of the processing time was spent transferring data from one software package to another. This arrangement was cumbersome and fraught with risk of error, which was only somewhat mitigated by extensive practice prior to the workshops.

TABLE 1 Comparison of Features of SLOCOG and SACOG Workshop Models

Feature	San Luis Obispo COG	Sacramento Area COG
Inputs changed	Land uses	Road and Transit Networks
Global constraint on inputs	# of new DUs and jobs	Total of Project Budgets
Modeling software	TransCAD	Cube/Voyager
Processing time (original)	17 min	8 h 35 min
Processing time (workshop)	4 min	15 min
Modifications made to model	Fewer TAZs Fewer periods	No feedback to distribution Fewer iterations Fewer periods No transit assignment Some parallel processing Projects as single entities
Link to land use software	Through Excel	Embedded/automatic

In contrast, SACOG's operators only dealt with a single software package. The PLACE³S land use program was modified to display and manipulate the Cube/Voyager networks and to prepare the files for Cube/Voyager runs. Cube/Voyager was then run within the PLACE³S shell and the run's outputs were displayed using PLACE³S' GIS functionality. This was a smoother arrangement than SLOCOG's and, by reducing the time needed for shuffling data, it enabled SACOG to devote nearly all of its 15 min to model run time.

WORKSHOP RESULTS

Participants who were not familiar with regional planning were surprised by traffic forecasts in the SLOCOG workshops, with most not realizing the importance of location. Prior to the workshop most of the dialogue on development in San Luis Obispo County centered on the number of units being proposed and their compatibility to the immediately adjacent land uses. People were surprised to find that the same number of jobs and dwelling units produced different levels of traffic congestion depending on where they were located in the county. Specifically, there was a tendency to concentrate residential developments in certain towns while turning other towns into employment centers. The traffic forecasts for groups that followed this pattern had much higher levels of congestion on the connecting highways than the groups that had a diversity of land uses within each town. This led to a consensus on the need for better land use. In addition, participants wanted compact mixed-use development of a kind that is not even an allowable land use category under most general plans in the county.

The SACOG workshops revealed a disconnect between agency and public opinion. Specifically, public works agencies were pursuing projects that did not interest the public, while participants wanted certain projects (toll roads, major urban bridges) that the agencies thought were politically impossible.

Both workshops attracted a lot of participants including many elected officials who got a new perspective on what the electorate wants.

LESSONS LEARNED

The most obvious lesson is that it is possible to forecast traffic in a visioning workshop and that doing so will influence the results in important ways.

Performing complex technical tasks in a hurry in front of an audience is inherently risky. It is inadvisable unless there is time for testing and practice beforehand and backups for all hardware components.

Modelers must accept that a workshop model has a different purpose than a conventional model and that some functionality will have to be sacrificed for speed. When deciding on how to modify a model it is best to start with the few key indicators that you plan to show participants, then work backwards to determine the necessary model components.

In the SLOCOG workshops much of the time was spent inputting similar data at different tables. This can be avoided by allowing participants to select from a menu of "starter sets" that allocate about half of the new development. Each starter set should represent a theme such as (for networks) "facilitate long-distance auto travel" or (for land uses) "infill within existing urban boundaries" and contain the most prominent proposals consistent with that theme. Participants are expected to delete unwanted projects and add new ones, but giving them something to work from helps groups to reach consensus faster.

The final lesson is that visioning workshops are meaningless unless the agencies approach them with an open mind and a willingness to act. Both sets of workshops revealed public preferences that were in conflict with projects that agencies considered "done deals." The workshops were a success in that they brought such conflicts to light; it remains to be seen how much influence they will have on the projects that are actually implemented.

BREAKOUT SESSION

EMERGING MODELING CONSIDERATIONS

Companionship for Leisure Activities

An Empirical Analysis Using the American Time Use Survey

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The activity-based travel-modeling paradigm recognizes that individuals undertake activity and travel not only independently but also together with other household and nonhousehold members. It has also been argued that the desire for interaction with other people is an important stimulus for activity-travel generation and therefore warrants treatment in travel-demand models. However, Axhausen (2005) notes that this important social dimension of activity-travel behavior is not accommodated in travel modeling. Further, the modeling of interpersonal interdependencies in activity-travel patterns is necessary for realistic forecasts of travel patterns under alternate socio-economic-technological scenarios and due to changes in land use and transportation system characteristics. The following examples serve to illustrate this point:

1. Vehicle occupancy levels are determined by individuals' decisions to travel together, which are motivated by the desire to participate in the destination activity jointly. Thus, the modeling of joint activity-travel pursuits is necessary to determine the volume of vehicular travel in the system, and consequently for the evaluation of policies such as HOV/HOT lanes (Vovsha et al. 2003). Similarly, the individuals' response to carpooling incentives depends on their ability to synchronize their travel patterns with those of others.

2. Though participation in leisure activities is constrained by individuals' obligations (Gliebe and Koppelman 2002; Srinivasan and Bhat 2006), employer-based demand management strategies (such as flextime and telecommuting) could lead to increased leisure time and likelihood of joint activities, as well as alter the travel

patterns of persons not directly impacted by the policy. These secondary impacts cannot be captured by models that do not accommodate interpersonal interactions (Srinivasan and Bhat 2006).

3. Individuals may be willing to travel farther and pursue activities for longer durations when the activity or travel is being pursued with family or friends. Further, such joint activity could be restricted to certain periods of the day. For example, Kemperman et al. (2006) identify three peak periods for social activity participation using data from The Netherlands. The timing and durations of trips and stops have substantial implications for determining the impacts of mobile-source (i.e., from vehicles) emissions on air quality.

4. When individuals participate in activities with non-household members, they may also undertake travel to pick up and drop off their companions. Such additional travel cannot be effectively captured by individual-level models.

5. Social activities are perhaps not as flexible as they have been treated traditionally (Kemperman et al. 2006). For example, some of the joint leisure activities pursued with nonhousehold members could be at the residence of friends or family. Consequently, the destination choice for such travel may have limited sensitivity to the transportation system characteristics (see also Carrasco et al. 2006).

6. The increasing adoption of ICTs (information and communication technologies) like cell phones, Internet, and e-mail can have strong impacts on the social lifestyles of people and hence on activities pursued with family and nonfamily members (Carrasco and Miller 2006).

7. The popularity of modeling travel during weekends and for special events reinforces the need to accommodate joint activity and travel patterns in travel models.

Recent years have seen increasing efforts in the field of transportation engineering on studying interpersonal interactions in activity–travel patterns. These studies may be classified into two categories. The first category adopts econometric modeling methods to relate joint activity–travel choices with characteristics of the decision makers (see Srinivasan and Bhat 2006). Most of these studies use data from conventional travel surveys but very few have examined individuals’ interactions with nonhousehold members. The second category is largely focused on the concept of social networks and seeks to explore the nature and extent of individuals’ social interactions (see Arentze and Timmermans 2006). Thus, this latter group of studies is not restricted to analyzing within-household interactions.

Despite this increasing interest, our empirical knowledge of individuals’ interactions with nonhousehold members is limited, largely because conventional household–travel surveys (which form the basis of activity–travel modeling) typically do not collect this data. An exception is the recent CentreSIM travel survey (Goulias and Kim 2005), which included an open-ended question, “with whom was this activity episode undertaken,” to collect data from about 1,400 individuals on the types of companions with whom each activity was undertaken. The first analysis results indicate that approximately one-third of activity–travel episodes and daily time is spent alone and a significant fraction of joint episodes are pursued with nonhousehold members (both relatives and nonrelatives).

The goal of this study is to contribute to the understanding of activities and travel pursued by individuals jointly with household and nonhousehold members. Toward that end, there are two major tasks. First, an analysis is undertaken to determine the extent to which each activity type is pursued jointly. Further, this analysis aims to illustrate the differences in the companion-type choices (household versus nonhousehold members) across the activity types. The next task is focused on leisure activities. The motivation for this focus is that, among all activity types, the desire for companionship for leisure is likely to be highest. Specifically, models are developed to examine the impacts of demographic characteristics, day of the week, and activity episode durations on the choice of companion type.

The rest of this paper is organized as follows. The section immediately below describes the data used in this analysis. The empirical results are presented in the section that follows. The final section provides a summary and highlights the insights from this study.

DATA DESCRIPTION

This study uses data from the American Time Use Survey (ATUS). Conducted by the Census Bureau under contract with the Bureau of Labor Statistics, ATUS collects detailed individual-level daily time use information. The sample is drawn from a subset of households responding to the Current Population Survey interviews. One individual aged 15 years or older is selected from each household for the survey. Data collection began in January 2003. Currently, data samples collected in 2003 (412,611 activity episodes from 20,000 individuals) and 2004 (279,042 activity episodes from 13,973 individuals) are available. Additional details can be obtained from the ATUS website, <http://www.bls.gov/tus/home.htm>.

The ATUS data are attractive for our analysis for several reasons. First, the data sample is large (34,693 persons surveyed over 2 years) and represents the nation as a whole as opposed to a specific geographic area. Second, the survey obtained information on all persons (both household and nonhousehold members) accompanying the respondent for each activity episode. The companions were classified using the scheme presented in Table 1. Third, the survey used a disaggregate three-tier activity classification scheme thereby facilitating the analysis joint activity participation at a fine resolution of activity types.

It is also necessary to point out that an issue with using ATUS for analyzing joint activity participation decisions is the absence of time use information for the respondents’ companion(s). ATUS collects time use data only for one person per household. Therefore, the complete activity participation decisions of even the respondents’ own household members are unknown. Consequently, it is not

TABLE 1 Companion-Type Classification Scheme Adopted in ATUS

Household Members
Spouse (husband/wife)
Unmarried partner
Own household child
Grandchild
Parent (father/mother)
Brother/sister
Other related person (aunt, cousin, nephew)
Foster child
Housemate/roommate
Roomer/boarder
Other nonrelative
Nonhousehold Members
Own nonhousehold child
Parents or parents-in-law (not living in household)
Other nonhousehold family members (age <18)
Other nonhousehold family members (age ≥18)
Friends
Co-workers/colleagues/clients
Neighbors/acquaintances
Other nonhousehold children (age <18)
Other nonhousehold adults (age ≥18)

possible to capture the impact of the time constraints of *all* the individuals on the joint time–investment decisions. However, it is possible to examine the impacts of other factors such as individual and household socioeconomic characteristics, day of the week, and seasonal factors.

EMPIRICAL ANALYSIS

This section, divided into two parts, presents an empirical analysis of the choice of companion types for activities and travel. The first part examines all in-home, out-of-home, and travel activities. The objective is to quantify the extent of joint activities and travel. The second part next focuses on the companion-type choices for out-of-home leisure activities. Specifically, multinomial logit (MNL) models are presented for the determination of the companion types for three kinds of leisure activities.

OVERALL AGGREGATE ANALYSIS

Table 2 presents descriptives on the number of episodes of each activity type in the sample and the percentage of joint

activities of each type. The statistics are presented separately for weekdays and weekend days. It is important to note that half of the ATUS sample corresponds to a weekend day (25% each for Saturday and Sunday) and half corresponds to a weekday (10% for each weekday).

The results indicate that, during weekdays, 32.4% of all in-home episodes are joint whereas 35.3% of all the weekend in-home episodes are joint. Among the in-home activity types, episodes for caregiving and socializing are by definition pursued jointly. On the other hand, sleep, personal care, and work or school episodes are solo. Among the remaining in-home activity types, eating and drinking and watching television are the ones that are most likely to be pursued with other individuals. In the context of in-home episodes, it is necessary to note that the survey question on the companion type was “Who accompanied you in this activity or who was in the room with you?” This implies that the above estimates of joint episodes could be skewed high because it is possible for other household members to be present in the same room as the respondent even when he or she is pursuing the in-home activity independently.

The out-of-home activity episodes are significantly more likely to be joint compared with in-home episodes.

TABLE 2 Descriptives on Total and Joint Episodes by Activity Type and Day of the Week

	Weekday			Weekend		
	Total	Joint Freq.	%	Total	Joint Freq.	%
In-home activities						
Sleep	37,338	0	0.00	38,770	0	0.00
Personal care	26,174	0	0.00	23,144	0	0.00
Household chores	45,823	14,111	30.79	44,255	16,332	36.90
Caregiving	14,490	14,490	100.00	10,812	10,812	100.00
Work and school related	4,406	0	0.00	3,148	0	0.00
Eating and drinking	23,316	13,721	58.85	23,382	15,394	65.84
Socializing	4,775	4,775	100.00	5,059	5,059	100.00
Television and music	24,741	11,884	48.03	25,577	13,840	54.11
Other leisure	19,036	5,310	27.89	18,006	5,748	31.92
Miscellaneous	6,239	2,536	40.65	5,851	2,667	45.58
Overall (in home)	206,338	66,827	32.39	198,004	69,852	35.28
Out-of-home activities						
Household and personal services	6,377	2,802	43.94	4,918	2,894	58.85
Serve passenger	6,458	6,458	100.00	3,451	3,451	100.00
Work and school	22,467	0	0.00	5,844	0	0.00
Shopping	11,162	5,045	45.20	13,815	8,539	61.81
Eating and drinking	10,718	7,927	73.96	9,407	8,356	88.83
Socializing	4,842	4,842	100.00	7,765	7,765	100.00
Passive leisure	5,472	3,661	66.90	5,300	4,298	81.09
Active leisure	2,857	1,470	51.45	2,715	1,869	68.84
Religious, civic, volunteer	1,911	1,417	74.15	5,230	4,364	83.44
Miscellaneous	7,066	4,162	58.90	6,053	4,329	71.52
Overall (out of home)	79,330	37,784	47.63	64,498	45,865	71.11
Travel activities						
Driver	57,855	19,612	33.90	46,728	23,847	51.03
Passenger	9,395	9,395	100.00	15,622	15,622	100.00
Walk or bike	6,018	1,916	31.84	4,623	2,113	45.71
Public transportation	2,046	662	32.36	1,196	616	51.51
Overall (travel)	75,314	31,585	41.94	68,169	42,198	61.90

Specifically, 47.6% of all weekday episodes and 71% of all weekend episodes are joint. Within the class of out-of-home activities, serve-passenger and socializing are by definition taken to be joint, and work and school activities are defined as solo. Among the remaining out-of-home activity types, eating and drinking, leisure, and religious-civic-volunteer episodes are most likely to be pursued with other individuals. Finally, for every out-of-home activity type, the volume of joint episodes is higher during weekend days than weekdays.

A total of 42% of weekday travel episodes and 62% of weekend travel episodes are undertaken with other persons. Again, the percentages of joint travel are higher by each mode during the weekend compared with the weekday. Finally, travel episodes undertaken as a passenger are by definition joint.

Table 3 presents descriptives on the companion types for joint activity episodes. Specifically, it presents the percentages of joint episodes of each type that are pursued with only household members, with only nonhousehold members, and with both household and nonhousehold members. As in Table 2, the results are presented separately for weekdays and weekend days. Note that the numbers sum to 100% across the three columns within each of the two main columns. Further, the activity types that are solo by definition are not included.

On examining the joint in-home episodes, we find that the companions are predominantly household mem-

bers. The percentage of episodes undertaken with only household members decreases from weekdays to weekend days, whereas the percentage of episodes undertaken with only nonhousehold members and with both household and nonhousehold members increases from weekdays and weekend days. Overall, this indicates that nonhousehold members are more likely to be companions for in-home activities during weekend days. Within the class of in-home activity types, socializing and miscellaneous episodes are most likely to include nonhousehold companions.

The results for out-of-home episodes indicate that joint episodes are most likely to be pursued solely with nonhousehold members, especially during weekdays. The percentage of episodes pursued with both household and nonhousehold members is higher during the weekend than the weekday. Finally, we also observe that about 45% of weekday and 56.5% of weekend joint episodes include household members. This suggests that, unlike for in-home episodes, household members are more likely to be companions for out-of-home joint episodes during the weekends. Within the class of out-of-home activity types, shopping episodes are most likely to be pursued with only household members. On the other hand, socializing, leisure, and eating and drinking are more likely to be undertaken with nonhousehold companions.

Finally, results from Table 3 also indicate that about 60% of all joint travel is undertaken with only house-

TABLE 3 Descriptives on Companion Type for Joint Episodes by Activity Type and Day of the Week

	Weekday			Weekend		
	Only HH	Only non-HH	Both	Only HH	Only non-HH	Both
In-home activities						
Household chores	85.98	9.23	4.79	83.61	9.97	6.42
Caregiving	96.86	0.19	2.95	95.19	0.28	4.53
Eating and drinking	87.81	5.75	6.44	83.60	6.15	10.26
Socializing	55.66	26.12	18.22	40.23	28.98	30.80
Television and music	89.46	6.80	3.74	86.64	7.57	5.79
Other leisure	88.21	8.47	3.31	86.10	8.99	4.91
Miscellaneous	48.11	39.59	12.30	49.49	33.97	16.54
Overall (in home)	85.91	8.42	5.67	81.76	9.36	8.88
Out-of-home activities						
Household or personal services	34.05	54.89	11.06	33.17	46.37	20.46
Serve passenger	58.67	25.29	16.04	30.80	41.47	27.73
Shopping	60.77	31.81	7.41	63.47	26.33	10.20
Eating and drinking	16.72	72.75	10.53	27.93	44.03	28.04
Socializing	4.05	72.47	23.48	5.51	54.04	40.45
Passive leisure	12.05	79.46	8.49	21.85	58.38	19.78
Active leisure	26.39	65.17	8.44	32.48	51.52	16.00
Religious, civic, volunteer	14.89	68.03	17.08	39.69	41.04	19.27
Miscellaneous	37.05	46.28	16.67	35.50	42.13	22.36
Overall (out of home)	31.53	55.07	13.40	32.75	43.57	23.68
Travel activities						
Driver	68.40	23.98	7.62	66.76	22.40	10.84
Passenger	50.22	41.27	8.52	54.42	32.54	13.05
Walk or bike	49.53	44.00	6.47	58.16	29.20	12.64
Public transportation	25.23	68.43	6.34	41.07	44.32	14.61
Overall (travel)	60.94	31.26	7.79	61.39	26.81	11.80

HH = household.

hold members as companions. Joint travel during weekdays is more likely to be pursued with only non-household members than joint travel during weekends. This is consistent with the findings for the companion types for out-of-home activity episodes.

In summary, the results from Tables 2 and 3 highlight that joint activity–travel constitutes a significant proportion of individuals’ overall activity–travel patterns. In the next section, we focus on certain leisure activities (socializing, passive leisure, and active leisure) for further analysis. However, the summary statistics discussed here suggest that detailed analysis of all other nonleisure activity types is also warranted.

Analysis of Out-of-Home Leisure Activities

This section of the empirical analysis focuses on individuals’ companion-type choices for three types of out-of-home leisure activities—socializing (visiting friends, attending a party), passive leisure (attending movies, sports events), and active leisure (participation in sports or exercising). The choices and the sample shares for each of these three activity types are presented in Table 4. Socializing activities are joint by definition and are equally likely to be undertaken with family members, nonfamily members, and with a mixed composition. Passive leisure episodes are most likely to be pursued alone or with nonhousehold other members (often colleagues).

Active leisure episodes are most likely to be pursued independently. When undertaken with other individuals, the companions are most likely to be household members or friends. Finally, the last two alternatives have been combined into a single category for the passive and active leisure episodes. Thus, each model has six alternatives in the universal choice set.

Companion-Type Model for Socializing Activities

The MNL model for the companion-type choice for socializing activities is presented in Table 5. The “household members only” alternative is chosen as the reference category. This alternative and the “household and nonhousehold family members” alternative are not available for individuals in single-person households. All other alternatives are available for all individuals.

Empirical results indicate that short-duration episodes are more likely to be undertaken with other non-household members (often colleagues), whereas long-duration episodes are undertaken with a mixed composition of companions involving household and nonhousehold family members and others. Weekday episodes are more likely to be pursued with non-household members.

As would be expected, younger individuals are more likely to undertake social activities with friends as indi-

TABLE 4 Sample Shares on Companion Type for the Three Types of Leisure Activities

	Socializing		Passive Leisure		Active Leisure	
	Freq.	%	Freq.	%	Freq.	%
Solo		NA	2,813	26.11	2,233	40.08
Only household members	624	4.95	1,380	12.81	995	17.86
Only nonhousehold family members	2,049	16.25	854	7.93	197	3.54
Only nonhousehold other	2,580	20.42	1,655	15.36	902	16.19
Only nonhousehold friend	2,305	18.28	2,598	24.12	688	12.35
Both household and nonhousehold family members	2,023	16.05	1,472	13.67	557	10
Mixed composition	3,026	24.00				
Total	12,607	100.00	10,772	100.00	5,572	100.00

NA = not applicable.

TABLE 5 Model for Companion-Type Choice for Socializing Activities

	Nonhousehold Family		Nonhousehold Friends		Nonhousehold Other		Household and Nonhousehold Family		Other Mixed Composition	
	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat
Constant	1.559	11.847	1.754	12.666	1.457	11.229	1.563	12.087	1.730	14.473
Activity episode duration					-0.004	-10.508	0.002	6.434	0.001	5.890
Weekday	0.479	8.293	0.739	13.420	1.205	21.818				
Age			-0.005	-2.796						
Male	-0.146	-2.379	0.516	9.002	0.467	8.023	-0.140	-2.402		
White	-0.301	-4.702								
Employed					0.441	8.475				
Student			0.553	7.604			-0.345	-3.738		
Married	-1.592	-12.336	-2.296	-17.691	-1.917	-15.008	-0.565	-4.234	-0.576	-4.589
No children in household	1.231	18.161	0.877	12.244	0.495	7.586			0.170	2.996
Log likelihood (convergence)										-19,263.24
Log likelihood (constants only)										-20,949.43

cated by the negative coefficient on the age variable. Men are found to prefer to socialize with nonfamily members to family members (either household or nonhousehold). Caucasians are found to have a lower propensity to engage in social activities with nonhousehold family members compared with individuals of other ethnicities.

Employed persons have a higher propensity to choose nonhousehold other members as companions for social activities. This is intuitive given that these companions are often co-workers. Students are more likely to socialize with friends and less likely to undertake joint social activities with household and nonhousehold family members.

Married individuals are more likely to undertake social activities with only household members (see the negative coefficients for all other alternatives). Further, the negative coefficients are strongest for the three alternatives that do not include household members. This indicates that married individuals participate in social activities with their spouses. Finally, the absence of children in the household favors socializing with nonhousehold members.

Companion-Type Model for Passive Leisure Activities

The MNL model for the companion-type choice for passive leisure activities is presented in Table 6. The “solo” alternative is chosen as the reference category. The “household members only” alternative is not available for individuals in single-person households. All other alternatives are available for all individuals.

Results indicate that passive leisure episodes of longer durations are more likely to be pursued jointly than solo. Further, among the joint episodes, shorter-duration activities are more likely to be pursued with nonhousehold other members as companions, as are weekday episodes. Otherwise, weekday episodes are more likely to be solo than joint. Finally, friends are more

likely to be companions than household or family members for weekday passive leisure activities.

Younger individuals are more likely to undertake passive leisure activities with nonhousehold members. Men are found to undertake passive leisure activities independently or with nonhousehold, nonfamily members as companions. Caucasians have a lower propensity to undertake solo activities compared with individuals of other ethnicities.

Employed persons have a higher propensity to choose nonhousehold other members as companions for passive leisure activities. This is intuitive given that these companions are often co-workers. These persons also prefer independent leisure to joint leisure with non-co-workers as companions. Students are more likely to pursue leisure with friends and colleagues and less likely to do so with nonhousehold family members.

Married individuals are found not to prefer pursuing joint leisure with only friends or nonhousehold family members. Solo episodes are favored over joint episodes with nonhousehold, nonfamily companions. However, joint episodes including household members as companions are preferred to solo episodes. Finally, the absence of children in the household favors pursuit of passive leisure with only nonhousehold friends and family. When children are present in the household, household members are the most favored companions for leisure.

Companion-Type Model for Active Leisure Activities

The MNL model for the companion-type choice for active leisure activities is presented in Table 7. The “solo” alternative is chosen as the reference category. The “household members only” alternative is not available for individuals in single-person households. All other alternatives are available for all individuals.

Results indicate that active leisure episodes of longer duration are more likely to be pursued jointly than solo.

TABLE 6 Model for Companion-Type Choice for Passive Leisure Activities

	Household Members		Nonhousehold Family		Nonhousehold Friends		Nonhousehold Other		Mixed Composition	
	Beta	<i>t</i> -stat	Beta	<i>t</i> -stat	Beta	<i>t</i> -stat	Beta	<i>t</i> -stat	Beta	<i>t</i> -stat
Constant	-1.108	-7.670	-0.194	-1.005	-0.288	-1.767	-0.294	-2.004	-0.007	-0.045
Activity episode duration	0.013	23.617	0.011	18.536	0.013	24.497	0.002	4.066	0.014	25.320
Weekday	-1.097	-14.038	-0.890	-10.322	-0.297	-4.220	0.292	4.840	-1.165	-15.323
Age			-0.018	-6.315	-0.026	-10.116	-0.013	-6.232	-0.022	-8.847
Male	-0.533	-7.800	-0.415	-5.413					-0.629	-9.778
White	0.360	3.299	0.192	1.792	0.362	4.049	0.141	2.012	0.369	3.696
Employed	-0.926	-10.598	-0.977	-10.348	-0.499	-6.211	0.478	5.952	-0.828	-9.965
Student			-0.242	-2.611	-0.587	-6.372	0.267	3.231		
Married	1.730	18.831	-0.262	-2.881	1.026	12.067			1.228	16.110
No children in household	-0.803	-10.183	0.477	4.719	0.280	3.457	-0.174	-2.852	-0.676	-8.088
Log likelihood (convergence)					-15,404.93					
Log likelihood (constants only)					-18,158.04					

TABLE 7 Model for Companion-Type Choice for Active Leisure Activities

	Household Members		Nonhousehold Family		Nonhousehold Friends		Nonhousehold Other		Mixed Composition	
	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat	Beta	t-stat
Constant	-0.524	-2.617	-1.962	-5.686	-0.351	-1.666	-0.982	-5.894	-0.075	-0.330
Activity episode duration	0.006	9.291	0.010	12.009	0.011	18.172	0.010	14.958	0.010	15.134
Weekday	-0.998	-12.074	-0.870	-5.587	-0.246	-2.995			-1.048	-10.061
Age	-0.010	-2.823	-0.015	-3.511	-0.030	-9.584	-0.016	-4.814	-0.046	-11.199
Male	-0.538	-6.669	-0.589	-3.872					-0.534	-5.421
White	0.298	2.230	0.510	1.990	0.259	2.174			0.532	3.171
Employed	-0.396	-4.414	-0.550	-3.508	-0.353	-3.923			-0.293	-2.702
Student					0.454	3.672	0.451	3.423		
Married	1.388	11.003			-0.426	-4.492	-0.363	-3.574	0.848	7.050
No children in household	-0.731	-7.662					-0.226	-2.215	-0.511	-4.543
Log likelihood (convergence)					-7,613.41					
Log likelihood (constants only)					-8,561.43					

Weekday episodes are most likely to be undertaken solo or with nonhousehold other members (co-workers). We also observe that friends are more likely to be companions than household members or family members for weekday active leisure activities.

Younger individuals are more likely to undertake active leisure jointly. As in the case of passive leisure, men are also found to undertake active leisure activities independently or with nonhousehold, nonfamily members as companions. Caucasians are less likely to undertake active leisure solo and with colleagues compared with individuals of other ethnicities.

Employed persons have a higher propensity to choose either independent active leisure or joint leisure with nonhousehold other members as companions. Students are more likely to pursue leisure with friends and colleagues.

Married individuals are found not to prefer pursuing joint leisure with only friends or nonhousehold family members. Solo episodes are favored over joint episodes with nonhousehold, nonfamily companions. However, joint episodes including household members as companions are preferred to solo episodes. Finally, the absence of children in the household favors pursuit of passive leisure with only nonhousehold friends and family. When children are present in the household, household members are the most favored companions for leisure.

SUMMARY AND CONCLUSIONS

Development of behaviorally oriented travel–demand models requires an understanding of the joint time investment decisions of individuals with household and nonhousehold members. This is increasingly recognized as one of the most critical and understudied issues in the activity-based travel–demand modeling field. This study contributes toward this goal by presenting an empirical analysis of companion types for different kinds of activity and travel episode types. Data from the 2003 and 2004 ATUS were used in this analysis.

Aggregate analysis indicates that a significant fraction of the daily activity–travel patterns of individuals is pursued with other persons. Out-of-home and travel episodes are more likely to be undertaken with other persons than in-home episodes. Further, solo activities and travel are found to be less likely on weekend days compared with weekdays. On further examining the companion types for joint activity episodes, household members are the most dominant companions for in-home activities and travel whereas nonhousehold persons are preferred companions for out-of-home episodes. Finally, the authors also observe that joint weekend out-of-home episodes are more likely to include household members as companions whereas joint weekday episodes are more likely to be undertaken with nonhousehold members.

MNL models were also developed to determine the impacts of demographic characteristics, episode durations, and day of the week on the choice of companion types for leisure activities. Nonhousehold companions were further classified into family, friends, and others for this analysis. Overall, the empirical results indicate similarities in the companion type choices for the three types of leisure activities (and in particular between active and passive leisure). Specifically, men prefer nonhousehold nonfamily members as companions. Employed persons and students are more likely to pursue social activities with nonhousehold other members (often co-workers) and friends, respectively. This indicates that increased opportunities to interact with nonhousehold members favor joint pursuit of social activities with nonfamily members as companions. Single individuals are more likely to spend leisure time with friends and other nonhousehold nonfamily members. In contrast, married individuals are found to have a higher propensity to pursue leisure jointly with their spouses and possibly children. Weekdays favor solo leisure episodes or joint episodes with nonhousehold members. Weekend episodes, on the other hand, are more likely to be undertaken with household members. Finally, the authors find the duration of the activity episode is related to the choice of companion type.

The empirical analysis in this paper highlights that joint activity–travel episodes warrant scrutiny for enhancing travel–demand models. The MNL model results indicate significant impacts of socioeconomic characteristics of individuals on companion-type choices for leisure activities. The impacts of transportation system characteristics and land use patterns on these choices are not examined for want of data. This is an avenue for further research.

REFERENCES

- Arentze, T., and H. Timmermans. 2006. Social Networks, Social Interactions, and Activity–Travel Behavior: A Framework for Microsimulations. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Axhausen, K. W. 2005. Social Networks and Travel: Some Hypothesis. In *Social Aspects of Sustainable Transport: Transatlantic Perspectives* (K. Donaghy, S. Poppelreuter, and G. Rudinger, eds.), Ashgate Publishing Limited, United Kingdom.
- Carrasco, J., and E. J. Miller. 2006. Exploring the Propensity to Perform Social Activities: A Social Networks Approach. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Carrasco, J., B. Hogan, B. Wellman, and E. J. Miller. 2006. Collecting Social Network Data to Study Social Activity–Travel Behavior: An Egocentric Approach. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Gliebe, J. P., and F. S. Koppelman. 2002. A Model of Joint Activity Participation Between Household Members. *Transportation*, Vol. 29, No. 1, pp. 49–72.
- Goulias, K. G., and T. G. Kim. 2005. An Analysis of Activity-Type Classification and Issues Related to the With Whom and For Whom Questions of an Activity Diary. In *Progress in Activity-Based Analysis* (H. J. P. Timmermans, ed.), Elsevier, Oxford, England.
- Kemperman, A., T. Arentze, and H. J. P. Timmermans. 2006. Social Commitments and Activity–Travel Scheduling Decisions. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Srinivasan, S., and C. R. Bhat. 2006. A Multiple Discrete Continuous Model for Independent and Joint Discretionary Activity Participation Decisions. *Transportation: Planning, Policy, Research, Practice*, Vol. 33, No. 5, pp. 497–515.
- Vovsha, P., E. Peterson, and R. Donnelly. 2003. Explicit Modeling of Joint Travel by Household Members: Statistical Evidence and Applied Approach. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1831, Transportation Research Board of the National Academies, Washington, D.C., pp. 1–10.

An Innovative Methodological Framework to Analyze the Impact of Built Environment Characteristics on Activity–Travel Choices

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There has been increasing interest in the land use–transportation connection in the past decade, motivated by the possibility that design policies associated with the built environment (BE) (land use, urban form, and street network attributes) can be used to manage and shape individual traveler behavior and aggregate travel demand. It is important to determine whether the empirically observed association between BE and travel behavior–related variables is a reflection of underlying causality or whether it is attributable to the relationship between BE and the characteristics of people who choose to live in particular BEs.

Literature debating the causal versus the associative nature of the relationship between the BE and travel behavior, including whether any causal effect is enough to cause a shift in travel patterns, is inconclusive. This relationship is the focus of design policies manifested in new urbanism and smart growth concepts. A review by Ewing and Cervero (2001) describes studies that have found elasticity effects of BE attributes on travel demand variables. Other recent studies have also found significant effects of BE on one or more dimensions of activity/travel behavior (see Rajamani et al. 2003; Krizek 2003; Shay and Khattak 2005; Bhat et al. 2005; Bhat and Singh 2000; and Rodriguez et al. 2005). However, several studies reviewed by Crane (2000) and some other works (see, for example, Boarnet and Sarmiento 1998; Boarnet and Crane 2001; Bhat and Lockwood 2004; Bhat et al. 2005; and Bhat and Zhao 2002) have found that BE measures have little to no impact on such dimensions of travel behavior as activity–trip frequency and nonmotorized mode use. However, because of different

estimation techniques, units of analysis, empirical contexts, travel behavior dimensions, and BE characteristics and their scales used across the studies, it is difficult to compare results. Academia agrees that it is premature to draw any conclusions about the impacts of BE on activity–travel behavior. Further, two issues need to be addressed: (a) The relationship between BE and travel behavior can be complex, and (b) the true causal impact of BE on travel behavior can be assessed only if the association due to demographics-based residential sorting is controlled for. These issues are discussed in the next two sections (see also Boarnet and Crane 2001; Crane 2000; Krizek 2003; and Handy 1996).

COMPLEX NATURE OF THE BUILT ENVIRONMENT–TRAVEL BEHAVIOR RELATIONSHIP

Three elements characterizing the complex relationship between BE and travel are discussed below.

Multidimensional Nature

BE and travel are multidimensional in nature. That is, there are many aspects to BE, including accessibility to transit stops, presence and connectivity of walk and bike paths, land use mix, street network density (such as average length of links and number of intersections per unit area), block sizes, and proportion of street frontage with buildings. Similarly, there are many dimensions of travel,

including car ownership, number of trips, time of day, route choice, travel mode choice, purpose of trips, and so forth. A fundamental question is what dimension of BE impacts what dimension of travel—a seemingly innocuous, but very complex, question. Many earlier research works have focused on the impact of selected BE characteristics on selected travel dimensions, but such analyses provide a limited picture of the many interactions leading up to travel impacts. In particular, the use of a narrow set of BE measures may render the measures as proxies for other BE measures, making it difficult to identify which element of the multidimensional package of BE measures is actually responsible for the travel impact. Similarly, focus on the impacts of BE on narrow dimensions of travel does not provide the overall effect on travel. For instance, a denser environment may be associated with fewer pick-up or drop-off activity episodes, but more recreational episodes (see Bhat and Srinivasan 2005). The net impact on overall travel will depend on the aggregation across the effects on individual travel dimensions. Finally, most empirical analyses consider a trip-based approach to analysis, ignoring the chaining of activities and the interplay of the effect of BE attributes on the many dimensions characterizing activity participation and travel.

Moderating Influence of Decision-Maker Characteristics

The second element is the moderating influence of decision makers' characteristics on travel behavior (individuals and households). These characteristics may include sociodemographic factors (such as gender, income, and household structure), travel-related and environmental attitudes (such as preference for nonmotorized or motorized modes of transportation and concerns about mobile source emissions), and perceptions regarding BE attributes (that is, cognitive filtering of the objective BE attributes). These may have a direct influence on travel behavior (for example, higher-income households are more likely to own cars) or an indirect influence by modifying the sensitivity to BE characteristics (for example, it may be that high-income households, wherever they live, own several cars and use them more than low-income households; this creates a situation where high-income households are less sensitive to BE attributes in their car ownership and use patterns than low-income households). Almost all individual and household-level analyses of the effect of BE characteristics on travel behavior control for the direct influence of decision-maker attributes by incorporating sociodemographic characteristics as determinants of travel behavior. A handful of studies also control for the direct impact of attitudes and perceptions of decision makers on travel behavior (see

Schwanen and Mokhtarian 2005; Kitamura et al. 1997; Handy et al. 2005; and Lund 2003). However, while there has been recognition that sensitivity to BE attributes can vary among decision makers (see Badoe and Miller 2000), most studies have not examined the indirect effect of demographics on the sensitivity to BE attributes. And, to our knowledge, no study has recognized the potential effect of unobserved decision-maker characteristics on the response to BE attributes. It is possible, though, that the varying levels and sometimes non-intuitive effects of BE attributes on travel behavior found in earlier empirical studies (for example, in Bhat and Gossen 2004) is, at least in part, a manifestation of varying BE attribute effects across decision makers in the population.

Spatial Scale of Analysis

The third element is the neighborhood shape and scale used to gauge BE measures. Most studies use predefined spatial units based on census tracts, zip codes, or transport analysis zones as operational surrogates for neighborhoods because urban form data are more readily available and easily matched to travel data at these scales. However, it is not clear how individuals perceive the neighborhood space and scale, and how they filter spatial information when making spatial choice decisions (see Golledge and Gärling 2003; Krizek 2003; and Guo and Bhat 2004, 2007 for detailed discussions). Further, it is possible that different BE attributes have different spatial extents of influence on travel choices, as illustrated by Guo and Bhat (2007) and Boarnet and Sarmiento (1998).

RESIDENTIAL SORTING BASED ON TRAVEL BEHAVIOR PREFERENCES

The second major issue in BE–travel behavior relationship is residential sorting based on travel behavior preferences. A fundamental assumption is that there is a one-way causal flow from BE characteristics to travel behavior. Specifically, the assumption is that households and individuals locate themselves in neighborhoods and then, based on neighborhood attributes, determine their travel behaviors. Thus, if good land use mixing has a negative influence on the number of motorized trips, the implication would be that building neighborhoods with good land use mix would result in decreased motorized trips, which would reduce traffic congestion. A problem with the theory is that it does not take a comprehensive view of how individuals and households make residential choice and travel decisions. Households and individuals who are auto-disinclined because of their demographics,

attitudes, or other characteristics, may search for locations with high residential densities, good land use mix, and high public transit service levels, so they can pursue their activities using nonmotorized travel modes. If this were true, urban land use policies aimed at, for example, increasing density or land use mix, would not stimulate lower levels of auto use, but would simply alter the spatial residence patterns of the population based on motorized mode use desires. Ignoring this self-selection in residence choices can lead to a spurious causal effect of neighborhood attributes on travel, and potentially lead to misinformed BE design policies.

The literature that has considered the self-selection issue (also referred to as the residential sorting issue) in assessing the impact of BE attributes on travel choices has done so in one of three ways.

Controlling for Decision-Maker Attributes

The first approach is to control for demographic and other travel-related attitudes and perceptions of decision makers that may impact the neighborhood type individuals choose. This can be accomplished by incorporating decision-making characteristics as explanatory variables in models of travel behavior. This is a creative, and simple, way of tackling the self-selection problem, but its use is limited because most travel survey data sets do not collect attitudinal data. Further, it is unlikely that all the demographic and travel lifestyle attitudes that have any substantive impact on residential sorting can be collected in a survey because it is difficult to gauge how close the estimated BE effects are to the true causal effect.

Instrumental Variables Approach

The second approach to alleviate the residential sample selection effect is a two-stage instrumental variable approach in which the endogenous explanatory BE attributes are first regressed on instruments that are related to BE attributes, but have little correlation with the randomness in the primary travel behavior of interest. The predicted values of BE attributes from this first regression are next introduced as independent variables (along with other demographic attributes of the individual) in the travel behavior relationship of interest. A problem with this approach, however, is that it is not applicable to the case in which the travel behavior equation of interest has a nonlinear structure, such as a discrete choice or a limited or truncated variable. There are control functions and related approaches to deal with the case of endogenous explanatory variables in the context of discrete choice and other nonlinear models (see Berry et al. 1995; Lewbel 2004; Louviere et al. 2005),

but these methods require tedious computations to recognize the sampling variation in the predicted value of the endogenous BE attributes to obtain the correct standard errors in the main equation of interest. Ignoring the sampling variance in the predicted values of BE attributes, as done by Boarnet and Sarmiento, can lead to incorrect conclusions about the statistical significance of the effects of BE attributes.

Using Before–After Household Move Data

The third approach is to examine the travel patterns of households immediately before and after a household relocation. The potential advantage of examining the same household in two different neighborhoods is that one can ostensibly control for the overall travel desires and attitudes of the members of a household, so that the before–after relocation changes in travel behavior may be attributed to the different BEs in the two neighborhoods. The idea in this approach is to consider the relocation as a treatment, with the associated travel behavior changes being the response variable. The assumption is that relocating households are in equilibrium in their pre-move neighborhood in terms of BE attributes, and moved because of factors unrelated to their preference of BE attributes (such as to upgrade the physical housing stock in response to higher incomes or a change in life-cycle). While such an approach can alleviate the self-selection problem, the relocating households are themselves a self-selected group, and may have moved because of dissonance in the pre-move neighborhood BE attributes.

PROPOSED MODELING FRAMEWORK

This section addresses some of the challenges discussed in the previous two sections. In particular, the authors propose a modeling framework that (a) accommodates differential sensitivity to BE and transportation network variables due to both demographic and unobserved household attributes and (b) controls for the self-selection of individuals into neighborhoods based on travel preferences. The framework can be used to control for residential self-selection for any kind of travel behavior variable and provides the correct standard errors regarding the effect of BE attributes. It is geared toward cross-sectional analysis, recognizing that almost all existing data sources available for analysis of BE effects are cross-sectional in nature. Unlike earlier studies, the methodology also models the residential location choice decision jointly with the travel behavior choice.

The results of applying the model formulation to an empirical analysis of residential choice and car owner-

ship decisions of San Francisco Bay area residents will be presented at the innovative modeling conference. The important findings from this application are as follows. First, BE attributes affect residential choice and car ownership decisions. Thus, policy decisions regarding changes in BE characteristics must be evaluated in the joint context of both decisions, so that spatial relocation patterns and car ownership changes can be analyzed. Such a complete picture enables a comprehensive assessment of potential travel-related changes due to BE policies. Second, the authors' findings support the notion that the commonly used population and employment density measures are actually proxy variables for such BE measures as street block density and transit accessibility. Third, in the context of car ownership decisions, both household demographics and BE characteristics are influential, with household demographics having a stronger effect. Fourth, there is variation in sensitivity to BE attributes due to both demographic and unobserved factors, in both residential choice as well as car ownership decisions. But, while the study examined demographic interactions and allowed random variations in sensitivity to several BE characteristics, most did not turn out to be statistically significant. Among demographics, income is a key variable in affecting the sensitivity to BE attributes and related variables. Unobserved household-specific factors also play an important role in the sensitivity to commute time and street block density (in the residential choice model) and employment density and street block density (in the car ownership model). Ignoring such systematic and random variations in sensitivity to BE attributes will, in general, lead to inconsistent results regarding the effect of BE attributes on travel behavior decisions, which can, in turn, lead to inappropriate policy decisions. Fifth, household income is the dominant factor in residential sorting. Specifically, low-income households consciously choose to (or are constrained to) locate in neighborhoods with low commute costs, long commute times, and high employment density compared with their high-income counterparts. Such low-income households also intrinsically choose to own fewer cars. Thus, ignoring income effects in car ownership (and, by extension, other travel decisions) can lead to an inflated effect of BE and related variables on travel behavior decisions. Other demographic factors that impact residential sorting based on car ownership preferences correspond to the presence of senior adults in the household and whether or not a person lives alone. Finally, and rather surprisingly, the results did not support the notion of residential sorting in car ownership propensity based on unobserved household factors. This implies that independent models of residential choice and car ownership choice (after accommodating the residential sorting effects of demographics) are adequate to examine BE effects on car ownership choice, in the cur-

rent empirical context. But, in general, it is important to consider the methodology developed in this paper to control for the potential presence of self-selection due to both observed and unobserved household factors. Only by estimating the joint model can one conclude about the potential presence or absence of self-selection effects due to unobserved factors.

REFERENCES

- Badoe, D. A., and E. J. Miller. 2000. Transportation–Land Use Interaction: Empirical Findings in North America, and Their Implications for Modeling. *Transportation Research Part D: Transport and Environment*, Vol. 5, No. 4, pp. 235–263.
- Berry, S., J. A. Levinsohn, and A. Pakes. 1995. Automobile Prices in Market Equilibrium. *Econometrica: Journal of the Econometric Society*, Vol. 63, No. 4, pp. 841–890.
- Bhat, C. R., and R. Gossen. 2004. A Mixed Multinomial Logit Model Analysis of Weekend Recreational Episode Type Choice. *Transportation Research Part B: Methodological*, Vol. 38, No. 9, pp. 767–787.
- Bhat, C. R., and A. Lockwood. 2004. On Distinguishing Between Physically Active and Physically Passive Episodes and Between Travel and Activity Episodes: An Analysis of Weekend Recreational Participation in the San Francisco Bay Area. *Transportation Research Part A: Policy and Practice*, Vol. 38, No. 8, pp. 573–592.
- Bhat, C. R., and S. K. Singh. 2000. A Comprehensive Daily Activity–Travel Generation Model System for Workers. *Transportation Research Part A: Policy and Practice*, Vol. 34, No. 1, pp. 1–22.
- Bhat, C. R., and S. Srinivasan. 2005. A Multidimensional Mixed Ordered–Response Model for Analyzing Weekend Activity Participation. *Transportation Research Part B: Methodological*, Vol. 39, No. 3, pp. 255–278.
- Bhat, C. R., and H. Zhao. 2002. The Spatial Analysis of Activity Stop Generation. *Transportation Research Part B: Methodological*, Vol. 36, No. 6, pp. 557–575.
- Bhat, C. R., S. Srinivasan, and K. W. Axhausen. 2005. An Analysis of Multiple Interepisode Durations Using a Unifying Multivariate Hazard Model. *Transportation Research Part B: Methodological*, Vol. 39, No. 9, pp. 797–823.
- Boarnet, M. G., and R. Crane. 2001. The Influence of Land Use on Travel Behavior: Specification and Estimation Strategies. *Transportation Research Part A: Policy and Practice*, Vol. 35, No. 9, pp. 823–845.
- Boarnet, M. G., and S. Sarmiento. 1998. Can Land-Use Policy Really Affect Travel Behavior? A Study of the Link Between Nonwork Travel and Land-Use Characteristics. *Urban Studies*, Vol. 35, No. 7, pp. 1155–1169.
- Crane, R. 2000. The Influence of Urban Form on Travel: An Interpretive Review. *Journal of Planning Literature*, Vol. 15, No. 1, pp. 3–23.

- Ewing, R., and R. Cervero. 2001. Travel and the Built Environment: A Synthesis. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1780, TRB, National Research Council, Washington, D.C., pp. 87–114.
- Golledge, R., and T. Garling. 2003. *Cognitive Maps and Urban Travel*. Research Paper No. 601, University of California Transportation Center.
- Guo, J. Y., and C. R. Bhat. 2004. Modifiable Areal Units: Problem or Perception in Modeling of Residential Location Choice? In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1898, Transportation Research Board of the National Academies, Washington, D.C., pp. 138–147.
- Guo, J. Y., and C. R. Bhat. 2007. Operationalizing the Concept of Neighborhood: Application to Residential Location Choice Analysis. *Journal of Transport Geography*, Vol. 15, No. 1, pp. 31–45.
- Handy, S. 1996. Methodologies for Exploring the Link Between Urban Form and Travel Behavior. *Transportation Research Part D: Transport and Environment*, Vol. 1, No. 2, pp. 151–165.
- Kitamura, R., P. L. Mokhtarian, and L. Laidet. 1997. Micro-Analysis of Land Use and Travel in Five Neighborhoods in the San Francisco Bay Area. *Transportation*, Vol. 24, No. 2, pp. 125–158.
- Krizek, K. J. 2003. Residential Relocation and Changes in Urban Travel: Does Neighborhood-Scale Urban Form Matter? *Journal of the American Planning Association*, Vol. 69, No. 3, pp. 265–281.
- Lewbel, A. 2004. *Simple Estimators For Hard Problems: Endogeneity in Discrete Choice Related Models*. Working Papers in Economics No. 604, Boston College, Mass.
- Louviere, J., K. Train, M. Ben-Akiva, C. R. Bhat, D. Brownstone, T. A. Cameron, R. T. Carson, J. R. DeShazo, D. Fiebig, W. Greene, D. Hensher, and D. Waldman. 2005. Recent Progress on Endogeneity in Choice Modeling. *Marketing Letters*, Vol. 16, No. 3, Dec., pp. 255–265.
- Lund, H. 2003. Testing the Claims of New Urbanism. *APA Journal*, Vol. 69, No. 4, pp. 414–429.
- Rajamani, J., C. R. Bhat, and S. Handy. 2003. Assessing Impact of Urban Form Measures on Nonwork Trip Mode Choice After Controlling for Demographic and Level-of-Service Effects. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1831, Transportation Research Board of the National Academies, Washington, D.C., pp. 158–165.
- Rodriguez, D.A., A. J. Khattak, and K. R. Evenson. 2005. Can Neighborhood Design Encourage Walking and Bicycling? Physical Activity on a New Urbanist and a Conventional Suburban Community. Presented at 84th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Schwanen, T., and P. L. Mokhtarian. 2005. What Affects Commute Mode Choice: Neighborhood Physical Structure or Preferences Toward Neighborhoods? *Journal of Transport Geography*, Vol. 13, No. 1, 2005, pp. 83–99.
- Shay, E., and A. J. Khattak. 2005. Automobile Ownership and Use in Neo-Traditional and Conventional Neighborhoods. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1902, Transportation Research Board of the National Academies, Washington, D.C., pp. 18–25.

ADDITIONAL RESOURCE

- Handy, S., X. Cao, T. J. Buehler, and P. Mokhtarian. 2005. The Link Between the Built Environment and Travel Behavior: Correlation or Causality? Presented at 84th Annual Meeting of the Transportation Research Board, Washington, D.C.

Innovative Methods for Pricing Studies

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In a recent forum on road pricing (1), attendees discussed limitations with current travel demand forecasting approaches for pricing studies. In addition, Cambridge Systematics, Inc. (CS) recently completed a paper on the limitations of studies used to advance toll projects (2) and on the opinions of Washington State's community leaders (3). Based on these sources and recent experience in developing forecasting models for toll projects, the authors have identified the following issues as important to improving existing travel models for pricing studies: inaccurate values of time for specific travelers, trip purposes, modes, and time periods; and lack of temporal detail and behavioral choice for time-of-day models.

CS's approach to advance travel models for pricing studies focuses on these issues as the most critical to be addressed in existing models. The authors have been involved in the development and application of these methods for trip-based models in Minnesota and Washington, as well as for activity-based models in San Francisco. The remainder of this paper describes innovative methods to incorporate advances to address these issues. In addition, the authors describe strategies to optimize tolls for pricing studies. Finally, more research is proposed to address additional limitations of existing models.

VALUES OF TIME

The estimation and application of the value of time in travel demand forecasting models is the most often cited problem for evaluating pricing projects. There are a

number of issues that present challenges, including how to distribute values of time:

- Across individual travelers (i.e., with different income levels);
- Across different trips (i.e., with different purposes and modes);
- Across different destinations (i.e., trips to the airport);
- Across different vehicle types (i.e., with different vehicle classes);
- Based on the types of goods being carried for truck trips; and
- For different types of congestion (i.e., recurring and nonrecurring congestion, such as accidents).

In a disaggregate travel demand forecasting system, these values of time could be set based on the traveler, the trip, the vehicle type, and the goods being carried and could remain consistent throughout the forecasting process, eliminating the application-related issues surrounding the values of time. At this time, most travel demand forecasting models are aggregate trip-based models, which makes the distribution of values of time for individual travelers, trips, and vehicles impossible. For these models, the only solution is to identify specific categories of travelers, trips, and vehicles and apply values of time for these categories. This is an effective means of distributing values of time within the forecasting system.

However, these trip-based modeling systems do not necessarily contain the same market segmentation throughout the system (i.e., to assess values of time by

income group, one must represent income group within each model component, including trip assignment). CS has completed two studies (in Minnesota and Washington) in which model improvements were implemented to address this issue. For example, if one segments the market into different trip purposes and income groups throughout the system, but the modal segments are not specifically represented in trip distribution, there will be new problems for tolls that are assessed by mode (i.e., where carpools and transit go free).

The Washington State model includes value of time in the mode choice model using time and cost coefficients for each type of traveler. In addition to income, other market segments affecting value of time, such as trip distance, time of day, gender, and age were considered. However, their effects were difficult to incorporate into the model stream and had marginal impact.

In Minnesota, in order to develop toll mode constants using other models, CS calculated the ratio of toll-alternative-specific constants to highway travel time coefficients for different market segments based on age, gender, income level, education level, and trip purposes. Based on the parameters of the SR-91 and the Congestion Road Pricing models and assumptions about the Twin Cities distribution of trip and traveler characteristics by purpose (including household income, gender, educational attainment, and age), the differences between the free highway mode and toll mode constants range from a 0.88-min penalty (noncommute trips by one-vehicle households) to a 2.89-min advantage (home-based work trips by two-vehicle households). The average equivalent times vary by auto availability level. The variation occurs because the equivalent time penalties of the toll mode constants are calculated by relating the market segments defined by the SR-91 analyses to the Metropolitan Council market segments. However, the auto availability market segmentation was intended for other model components (e.g., trip generation and distribution) and specifically for toll choice.

There are, of course, a number of activity- or tour-based models that disaggregate travelers and trips during the trip generation, distribution, and mode choice stages of the process. Most of these activity-based modeling systems still operate on an aggregate assignment basis, however, which only allows for assignment of trips by category or class rather than by vehicle. This leap between disaggregate and aggregate systems sacrifices the most important step of the modeling system for pricing studies—trip assignment. Dynamic pricing especially depends on disaggregate assignment techniques as well as the assignment of trips in much smaller time slices. As the number of categories needed to adequately represent the values of time within assignment is increased, it becomes clear that disaggregate assignments would greatly improve the capability to accurately assess pricing strategies. Nonrecurring

congestion also is difficult to represent without a microsimulation or dynamic traffic assignment process.

TEMPORAL DETAIL

Capturing variations in travel by time of day is essential to predicting transportation system performance and air quality impacts of the transportation sector. Many studies have been conducted to study travel demand by time of day. Much of this research has been limited to observing trends in service usage, such as vehicular volumes and the number of person trips. While important to understanding past and present usage patterns, these types of studies are less valuable for predicting future travel by time of day given changes in transportation service availability, quality, and policy. Possibly the behavior least accounted for in travel forecasting is peak spreading (e.g., persons rescheduling their travel from daily periods of high demand to the portions of the day where travel takes less time and is more reliable). Travel surveys and other monitoring activities have documented the correlation between decreasing service quality (congestion) and longer peak periods. Also, many planning agencies need to test the effectiveness of policy initiatives targeted at shifting travel demand to off-peak periods.

An essential component is the time-of-day choice model that provides sensitivity to travelers' temporal decisions with respect to sociodemographics, travel conditions, and cost of travel. This sensitivity is needed to effectively evaluate congestion pricing strategies and improve forecasting results. So in the time-of-day choice models, the inclusion of more temporal details or time periods will make the models more sensitive to congestion pricing. With most of the prior time-of-day choice modeling studies, the various time choices are represented by several temporally contiguous discrete time periods such as a.m. peak period, off-peak period, and p.m. peak period. There are drawbacks of using such an approach to model time-of-day choice (4). The use of discrete time periods requires a predetermined partitioning of the day into time intervals, the characteristics of which may or may not be the same in the future. This might preclude analyses of potential future congestion pricing strategies during time periods that are smaller than those used in the base year. Also, the discrete choice structure considers the time points near the boundaries of intervals as belonging to one or the other of the aggregate time periods. In reality, however, two closely spaced time points on either side of a discrete interval boundary are likely to be perceived as being similar rather than as distinct alternatives. So either many finer discrete time intervals have to be specified to obtain a reasonable time resolution, which might not be practical as this will involve estimating many parameters, or a distinction should be made between adjacent discrete time periods.

CS recently completed an FHWA research project on time-of-day models that resulted in a methodology for time-of-day choice models, trip-based models, and activity-based models. These were validated in case studies in Denver, Colorado, and San Francisco, California. The trip-based time-of-day modeling method was applied to a pricing scenario in the Denver region. Tolls were assumed on a (currently toll-free) 20-mi section of a circumferential freeway. Tolls were highest in the two peak periods (0.2 to 3.5 h long), with lower tolls in shoulder periods (1 to 3.5 h) and lowest tolls in off-peak periods. The time-of-day choice method estimated trips by time of day for half-hour periods. The application of the model for this scenario showed a modest amount of peak spreading resulting from implementation of the period-based tolls.

The tour-based time-of-day modeling method was applied to a pricing scenario for downtown San Francisco and estimated trips by time of day for half-hour periods. A hypothetical \$4.00 toll was applied for all auto trips entering downtown San Francisco during the a.m. peak period (6:00 to 9:00 a.m.). The largest effect appears to be on mode choice. About 20% of the reduction in downtown trips is due to people choosing not to travel downtown at all, about 70% is due to changes in mode, and about 10% appears to be due to time-of-day shifts. These results seem reasonable, as many downtown travelers may not have the flexibility to change their travel times.

For the Washington State Department of Transportation, CS updated the time-of-day choice models by dividing the five main periods (a.m. peak, midday, p.m. peak, evening, and night) into 30-min subperiods in order to model peak-spreading behavior (5). In addition to auto travel time variations between periods, the model was structured to be sensitive to auto travel cost differences between periods (i.e., to emulate time-of-day-specific congestion pricing). The new time-of-day choice models were estimated for eight trip purpose and direction combinations, using 32 alternatives.

These five time periods are used for transit, truck, and external trips. Auto trips are further subdivided into 32 time periods, as shown in Table 1.

The auto time-of-day model uses highway travel times from each of the five time periods to predict travel for 30-

min time periods. When estimating the time-of-day models, the chosen time period for each trip will be based on the midpoint between the reported trip departure and arrival times. Trip tables are developed for each time period, purpose, mode, and direction. These are applied to networks by mode and time period in the trip assignment model.

Multinomial logit (MNL) choice models were estimated for six home-based trip purpose and direction combinations—home to work (HW), work to home (WH), home to shop (HS), shop to home (SH), home to other (HO), and other to home (OH).

Two features were added to the time-of-day models to make them more sensitive to congestion pricing:

- The three periods where congestion occurs (a.m. peak, midday, p.m. peak) were further divided into 30-min subperiods, in order to model peak-spreading behavior. Because it would be impractical to perform a separate traffic assignment for each 30-min period, the distribution of trips across the subperiods was based on travel times for the same five periods that are included in the current model. As the congested travel time in the “peak of the peak” increases relative to the free-flow travel time, the peak tends to flatten, and a higher percentage of peak travelers will travel in the shoulders of the peak. Generally, this type of effect is not symmetric because there are different constraints for traveling earlier as opposed to traveling later. In the a.m. peak, for example, we expect more workers to shift toward the earlier shoulder of the peak rather than the later shoulder because many workers have to arrive at work before a specific time.

- Second, in addition to auto travel time variations between periods, the model is sensitive to auto travel cost differences between periods, for instance from time-of-day-specific congestion pricing. Because there are no data on such cost differences in the household survey, it is necessary to infer the sensitivity to travel cost by using the sensitivity to travel time multiplied by the appropriate value of time for each income group and travel purpose. The authors use the same values of time as in the mode choice models.

TABLE 1 Time-of-Day Choice Models

A.M. Peak	Midday	P.M. Peak	Evening	Night
5:00 a.m.–5:29 a.m.	10:00 a.m.–10:29 a.m.	3:00 p.m.–3:29 p.m.	8:00 p.m.–10:59 p.m.	11:00 p.m.–4:59 a.m.
5:30 a.m.–5:59 a.m.	10:30 a.m.–10:59 a.m.	3:30 p.m.–3:59 p.m.		
6:00 a.m.–6:29 a.m.	11:00 a.m.–11:29 a.m.	4:00 p.m.–4:29 p.m.		
6:30 a.m.–6:59 a.m.	11:30 a.m.–11:59 a.m.	4:30 p.m.–4:59 p.m.		
7:00 a.m.–7:29 a.m.	12:00 a.m.–12:29 p.m.	5:00 p.m.–5:29 p.m.		
7:30 a.m.–7:59 a.m.	12:30 p.m.–12:59 p.m.	5:30 p.m.–5:59 p.m.		
8:00 a.m.–8:29 a.m.	1:00 p.m.–1:29 p.m.	6:00 p.m.–6:29 p.m.		
8:30 a.m.–8:59 a.m.	1:30 p.m.–1:59 p.m.	6:30 p.m.–6:59 p.m.		
9:00 a.m.–9:29 a.m.	2:00 p.m.–2:29 p.m.	7:00 p.m.–7:29 p.m.		
9:30 a.m.–9:59 a.m.	2:30 p.m.–2:59 p.m.	7:30 p.m.–7:59 p.m.		

We estimated new MNL models for the six trip purpose and direction combinations, using 32 alternatives. Compared with the remainder of the modeling system, the a.m. and p.m. peak periods are both expanded to include wider shoulder periods. The a.m. peak, midday, and p.m. peak periods are set to be 5 h long and contain ten half-hour subperiods. The evening and night periods remain as single periods, spanning 3 and 6 h, respectively.

We use purpose-specific variables and shift variables to move trips earlier or later within each of the three larger periods. The shift variables are nonlinear; for example, it may take more than twice as much a.m. peak congestion to get someone to shift their departure time 30 min earlier than it does to get the same person to shift 60 min earlier.

The following variables were tested in the model estimation: sociodemographic (i.e., income and household size); land use and accessibility (i.e., total employment accessible by auto within 6 min and retail employment accessible by auto within 15 min); and origin–destination and level of service (i.e., auto in-vehicle generalized cost in minutes during each of the five periods, bridge dummy variable, and shared ride dummy variable).

All the variables that were tested and either retained or excluded in the utility equation for the logit choice models were based on their significance, whether the sign of the coefficient was logical, and whether the data can be forecasted by the metropolitan planning organization or the DOT. Variables that were tested but not included in the final models are the employment accessibility variables. A description of the variables retained in the final models and the impact of these variables on the temporal choice behavior of travelers are as follows:

- **Household income**—The dummy variable that indicates high-income group (>\$75K) has a significant coefficient specific to p.m. peak period in the WH model whereas in the HW model, the coefficient is significant in the a.m. peak period. This indicates that commuters from higher-income households are more likely to travel to work during the a.m. peak period and less likely to travel during the p.m. peak period. This is further corroborated in the WH model where the income coefficient for the a.m. period was insignificant (and not included), suggesting that commute trips from higher-income households are not as likely to be destined to home during the morning peak period. The income coefficients for the p.m. time period are greater than for other time periods in the WH model, indicating that higher-income commuters are more likely to return home during the p.m. peak period. The lower-income variable (<\$45K) has a negative coefficient in the a.m. peak period of the HW model, probably because lower-income jobs have more irregular hours than high-income jobs and are more likely to occur in off-peak periods.
- **Household size**—Larger households are less likely to travel to work in the a.m. peak than smaller households, as indicated by the negative and significant household size coefficient in the HW model. It may be that larger household sizes indicate the presence of children or more complicated household structures, which, combined with multiple workers in the household, lead to flexible or extended work schedules resulting in more reverse direction work trips. By contrast, smaller households are more likely to return home from work in the p.m. peak period, as indicated by the negative and significant coefficient in the WH model. It is possible that smaller households have fewer outside constraints on work hours and schedules, and work trips can occur in more traditional work hours.
- **Carpool dummy**—If a WH trip is made using the carpool mode of travel, then this variable is equal to 1; otherwise, it equals 0. The coefficient of this variable is very significant and positive in the HW model, and very significant and negative in the WH model. This coefficient is negative in the WH model, indicating that carpool trips from work to home are less likely to occur, and it is hypothesized that there are fewer opportunities for casual carpooling from work to home than vice versa. For nonwork trips, this is significant and positive in both directions of the trip except for trips returning home during the a.m. peak period where it is negative because carpooling is usually not an option from a nonhome–nonwork location.
- **Bridge dummy**—If a trip is made using one of three bridges in the Puget Sound region (namely Tacoma Narrows, I-90, and SR 520), then this variable is equal to 1; and, if not, it is 0. In the HW model, this coefficient was significant and positive in the a.m. peak period, indicating that it is more likely that trips across the bridge will be made during morning peak hours solely for work-related purposes. These coefficients were more significant in the midday and p.m. peak periods of the WH model, indicating a higher likelihood of trips across bridges in the reverse work commute direction. This was found to be significant and positive in the nonwork models during the midday period, indicating the propensity of nonwork travelers to opt for uncongested periods to perform nonwork activities.
- **Congestion level**—The level of congestion or delay is measured by the difference in generalized cost (in minutes) for a.m., midday, p.m., and evening time periods and the generalized cost for nighttime period. This variable is found to be negative and significant in all models, indicating that delay affects travel decisions by time-of-day choice significantly. The size of the coefficient in the HW model is less negative than in the WH model, indi-

cating a stronger negative effect on travel decisions for WH trips during the congested periods.

- Shift variables—Two kinds of shift variables are computed, namely, shift early (SE) and shift later (SL), which measure the difference between the time period indicator (on a scale from 1 through 24 with 0.5 increments) and the midpoint of the first three time periods (a.m., midday, and p.m. peak periods). SE is used when the time period indicator is less than the midpoint whereas SL is used when it is greater. The square of these variables is also used in the models to see the impact of very short and very long delays on temporal choice behavior. During model estimation, these shift variables are multiplied by the delay variable as well as other variables to see the combined effect on time-of-day choice. The coefficients for the delay variables multiplied by SE and SL are significant and positive, while these are negative when multiplied by the square of SE and SL. This indicates that travelers are more likely to switch their

time choice when undertaking trips that may generate either very short or very long delays.

The model statistics demonstrate that the rho-squared with respect to 0 is reasonable (0.191 for WH and 0.188 for HW), but the rho-squared with respect to the constants (0.003 for WH and 0.014 HW) shows that the constants account for nearly all the variation in time-of-day choices. While it may be desirable for the variables in the models to account for more of the time-of-day choices, the primary objective of the model is to provide sensitivity to trip characteristics, which is achieved by these models.

Additional steps are carried out for the time-of-day models:

- The models were estimated using the full set of variables listed above, with additional testing for the best specification of the shift variables. The estimation results by trip purpose are shown in Tables 2, 3, and 4.

TABLE 2 Home-Based Work Time-of-Day Choice Model

Alternatives	Variable	Definition	Home to Work		Work to Home	
			Coefficient	t-Stat	Coefficient	t-Stat
	Observations					
	Final log L					
	Rho-sq. (0)					
	Rho-sq. (constant)					
			6,931		6,076	
			-19,500.8		-17,032.7	
			0.188		0.191	
			0.014		0.003	
AM1-AM10	AM Delay	max(0, AM GC - NI GC)	-0.06172	-4.7	-0.4277	-3.2
MD1-MD10	MD Delay	max(0, MD GC - NI GC)	-0.2834	-6.0	-0.3935	-9.9
PM1-PM10	PM Delay	max(0, PM GC - NI GC)	-0.1747	-4.2	-0.100	constant
EV	EV Delay	max(0, EV GC - NI GC)			-0.1714	-5.7
AM1-AM5	AM Shift Early	AM Delay x (7.5-t)	0.1121	7.7		
AM1-AM5	AM Shift Early ²	AM Delay x (7.5-t) ²	-0.01914	-3.4		
AM6-AM10	AM Shift Later	AM Delay x (t-7.5)	0.01842	2.3		
AM6-AM10	AM Shift Later ²	AM Delay x (t-7.5) ²				
MD1-MD5	MD Shift Early	MD Delay x (12.5-t)	0.1063	4.4		
MD1-MD5	MD Shift Later	MD Delay x (t-12.5)	0.09548	2.8	0.1144	4.6
PM1-PM5	PM Shift Early	PM Delay x (17.0-t)	0.0766	2.8	0.09523	7.0
PM1-PM5	PM Shift Early ²	PM Delay x (17.0-t) ²	0		-0.03593	-4.8
PM6-PM10	PM Shift Later	PM Delay x (t-17.0)	0.05933	1.8	0.1056	9.4
PM6-PM10	PM Shift Later ²	PM Delay x (t-17.0) ²	0		-0.03027	-6.0
AM1-AM10	AM HH size	min(HH size,4)	-0.3419	-7.6		
AM1-AM10	AM Low Income	HH income <\$45K	-0.5176	-5.9		
AM1-AM10	AM High Income	HH income >\$75K	0.515	4.3		
AM1-AM10	AM Crossing	dummy(Bridge_N > 0)	0.3545	2.3		
MD1-MD10	MD HH size	min(HH size,4)	-0.3427	-6.6		
MD1-MD10	MD High Income	HH income>\$75K	0.461	3.4	0.6694	3.7
MD1-MD10	MD Shared ride	dummy(car occ.>1)	0.479	3.8	-0.5917	-3.5
MD1-MD10	MD Crossing	dummy(Bridge_N > 0)			0.618	2.6
PM1-PM10	PM HH size	min(HH size,4)			-0.05966	-2.1
PM1-PM10	PM High Income	HH income >\$75K			0.9454	5.6
PM1-PM10	PM Shared ride	dummy(car occ.>1)	0.6686	4.2	-0.5694	-4.6
PM1-PM10	PM Crossing	dummy(Bridge_N > 0)			0.6383	3.7
EV	EV High Income	HH income >\$75K			0.5285	2.7
AM1-AM5	AM HS Shift Early	AM HH Size x (7.5-t)	0.0722	4.0		
AM1-AM5	AM HI Shift Early	AM Low Inc x (7.5-t)	0.1194	2.3		
AM1-AM5	AM HI Shift Early	AM High Inc x (7.5-t)	-0.1216	-2.8		
AM1-AM5	AM BR Shift Early	AM Crossing x (7.5-t)	-0.4295	-5.8		
AM6-AM10	AM LI Shift Late	AM Low Inc x (t-7.5)	0.2483	3.8		
PM1-PM5	PM HI Shift Early	PM High Inc x (17.0-t)			-0.2217	-4.1

TABLE 3 Home-Based Shop Time-of-Day Choice Model

			Home to Shop		Shop to Home	
			3,590		5,616	
			-11,852.9		-17,311.8	
			0.047		0.111	
			0.011		0.004	
Observations			Coefficient	t-Stat	Coefficient	t-Stat
Rho log L						
Rho-sq. (0)						
Rho-sq. (constant)						
Alternatives	Variable	Definition				
AM1-AM10	AM Delay	max(0, AM GC - NI GC)	-0.06	constant	-0.3201	-2.4
MD1-MD10	MD Delay	max(0, MD GC - NI GC)	-0.06	constant	-0.06	constant
PM1-PM10	PM Delay	max(0, PM GC - NI GC)	-0.08281	-2.1	-0.06	constant
EV	EV Delay	max(0, EV GC - NI GC)	0		0	
AM1-AM5	AM Shift Early	AM Delay x (7.5-t)	0.4556	5.5		
AM1-AM5	AM Shift Early ²	AM Delay x (7.5-t) ²	-0.1914	-3.7		
AM6-AM10	AM Shift Later	AM Delay x (t-7.5)	0.07396	4.0		
AM6-AM10	AM Shift Later ²	AM Delay x (t-7.5) ²				
MD1-MD5	MD Shift Early	MD Delay x (12.5-t)	0.1124	5.0		
MD1-MD5	MD Shift Later	MD Delay x (t-12.5)	0.03864	0.8		
PM1-PM5	PM Shift Early	PM Delay x (17.0-t)	0.05506	2.0	0.1413	4.5
PM1-PM5	PM Shift Early ²	PM Delay x (17.0-t) ²			-0.0597	-3.2
PM6-PM10	PM Shift Later	PM Delay x (t-17.0)	0.02994	1.3	0.01379	1.7
PM6-PM10	PM Shift Later ²	PM Delay x (t-17.0) ²				
AM1-AM10	AM Shared ride	dummy(car occ.>1)			-1.896	-4.4
MD1-MD10	MD Shared ride	dummy(car occ.>1)	0.5574	5.6		
PM1-PM10	PM Shared ride	dummy(car occ.>1)	0.9826	9.3		
EV	EV Shared ride	dummy(car occ.>1)			0.4935	5.7
AM1-AM5	AM SR Shift Early	AM Shared Ride x (7.5-t)	-1.255	-4.9		
AM6-AM10	AM SR Shift Late	AM Shared Ride x (t-7.5)			0.7076	2.6
MD1-MD5	MD HS Shift Early	MD HH Size x (12.5-t)	-0.09479	-4.2		
MD1-MD5	MD SR Shift Early	MD Shared Ride x (12.5-t)			-0.2199	-4.0
MD6-MD10	MD HS Shift Late	MD HH Size x (t-12.5)	-0.2284	-5.9		
PM1-PM5	PM HS Shift Early	PM HH Size x (17.0-t)	-0.09581	-2.6	-0.09922	-4.3
PM1-PM5	PM SR Shift Early	PM Shared Ride x (17.0-t)	-0.237	-2.8		
PM6-PM10	PM SR Shift Late	PM Shared Ride x (t-17.0)			0.1159	2.8

- Travel cost differences by time of day are added separately into the models, but as part of the generalized cost impedance used in trip distribution. This comes from the assignment procedure as a separate price or toll skim by time of day. Unlike travel time, however, the user is able to specify this cost to remain constant over a specific period (e.g., a congestion pricing policy operating only between 6:00 and 9:00 a.m.).

- The models are applied in iteration with traffic assignment, as the time-of-day models use the auto travel times from assignment, but in turn provide a different peaking factor (peak-hour demand) to use in the 1-h assignment. So, the assignment process constrains the amount of peak spreading predicted by the time-of-day models.

In the application of the time-of-day model, we assign the peak 60-min time period for the a.m. peak and mid-day time periods as input to the feedback process of travel times for trip distribution and mode choice. After the final iteration, the trips in each 30-min period are aggregated back to the five time periods (a.m. peak, p.m. peak, evening, and night) for evaluation of performance on the system.

These models have been integrated within the four-step trip-based modeling system and are being used to optimize throughput in select corridors by applying as many as 15 sets of toll rates that vary by direction and facility.

TOLL OPTIMIZATION STRATEGIES

To set rational toll policies that meet operational and revenue goals, the data from the travel model require a post-processing methodology, in part to perform simple accounting functions not available in normal travel models (such as revenue calculations), as well as to perform more complex toll optimization procedures, taking operation constraints into account. This methodology adopts the language of optimization as its core approach. Policy goals that do not have a specific numerical target, such as throughput or revenue maximization, are expressed as an objective function. Goals that have a specific target—such as maintaining a specific level of service in a HOT lane—are expressed as constraints on the objective.

Toll optimization occurs in two phases, as illustrated in Figure 1. First, the travel model is run for a set of toll rates that remain constant throughout the day. Then, these flat

TABLE 4 Home-Based Other Time-of-Day Choice Model

Alternatives	Observations Rho-sq. (0) Rho-sq. (constant)	Variable	Definition	Home to Other		Other to Home	
				Coefficient	t-Stat	Coefficient	t-Stat
				12,816		12,277	
				-42,890.3		-36,732.7	
				0.034		0.137	
				0.007		0.014	
AM1-AM10	AM Delay	$\max(0, \text{AM GC} - \text{NI GC})$	-0.06	constant	-0.3936	-5.9	
MD1-MD10	MD Delay	$\max(0, \text{MD GC} - \text{NI GC})$	-0.06	constant	-0.2209	-8.6	
PM1-PM10	PM Delay	$\max(0, \text{PM GC} - \text{NI GC})$	0.94	constant	-0.10	constant	
EV	EV Delay	$\max(0, \text{EV GC} - \text{NI GC})$	0		0		
AM1-AM5	AM Shift Early	AM Delay $\times (7.5-t)$	0.0705	7.9			
AM1-AM5	AM Shift Early ²	AM Delay $\times (7.5-t)^2$					
AM6-AM10	AM Shift Later	AM Delay $\times (t-7.5)$	0.0533	6.6	0.0659	1.3	
AM6-AM10	AM Shift Later ²	AM Delay $\times (t-7.5)^2$					
MD1-MD5	MD Shift Early	MD Delay $\times (12.5-t)$	0.06646	6.9			
MD1-MD5	MD Shift Later	MD Delay $\times (t-12.5)$			0.07048	3.5	
PM1-PM5	PM Shift Early	PM Delay $\times (17.0-t)$	0.02375	2.9	0.1184	5.6	
PM1-PM5	PM Shift Early ²	PM Delay $\times (17.0-t)^2$			-0.05623	-4.5	
PM6-PM10	PM Shift Later	PM Delay $\times (t-17.0)$	0.04191	8.9	0.02461	6.1	
PM6-PM10	PM Shift Later ²	PM Delay $\times (t-17.0)^2$					
AM1-AM10	AM HH size	$\min(\text{HH size}, 4)$			0.5104	9.8	
AM1-AM10	AM Shared ride	$\text{dummy}(\text{car occ.} > 1)$	1.181	10.2	-2.04	-14.7	
MD1-MD10	MD HH size	$\min(\text{HH size}, 4)$	-0.2226	-9.1			
MD1-MD10	MD Shared ride	$\text{dummy}(\text{car occ.} > 1)$	0.3611	3.4			
MD1-MD10	MD Crossing	$\text{dummy}(\text{Bridge}_N > 0)$	0.2625	1.8			
PM1-PM10	PM Shared ride	$\text{dummy}(\text{car occ.} > 1)$	1.032	9.0	0.3235	4.7	
EV	EV Shared ride	$\text{dummy}(\text{car occ.} > 1)$			0.5723	9.8	
AM1-AM5	AM SR Shift Early	AM Shared Ride $\times (7.5-t)$	-0.5179	-8.2			
AM6-AM10	AM HS Shift Late	AM HH Size $\times (t-7.5)$	-0.0513	-2.7	-0.2111	-4.9	
AM6-AM10	AM SR Shift Late	AM Shared Ride $\times (t-7.5)$	-0.5855	-10.5	0.7224	6.9	
MD1-MD5	MD SR Shift Early	MD Shared Ride $\times (12.5-t)$			-0.1739	-3.8	
MD6-MD10	MD HS Shift Late	MD HH Size $\times (t-12.5)$	0.182	7.7			
MD6-MD10	MD SR Shift Late	MD Shared Ride $\times (t-12.5)$	-0.262	-5.2			
PM1-PM5	PM HS Shift Early	PM HH Size $\times (17.0-t)$	0.1518	6.7	-0.09922	-4.3	
PM1-PM5	PM SR Shift Early	PM Shared Ride $\times (17.0-t)$	-0.5215	-8.9	0.1104	2.2	
PM6-PM10	PM SR Shift Late	PM Shared Ride $\times (t-17.0)$	-0.1959	-4.3	0.1915	4.8	

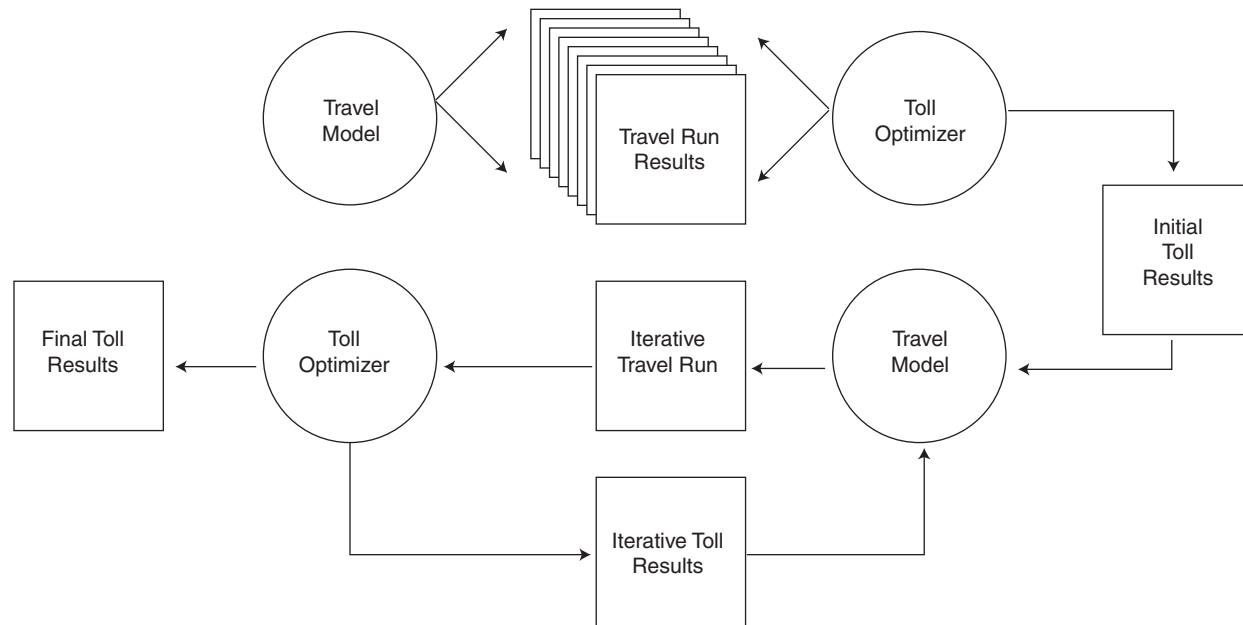


FIGURE 1 Toll optimization.

toll rates are fed into the toll optimizer, which uses them to select an initial estimate of a set of tolls that meet the constraints, while also optimizing the policy goals. These toll levels are then fed back into the travel model; the outputs from this run are examined by the toll optimizer and given a score, based on how well they meet objectives and constraints. The toll optimizer uses these results to create a new estimate of optimal tolls, which are fed back into the travel model. This process continues as the scores of the resultant toll scenarios increase by a threshold amount. Once the deltas between scores drop below this threshold amount, the tolls are considered optimized.

ADDITIONAL AREAS OF RESEARCH

There are additional limitations of existing models that should be addressed, as follows:

- Lack of representation of modal options in distribution models;
- Lack of representation of reliability in evaluating travel choices;
- Inability of static demand models to represent dynamic pricing options;
- Need to evaluate fairness as important in implementation;
- Need to represent overall societal benefits for road pricing strategies;
- Need to represent safety as a performance measure; and
- Need to better understand and communicate risk and uncertainty.

The authors believe that innovative approaches can be developed and integrated with existing models to address these issues and that this will significantly improve forecasting of the impacts of pricing strategies. For example, the lack of representation of modal options in trip distribution models means that for pricing strategies that allow carpools or transit users to travel toll-free, the impact of tolls on trip distribution patterns needs to be performed for toll users and toll-free users separately. Simultaneous trip distribution and mode choice models would address this particular issue, but there are few of these available and they have not been used in pricing studies (to the authors' knowledge).

Another issue is the lack of reliability in evaluating pricing strategies. Previous research indicates that travel time reliability is as important as value of time, if not more so. At the same time, there has been less research on how reliability affects travelers' route choices. Although great strides have been made in measuring reliability, there is less progress in considering reliability in forecasting models.

Another consideration for any pricing study is that an important driver of travel demand is growth in household, employment, and income levels. It is common to use the socioeconomic data approved by the planning agencies within a region, and while these forecasts may work for the purpose for which they were intended, they have not been evaluated for their suitability for use in traffic forecasts intended to provide conservative assumptions for purpose of revenue estimates. Indeed, planning forecasts for typical projects may be conservative in the other direction, trying to anticipate worst-case scenarios for future highway needs.

REFERENCES

1. *Expert Forum on Road Pricing*. Sponsored by Federal Highway Administration, Arlington, Va., November 14–15, 2005.
2. Cambridge Systematics. *Washington State Comprehensive Toll Study Interim Report*. Background Paper No. 6: Limitations of Studies Used to Advance Toll Projects, prepared for the Washington State Transportation Commission, November 2005.
3. Cambridge Systematics. *Washington State Comprehensive Toll Study Interim Report*. Background Paper No. 2: Ascertainment Interviews: Opinion of Washington's Community Leaders, prepared for the Washington State Transportation Commission, November 2005.
4. Bhat, C. R., and J. L. Steed. A Continuous-Time Model of Departure Time Choice for Urban Shopping Trips. *Transportation Research Part B: Methodological*, Vol. 36, No. 3, 2002, pp. 207–224.
5. Kuppam, A. R., M. L. Outwater, M. Bradley, L. Blain, R. Tung, and S. Yan. Application of Time-of-Day Choice Models Using EMME/2 – Washington State DOT Congestion Relief Analysis. Presented at 19th International EMME/2 User's Group Conference, Seattle, Wash., October 19–21, 2005.

BREAKOUT SESSION
VALIDATION

Proposed Validation and Sensitivity Testing of Denver Region Activity-Based Models

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Traditional four-step travel modeling procedures have evolved over the last half of the 20th century. Many improvements were made incrementally and subjected to either formal or informal validation and sensitivity tests. Formal validation tests were normally applied at the end of the model calibration process and, quite frequently, focused on the “super test”—the concept that reproduction of observed traffic volumes and transit boardings at some reasonable level of aggregation somehow showed that the models were, in fact, valid. Informal validation and sensitivity tests, unfortunately, too often consisted of discovering modeling problems after illogical travel forecasts were produced.

In the late 1990s, FHWA commissioned the development of a *Model Validation and Reasonableness Checking Manual* through the Travel Model Improvement Program (1). This manual summarized validation standards and recommended a process that focused on the validation of the individual four-step model components as well as the traditional overall model system validation focused on traffic volumes and transit boardings.

Sensitivity testing has been somewhat less formal. It has frequently focused on the sensitivity of individual model components using measures such as elasticity. Sensitivity testing of modeling systems by validating model results over time has not been as common because it requires observed travel data from more than one point for the same region. Even if such data did exist, many regions do not have measurable changes in their transportation system such as the addition of new roadway capacity or the opening of a new transit line. Without

major changes to the underlying transportation system, it is difficult to test the veracity of the underlying models (unless the test proved that the models were, in fact, poorly calibrated).

In 1997, the Denver Regional Council of Governments (DRCOG) initiated the collection of travel survey data to update its traditional four-step travel model and for the longer-term development of state-of-the-art modeling techniques. The “refresh” of the traditional model using these data took place from 2002 to 2004 and included model component validation, validation to the 1997 base year, and validation to travel conditions in 2001. Between 1997 and 2001, Denver’s light rail system more than doubled in length with the opening of the 8-mi-long Southwest LRT line, enhancing the effectiveness of transit component calibration and validation.

As with its current trip-based model, DRCOG is committed to rigorous validation and sensitivity testing of its activity-based modeling (ABM) system that will be developed over the next 18 months. The system is designed to make use of the most recent developments in ABM theory to better represent the travel decision-making process and provide reasonable sensitivity to a wider range of future travel options and constraints. The downfall is that there are a number of places where the models can fail. DRCOG has addressed this concern by committing approximately the same budget to the validation and sensitivity testing of the ABM that it committed to the entire refresh of the existing traditional four-step travel model. Perhaps a statement made by Chandra Bhat and Frank Koppelman in a recent

focus group discussion best summarizes DRCOG's philosophy:

Researchers and practitioners have not thought carefully enough about the criteria for validation of models. Researchers have the habit of asking practitioners to believe that activity-based methods will produce better impact assessment and forecasts because such models more appropriately represent the actual decision process (we plead guilty to this charge). There is a good basis for this line of thought, but researchers need to go beyond this argument. They need to develop clear validation criteria and demonstrate the value of activity-based methods in ways that are easily understood. (2)

Because the ABM development process for the Denver region has just begun, this paper focuses on the initial plans for the validation and sensitivity testing of the models.

DRCOG ACTIVITY-BASED MODEL APPROACH

The ABM approaches for the Denver region will be based on those used in other parts of the country, particularly the San Francisco Transportation Authority. Most of the components will be nested or multinomial logit (MNL) models, sensitive to person and household demographic variables and transportation level-of-service variables. Anticipated model components include:

- Synthetic population generator;
- Regular workplace location choice model for each worker;
- Regular school location choice model for each student;
- Household auto ownership choice model;
- Daily activity pattern choice model for each person-day;
- Number of tours choice model for each person day;
- Work-based sub-tour generation;
- Tour-level destination choice;
- Tour-level mode choice;
- Tour-level time-of-day choice;
- Trip-level destination choice;
- Trip-level mode choice (conditional on tour mode choice); and
- Trip-level time-of-day choice (conditional on time windows remaining after all previous choices).

Several components will be transferred or adapted from the existing four-step model for the region. Examples include the area-type and parking cost models, and traffic and transit assignment procedures.

DRCOG VALIDATION AND SENSITIVITY TESTING APPROACH

A plan describing the validation tests to be conducted for the ABM components and the overall model system has been developed with the specification of the ABM for the region. It includes the standards by which the tests will be evaluated, such as:

- Checks to ensure that the model component is producing the correct results (i.e., verification of computations);
- Comparisons of model parameters to comparable parameters in similar models in other areas;
- Disaggregate validation of all model components estimated using disaggregate methods and comparing the model outputs to the estimation data;
- Testing of each model's sensitivity to variables through controlled modification of those input variables;
- Comparisons of the model component outputs to the results from the survey data set; and
- Comparisons, where data are available, of the base year outputs from each model component to independent observed data (e.g., comparisons of mode choice model outputs to linked trips estimated from transit boarding counts).

The above tests are typical of model validation tests that have been recommended in documents such as the *Model Validation and Reasonableness Checking Manual (1)* and should be performed for all model development efforts.

Because there are more components in the proposed ABM than in a conventional trip-based model, there will be significantly more component testing. It will be important to design validation tests that are appropriate for each component. While some tests will be analogous to those performed for components of trip-based models, others will be different. Examples of similar tests include comparisons of modeled trip length frequencies with those from the household survey (tour lengths must also be compared) and comparisons of modeled and observed mode shares. Examples of tests to be performed without comparable trip-based tests include the number of trips per tour by purpose, amount of time spent in activities versus traveling on tours by purpose, and the number of activities performed by each person. The DRCOG model validation plan (3) provides a list of all tests to be performed.

One difficulty in performing the tests is the lack of experience to determine standards. For example, how close should the modeled number of activities per person be to the observed number? In some cases, established standards for trip-based models may be used to inform the choice of standards for the ABM. In other cases, the

acceptable error ranges will be determined by estimating the variation expected in aggregate model statistics (such as vehicle miles traveled [VMT]) resulting from the deviation on the particular model component, in effect tying new validation tests that as yet have no standards to existing tests that do have such standards.

Sensitivity testing will also play an important role in the validation of the ABM components. There are no established standards for reasonable elasticities for some of the newer model components, so this will be more of a reasonableness test than anything else. In such cases, it may not be possible to tie these tests to existing tests with standards already developed. In such cases, it may be possible to compare Denver model test outcomes with observed outcomes in other cities with conditions similar to those being evaluated in the sensitivity tests.

Significant effort will be placed on the validation of the overall model system. Again, this will be comparable to previously recommended validation procedures and will include the following:

- Reasonableness and logic checks of demographic and network data or skim data input to the models;
- Traditional validations for the model estimation year (1997) and for 2005 against independent observed data. Depending on data availability, these traditional checks will include:
 - Root-mean-square error of modeled to observed traffic volumes by appropriate segmentation variables (such as facility type, traffic volume level, and so forth)
 - Matching regional observed VMT within approximately 1% error
 - Matching observed VMT by facility type
 - Matching VMT by area type
 - Matching total transit boardings
 - Matching transit boardings by sub-mode
 - Rapid transit boardings by corridor, sub-mode, and station
 - Park and ride lot usage
 - Matching a series of at least 10 highway and transit screenline volumes
 - Highway volumes on individual freeways
 - Toll road usage
 - Acceptable matching of peak and off-peak speeds
 - Roadway speeds by several time-of-day periods (a.m. versus p.m. versus off-peak, and so forth); and
- Tests of the sensitivity of the overall model system to input variables (similar to the procedures used for the model component sensitivity testing).

The ABM will be subjected to the same validation standards that were used for the recently refreshed four-step model. Results are expected to be as good as or better than

those produced using the four-step model. While this may seem to be a rather lenient standard, it must be remembered that the four-step model was, in fact, calibrated to produce reasonable validation results for 1997 and 2001. One would expect that, because the ABM can consider more aspects of personal activity performance and travel behavior, the amount of “adjustment factoring” not tied to specific measurable behavior should be less in the ABM.

Another validation activity under consideration is “back-casting” to a prior year (besides the model estimation year of 1997). This will be done if the necessary data are available and the resources to perform the back-cast are available.

In addition to specifying traditional model validation standards, input and coordination with federal agencies will be sought in the validation and sensitivity testing of the ABM for the Denver region. This will be particularly important in the development of the ABM because operational experience with them is limited; federal agencies may be expected to evaluate them closely for validity and for consistency with the calibration outcomes of the numerous trip-based models in existence. DRCOG intends to involve federal agencies early in the process, through oversight panels or other means, and will include its requirements in the calibration and validation plan at the earliest point.

TEMPORAL AND POLICY SENSITIVITY TESTING

The normal validation testing outlined above includes some temporal validation in that the model will be validated against observed travel data for 1997 and 2005. Such testing is crucial for model validation but does not address the hypothesized true value of ABMs—the production of better impact assessment information and travel forecasts that will result from the more appropriate representation of the actual decision process.

Two approaches will be used to test the sensitivity of the ABM. The first will be the application of the ABM for an existing forecast year and scenario and comparison of those results to those produced by the calibrated four-step model. While the “true” results for such a forecast year cannot be known, the results from the four-step model provide one outcome that has been deemed reasonable. Several questions will be asked:

- How similar are the results? The traditional validation measures outlined in the previous section regarding traffic volumes and transit boardings can be used to measure the similarity.
- Which model produces more believable results? Two outcomes are possible: the forecasts from the two models are not substantially different or the forecasts are substantially different. In either case, an assessment will

need to be made whether or not the outcome is acceptable because either outcome, ultimately, will need to be supported by local decision makers.

The second approach for testing the ABM will be directed at assessing the desire to develop a model that is more sensitive to policy variables. The policy-oriented tests will include evaluation of

- Outcomes in designated transit-oriented development areas;
- Effects of different regional development densities (e.g., single-family housing versus multi-family, and so forth);
- Development in known industrial areas;
- Development of specific “greenfield” areas, to see how well the model can predict the spread of the urban area; and
- Outcomes in redevelopment areas.

The policy-oriented tests will be even more subjective than the comparison of forecasts from the ABM and the

traditional four-step model. To improve the usefulness of the tests, it will be important to reach a consensus regarding the expected outcome. If the outcome from the model does not match the expected outcome, the results will need to be assessed to determine whether they are illogical or providing valuable information that would modify the expected outcomes developed prior to running the model. As discussed above, the definition of reasonableness may be derived from observed conditions in other cities.

REFERENCES

1. *Model Validation and Reasonableness Checking Manual*. Travel Model Improvement Program, Federal Highway Administration, February 1997.
2. Bhat, C., and F. Koppelman. Travel Model Improvement Program e-mail, December 16, 2005.
3. Parsons Corporation and Cambridge Systematics, Inc. “Validation Plan for the DRCOG Activity-Based Model.” March 2006.

Validation and Assessment of Activity-Based Travel Demand Modeling Systems

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The past decade has seen the rapid development of activity- and tour-based travel demand modeling systems. Several metropolitan planning organizations (MPOs) in the United States and metro areas in Europe have implemented such systems to take advantage of the derived nature of travel demand and interdependencies among trips. Despite the appeal of these models, their widespread implementation appears to be hindered by the absence of a detailed validation and assessment of this new wave of model systems. Many MPOs will not adopt such models until they are tested. These sentiments were expressed 10 years ago in New Orleans at the Travel Model Improvement Program (TMIP) Conference on Activity-Based Travel Modeling and more recently in e-mail forums such as the TMIP Listserv. The conference in Austin will bring model developers and MPO staff together to discuss validating and assessing activity-based models.

VALIDATION OF ACTIVITY-BASED TRAVEL DEMAND MODELS

Validation of travel demand models involves the refinement and adjustment of model components to ensure that predictions replicate base-year travel conditions and statistics within an acceptable margin of error. There are numerous measures against which model predictions are often compared; these include vehicle miles of travel, vehicle hours of travel, mode split (by purpose), trip length distributions (by purpose), and total trips and trip rates (by purpose). These measures may be compared

across the study or model area and for specific planning districts or market areas. In addition, model-predicted volumes are often compared with observed ground counts for major corridors and across screenlines and cutlines. Thus, the traditional notion of model validation has centered on replication of observed base-year travel conditions within a margin of acceptable error. Existing four-step models that are in use to develop long-range transportation plans and undertake major investment studies have been subjected to such validation procedures to replicate base-year travel conditions.

Activity-based travel demand models, like trip-based models, could (and may have to) be adjusted so that they replicate base-year travel conditions. Otherwise, it is unlikely that MPOs will be motivated to make the transition to innovative model systems. Areas that have transitioned to tour-based or similar model systems have subjected their models to validation procedures to ensure that the model predictions replicate a host of base-year travel conditions.

If activity-based travel demand models are validated to base-year travel conditions (similar to existing four-step models), two questions arise:

1. Should activity-based travel demand models be held to a higher standard of validation?
2. Should activity-based travel demand models be able to replicate base-year travel conditions with fewer adjustments and refinements (or none at all) when compared with existing four-step models?

There are no easy answers. If MPOs are motivated to transition to the new wave of model systems only if activity-based models perform better than four-step travel models, then the more important question is: What constitutes a better model? If a better model is defined in terms of meeting a higher standard of validation with the same number of or fewer adjustments to model components and parameters, then it is likely that the answer to both questions is yes. Clearly, this is open to debate.

The debate also speaks to the merit of performing comparisons with four-step models. There is no doubt that any model can be adjusted, refined, tweaked, and—if all else fails—hammered to replicate base-year conditions. Thus, simply comparing models is not enough. This, the authors believe, is important because the state of the practice appears to be focused on using replication of base-year travel patterns as the sole or primary yardstick to assess models' performance. On the other hand, the primary objective of travel model development is forecasting future travel patterns when conditions may be quite different from base-year conditions or assessing travel pattern shifts after the implementation of a major change in transportation services or policies, not replicating base-year patterns. Thus, the emphasis needs to be on capturing travel behavior patterns adequately from base-year data, so that these behavioral patterns are transferable.

The above discussion raises the issue of assessing the performance, usefulness, and robustness of alternative travel demand modeling, without focusing on replicating base-year travel patterns. This issue is discussed next.

ASSESSMENT OF ACTIVITY-BASED TRAVEL DEMAND MODELS

The question of what constitutes a better model is open to debate. There is a belief that the superiority of a model is best judged in terms of the validation to base-year traffic conditions. However, given that any model can be adjusted to replicate a given set of base-year traffic conditions, such measures are not always useful.

The quality of a travel demand model system is better judged on its ability to respond to a range of scenarios and policies of interest. It is in this context that a true assessment can be performed and comparisons between existing four-step travel models and newer activity-based model systems become meaningful. Thus, assuming that there are two models—an existing four-step travel model and a newer activity-based travel model—that have been validated to a set of base-year traffic measures, here is how the performance, usefulness, applicability, and robustness of the model systems can be assessed and compared.

Changes in Land Use, Socioeconomic, and Demographic Characteristics

Travel demand models should be responsive to changes in land use, socioeconomic, and demographic characteristics (i.e., the inputs that play a key role in driving travel forecasts). Activity-based model systems should be subjected to sensitivity tests in which population and employment characteristics are altered, both across the region and in selected zones, land use subdivisions, or market areas. Characteristics that might be subjected to change include population and employment totals; household distributions by zone, income, car ownership, size, dwelling unit type, and number of children; employment distributions by zone and occupation, industry, and type; and person distributions by age, employment status, and gender. These variables should be subjected to a range of changes.

Changes in Multimodal Transport Network Characteristics

Travel demand models should be responsive to changes in transport network characteristics, which directly impact modal level of service attributes such as distance, time, and cost. There are a variety of ways in which these changes can be introduced. First, attributes associated with existing modal facilities may be changed. Attributes such as highway network speeds and transit route frequencies may be altered. Second, new facilities may be introduced. New highway links, new transit routes, new transit stops, new bicycle and pedestrian facilities, and so on may be introduced into the system. A consideration in determining the efficacy of a model is to examine the model's ability to quantify induced or suppressed travel demand that may occur because of the modal change.

Implementation of Transportation Policies

Travel demand models should be responsive to a range of contemporary and emerging transportation policies and issues. These include, but are not necessarily limited to,

- Pricing policies such as value pricing, variable (time of day) pricing, area-based congestion pricing, parking pricing, tolls, public transit fare policies (free fare zones, free intermodal transfers, and so forth), cash subsidies, fuel prices and taxes, and employer reimbursement schemes;
- Policies aimed at encouraging alternate mode use including HOV–HOT lanes, rideshare programs, mixed land use development, transit- and pedestrian-oriented

development, neo-traditional neighborhood development, and new transit, bicycle, and pedestrian facilities and services; and

- Alternative work and school arrangements such as satellite or home-based telecommuting, flexible work hours, and distance-learning classes.

Travel demand models should be able to provide quantifiable impact measures, by market segment, that address issues such as market equity, social exclusion, environmental justice, quality of life, and environmental (emissions) impacts of policy measures.

Some of the policies identified here can be reflected by adjusting a modal level-of-service variable associated with one or more facilities. For example, a new toll on a bridge can be reflected by imposing a cost on the specific highway links that represent the bridge. Other policies may be subtler and may not be as easy to capture or in a model. For example, how does one represent a flexible work hour policy to reflect its impacts on travel behavior? Potentially, activity-based travel demand models that include consideration of work constraints, flexibility and rigidity of different activities, and activity interdependencies would be able to accommodate the effects of a flex work hour policy.

Consideration of New Technologies

Technology is playing an increasingly bigger role in shaping human activity patterns, residential and work location choices, travel behavior, use of time, and freight logistics. The interactions between technology and travel behavior are closely intertwined with people's use of time. On the one hand, technology may substitute for travel while, on the other hand, technology may complement or lead to more (spontaneous) travel. Similarly, there are new transportation technologies including traveler information and guidance and navigation systems, intelligent transportation systems, and alternative fuel vehicle technologies that impact travel behavior. Travel demand models used for forecasting should reflect the telecommunications–travel behavior interaction.

Changes to Spatial and Temporal Resolution

Many implementations of tour-based model systems are based on the traditional zone-based spatial representation of a region and discrete time-of-day periods. Until models move toward a truly continuous representation of the space–time domain (which is happening at a rapid pace in R&D), the rather discrete representation of space and time is likely to continue. In such case, it would be

desirable to have a model system that is reasonably robust to changes in spatial and temporal resolution. It is possible that zone systems will be altered, zones will be split, and zones will be added. In general, a travel demand model should be aspatial and thus unaffected by the definition of the zonal system. If additional time-of-day periods are desired, it should be easy to re-estimate and recalibrate the components of the model system affected by the re-definition of time periods.

Accommodation of Emerging Behavioral Paradigms and Concepts

There is literature documenting behavioral phenomena inadequately captured by traditional travel demand modeling paradigms. Despite concern about the lack of a sound behavioral theory driving or underlying innovative model development, there is a growing body of work that is helping to identify behavioral paradigms and concepts that ought to be incorporated into models of activity and travel demand. While one may debate the need to accommodate these concepts, the profession must move toward recognizing established behavioral relationships, if only to make the models more defensible and explicable. Some concepts include the following:

- Interdependencies and interactions: There are interdependencies and interactions that are key to activity–travel demand modeling. These include modal, temporal, and spatial (location) interdependencies among trips in a chain and among chains in a daily activity–travel pattern, interdependencies in activity engagement across days and weeks, interactions among household members, and residence–work–school location interdependency.

- Constraints and flexibility: There is much to be learned about constraints and flexibility associated with various activities and their attributes; much has been discovered as well. There are many constraints that play a key role in shaping activity–travel patterns, including modal, situational, institutional, household (obligatory), and personal constraints.

- Positive utility of travel: There is some evidence that suggests that travel is not purely a disutility that is minimized by individuals. A model system that could accommodate alternative utilitarian paradigms might be able to capture the situations in which travel, by itself, offers a positive utility.

- Time use and activity patterns: Travel demand is inextricably tied to the demand for pursuing activities that are distributed in time and space and the time available to pursue them. Thus, time use and activity analysis play an important role in modeling travel demand. His-

tory dependency in time allocation and activity participation, in-home versus out-of-home activity substitution and generation, induced demand, and travel efficiency (say, through chaining of trips) are but a few of the concepts that merit recognition.

- Behavioral processes and decision rules: Recent work in activity-travel modeling has focused on the behavioral processes and decision-making rules that people employ when scheduling and executing activities and trips. Rule-based heuristics, in addition to random utility theory-based models, are being incorporated into models to reflect these behavioral processes in microsimulation frameworks. Understanding behavioral processes is key to developing robust model structures, specifications, and forms.

Comparisons Between Model Systems

The discussion so far has dwelled on how one might assess the performance of an activity-based travel demand model system. However, the following questions remain:

1. How does one know or determine whether the activity-based travel demand model is giving the right answer or level of sensitivity for a particular scenario?
2. In comparing the outputs (in response to a scenario analysis) between an existing four-step travel demand model and an activity-based travel demand model, how does one know or determine which one is right or more accurate (in cases in which it is not obvious)?

CONCLUSIONS AND CONTENT OF PRESENTATION

This white paper raises important questions regarding the potential adoption of new and innovative activity-based travel demand modeling systems in practice. The proposed presentation serves to deliver the following

information with a view to stimulate discussion among conference participants on how best to validate and assess activity-based model systems vis-à-vis existing four-step models:

1. *Model validation guidelines* for activity-based travel demand models including information on what base-year traffic conditions activity-based travel demand models should replicate, the margins of error that are acceptable, and the extent to which adjustments of model components and parameters are acceptable;

2. *Model assessment guidelines* for activity-based travel demand models including the range-of-sensitivity tests, policy measures, land use scenarios, and technologies to which the activity-based models should be subjected, the model outputs that should be examined, and the acceptable ranges of responses in model outputs;

3. *Model comparison guidelines* for comparing activity-based travel demand models with existing four-step travel demand models including the development and presentation of a *comprehensive matrix* that clearly shows how and where four-step models, tour-based models, and activity-based microsimulation models are applicable to addressing a range of issues; and

4. *The design of comprehensive experiment(s)* for performing controlled comparisons of activity-based travel model outputs and existing four-step travel model outputs. A variety of scenarios have played out in the real world, thus providing real-world data against which model predictions can be assessed. Both activity-based and existing four-step travel models can be applied to these situations and the outputs can be assessed against real-world observational data.

The presentation will also include results of model validation and assessment exercises that have been undertaken using the Florida Activity Mobility Simulator and Comprehensive Econometric Microsimulator of Daily Activity Patterns to illustrate how the guidelines presented can be used to assess and validate activity-based travel demand models.

Modeling of Peak Hour Spreading with a Disaggregate Tour-Based Model

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Over the last decade in all metropolitan areas, growing peak period congestion has been accompanied by increased demand from the peak hour into the shoulder hours of the peak period. Conventional forecasting models generally adopt static diurnal factors and do not model time-of-day (TOD) choice, and are generally not well formulated to extend their capabilities to model travel by hour of day as a function of level of service and other factors, including simulation of peak hour spreading. As a disaggregate tour-based model, the Mid-Ohio Regional Planning Commission (MORPC) travel forecasting system fully incorporates a TOD choice model for a 19-h average weekday. Because the TOD model is sensitive to travel times, peak hour spreading as the consequence of increased levels of peak period congestion should be evident in the model's application. This paper explores this aspect of the MORPC tour-based model in application, comparing observed traffic data with the simulated hourly demand results from a series of tests of the model. (References 1–11 refer to TOD modeling and the Columbus tour-based model.)

MORPC TIME-OF-DAY MODEL

In October 2001, MORPC contracted PB Consult to develop a set of regional travel forecasting models. It developed a disaggregate tour-based model applied with the microsimulation of each individual household, person, or tour, mostly using Monte Carlo realization of each possibility estimated by the models, with a random number series to determine which possibility is chosen for that record.

The set consists of nine models that are linked and applied sequentially. They are: population synthesis, auto ownership, daily activity pattern (mandatory tour generation), joint tour generation, individual non-mandatory tour generation, tour destination choice, TOD choice, tour mode choice, and stops and trip mode choice.

The tour destination, TOD, and tour mode choices' models are logit based and applied together. The "Log-Sum" composite impedance measure from the mode choice model is available to the other choice models, making them sensitive to changes in travel times due to congestion. The TOD model is based on the "time windows" concept, accounting for use of a person's time budget over the day (16 h available per person). These models are applied at the tour level, yielding the primary destination, TOD, and mode choice for the entire tour, and consider both the outbound and inbound portions.

The TOD model is a hybrid discrete choice departure time and duration model, with a temporal resolution of 1 h for the modeled period between 5:00 a.m. and 11:00 p.m. All tour departures before 5:00 a.m. were shifted to the 5:00 a.m. hour, and all tour arrivals after 11:00 p.m. were shifted to 11:00 p.m. The TOD model is applied sequentially among tours, with mandatory (work, university, and school) tours scheduled first. The model determines the departure time of each tour and the duration of the activity associated with the tour. Therefore, the 190 departure and arrival time combinations can be applied with relatively few variables. As a result of this time-windows constrained formulation, the timing of the departure and arrival times on both legs of the tour

is determined both by the duration of the activities and by the travel times to and from them. See Vovsha and Bradley (1).

STATUS OF THE TIME-OF-DAY MODEL VALIDATION

In the development of the MORPC TOD model, a disaggregate validation was achieved using the Home Interview Survey (HIS) data records. The MORPC validation report shows the results for the TOD model versus the observed values from the HIS, which, as expected, match. The TOD model, however, has not yet been fully validated against external data. MORPC does not have a sufficient number of traffic counts by peak hour or peak period to validate either the hour-grained TOD model or the period-level traffic assignments. To date, only the 24-h traffic and transit assignments have been validated (with respect to counts) and used for official planning purposes. The hour-level detail in the MORPC microsimulation results is aggregated to four general time periods (3-h a.m. and p.m. peaks, midday, and night-early morning) for highway and transit network loading. The hourly detail, however, is available in the final simulated tour-record-level disaggregate output.

TIME-OF-DAY COMPARISON BETWEEN THE TIME-OF-DAY MODEL AND TRAFFIC COUNTS

The Ohio Department of Transportation (ODOT) collects traffic monitoring data for Interstate, U.S., and state routes in the state of Ohio. Traffic monitoring data include vehicle volume, vehicle classification, and weigh-

in-motion. Data are collected using manual, portable (road tube), and permanent automatic traffic recorders and intelligent transportation systems methods. Traffic count data are published by hour and vehicle type by functional class on a statewide basis (12).

Table 1 shows the percent of half tours (departures and arrivals) and trips from the model and the percent of passenger vehicle traffic by hour of day for the base year 2000. As noted earlier, the model schedules tours between 5:00 a.m. and 11:00 p.m. Therefore, those hours account for traffic between midnight and 5:00 a.m., and are not directly comparable with the traffic count data. The traffic data by functional class are accumulated on a statewide basis; as such, the summary tables may not be as representative as data solely from the Columbus region. To calculate the average, the share by functional class was weighted by vehicle-miles-traveled share, as reported in the Highway Performance Monitoring System.

Although number of tours or trips cannot be compared directly with traffic counts, several observations can be garnered. As seen from Table 1, the model is showing more tours starting or concluding in the a.m. peak hour and period than the p.m. peak hour and period. This can be partly explained by the model simulating an average weekday, as opposed to an average day. Furthermore, because both the HIS and the model show that people are more likely to make a stop on the inbound half of the tour, the trips are more balanced to the p.m. peak than the half tours. However, part of the apparent underestimation may be explained from the underreporting of nonmandatory tours in the HIS. While the model has been calibrated to take the underreporting into account, it is possible that some tours are still being missed.

TABLE 1 Percent of Tours, Trips, and Passenger Vehicle Traffic by Hour of Day, Base Year 2000

Hour	MORPC Model (%)		Average	Traffic Counts by Functional Class Total Urban Areas Statewide (%)				
	Half Tours	Trips		11	12	14	16	17
5	2.1	1.9	1.8	1.9	2.4	1.7	1.6	1.4
6	2.7	2.6	4.6	5.2	5.5	3.9	3.8	3.7
7	8.1	7.7	6.9	7.7	7.2	6.0	6.0	5.9
8	9.0	8.5	5.6	6.1	5.6	5.2	5.2	5.2
9	5.8	5.5	4.7	4.8	4.5	4.8	4.6	4.6
10	4.4	4.4	4.7	4.4	4.8	5.1	4.8	4.8
11	4.3	4.4	5.3	4.8	5.1	5.9	5.8	5.8
12	4.6	4.6	5.7	5.3	5.3	6.2	6.2	6.3
13	5.3	5.4	5.8	5.7	5.4	6.0	5.9	6.0
14	5.3	5.2	6.4	6.4	6.1	6.5	6.5	6.7
15	6.4	6.1	7.6	7.7	7.5	7.5	7.6	7.9
16	7.5	7.4	8.1	8.2	8.2	7.8	8.1	8.2
17	7.0	7.3	8.2	8.3	8.3	7.9	8.2	8.3
18	6.7	7.1	6.2	6.1	6.0	6.2	6.5	6.5
19	5.5	5.7	4.6	4.2	4.3	4.9	5.1	5.1
20	4.4	4.5	3.8	3.5	3.6	4.1	4.3	4.3
21	4.5	4.7	3.2	3.0	3.1	3.4	3.5	3.3
22	3.2	3.4	2.3	2.2	2.4	2.3	2.4	2.3
23	3.4	3.7	1.6	1.5	1.8	1.6	1.5	1.5
Total	100.0	100.0	97.3	97.2	97.1	97.1	97.6	97.8

The formulation of the model also affects the TOD distribution obtained. The MORPC models are structured and applied in an ordered manner determined by a hierarchy of tour purposes. A tour activity lower in the hierarchy is not permitted to start until all tours with higher priority are scheduled. Therefore, if a person has both a joint eating-out tour and an individual shopping tour, that person is required to complete the joint tour before the shopping tour can be scheduled. Consequently, the scheduling of the shopping tour is dependent on the available time windows for the other parties in the joint tour. As Vovsha and Bradley (1) mention, there is a dearth of information regarding travel prioritization. Given that deficit of information, this is probably the best we can expect this model to perform at this time. In addition to travel prioritization, the temporal granularity of the TOD model means there is a constraint of only one half tour per hour. Therefore, if a person arrives home from work at 5:15 p.m., that person is not permitted to start another tour until 6:00 p.m. However, this definition only affected 1% of the cases from the HIS and is probably not a major issue (1).

PEAK HOUR SPREADING

Over the last decade or more, as congestion has increased in urban transportation networks such as those in Ohio, peak traffic levels have grown to increasingly extend

beyond the peak hour to the shoulder hours of the peak period. Table 1 shows that the peak hour in Ohio’s urban areas is 5:00 to 6:00 p.m. and the peak 3-h period is 5:00 to 8:00 p.m. Despite the lack of direct comparability of the measures in this table, it is apparent that the model is not simulating the same p.m. peak period as is seen in the statewide urban area traffic counts, and may also be somewhat skewed with respect to diurnal patterns in the Columbus region. The p.m. peak 3 h in the 2000 model run are between 4:00 and 7:00 p.m. This could be a consequence of various and imperfect temporal definitions of travel in both the model and the count data, as mentioned above.

Table 2 shows the time series count data available for Ohio’s urban areas and the share of traffic in the peak hour of the peak period by functional class. Also shown is the general trend of that share.

As seen in this table, the peak hour share of peak period traffic is trending toward a fully flat 3-h peak period, approaching a one-third share, with declines on the freeways and major arterials to other hours and to lower-class facilities. This phenomenon is impossible to simulate with static diurnal factors, and difficult to model in an aggregate travel forecasting model.

Because the MORPC disaggregate tour-based TOD model simulates tour durations and incorporates the feedback of travel skims, the model accounts for peak spreading as a result of travel time changes due to congestion. Table 3 shows the number of half tours and trips by hour of the modeled day for both 2000 and 2030. Note that

TABLE 2 Share of Traffic During the P.M. Peak Hour: Ohio Urban Areas

Functional Class	1997 (%)	1999 (%)	2000 (%)	2001 (%)	2002 (%)	2003 (%)	2004 (%)	Trend (%)
11	34.2	35.7	34.3	36.4	35.1	34.9	34.1	-0.015
12	34.9	32.2	34.6	35.5	34.2	34.2	33.8	-0.012
14	34.2	33.6	34.0	33.6	33.4	33.3	34.1	-0.054
16	32.9	34.6	34.5	34.0	34.1	34.1	34.1	0.097
17	N/A	34.4	34.0	35.0	33.6	34.1	34.8	0.011

TABLE 3 MORPC Model: Tours and Trips by Hour of Day, 2000 and 2030

Hour	2000				2030			
	Half Tours	% of Total	Trips	% of Total	Half Tours	% of Total	Trips	% of Total
5	86,111	2.08	110,240	1.95	133,320	2.22	165,170	2.07
6	112,980	2.72	145,468	2.57	179,695	3.00	224,773	2.81
7	336,104	8.10	435,320	7.68	497,961	8.31	636,165	7.95
8	374,728	9.04	480,570	8.48	534,396	8.91	676,048	8.45
9	239,492	5.77	312,174	5.51	331,749	5.53	424,625	5.31
10	181,222	4.37	249,196	4.40	252,912	4.22	336,512	4.21
11	180,142	4.34	246,680	4.35	254,557	4.25	337,227	4.22
12	189,910	4.58	258,258	4.56	272,788	4.55	360,854	4.51
13	221,694	5.35	303,500	5.36	320,789	5.35	426,945	5.34
14	218,487	5.27	295,771	5.22	307,827	5.14	406,733	5.09
15	266,148	6.42	347,570	6.14	359,270	5.99	461,114	5.77
16	309,215	7.46	420,063	7.42	429,524	7.17	574,106	7.18
17	288,419	6.95	415,649	7.34	430,805	7.19	605,927	7.58
18	276,453	6.67	399,523	7.05	418,370	6.98	590,080	7.38
19	227,278	5.48	320,808	5.66	329,388	5.49	451,780	5.65
20	180,435	4.35	256,601	4.53	262,833	4.39	363,319	4.54
21	185,671	4.48	264,169	4.66	268,817	4.48	370,925	4.64
22	133,058	3.21	195,234	3.45	199,684	3.33	283,582	3.55
23	139,771	3.37	208,019	3.67	209,693	3.50	301,945	3.78

trips are segments of tours broken by model stops, and are the units of demand that are aggregated to zone-to-zone trip tables for use in the highway and transit assignments.

The hourly base year and forecast distributions of modeled tours for 2000 and 2030 traffic are shown in Table 4. One important finding is that the model responds to the growth in demand over time and the concomitant increases in congestion by spreading the peak hour demand as expected. The 2030 tour arrival times are later in the day than are modeled for 2000. Also, while 4:00 p.m. is the definitive peak hour in 2000, 4:00 and 5:00 p.m. carry almost the same proportion of tours in 2030, showing that the demand is neither fixed or diminished, but is shifted to utilize capacity in other hours of the day with higher level of service.

So while the alignment of the simulated peaking patterns in the base year may be somewhat skewed compared with the best available counts, the tour-based nature of the MORPC model supports a TOD model that forecasts a reasonable response to growth in congestion—a desirable feature that would be difficult to implement within the platform of a conventional model.

FUTURE RESEARCH AND POTENTIAL APPLICATIONS

As noted above, more data need to be developed and applied before it can be determined if all of the explicit TOD information that is produced by the disaggregate MORPC travel model can be validated and used in practice for planning and policy analysis. Very few external data exist with which to validate the TOD component other than traffic counts, and unfortunately traffic counts and tours are not directly comparable. If more hourly traffic counts were collected and the trip tables were generated and assigned on an hourly basis, the model could be further calibrated and eventually validated.

Eventually, the output of the disaggregate tour-based MORPC model could be exported to dynamic traffic assignment procedures, used in refining the application of matrix estimation results to future demand matrices, and in the development of design hour traffic. As shown in this specific exploration of the MORPC TOD model, it can already be used to provide an estimate of peak spreading for planning studies.

TABLE 4 MORPC Model: Hourly Shares of Half Tours and Trips in the P.M. Peak Period

Hour	2000		2030	
	% Tours	% Trips	% Tours	% Trips
16	35.38	34.01	33.59	34.23
17	33.00	33.65	33.69	34.23
18	31.63	32.34	32.72	33.34

REFERENCES

1. Vovsha, P., and M. Bradley. A Hybrid Discrete Choice Departure Time and Duration Model for Scheduling Travel Tours. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1894, Transportation Research Board of the National Academies, Washington, D.C., 2004.
2. Hounsell, N.B. Understanding the Effects of Congestion: Peak Spreading and Congestions. *Transportation Planning Systems*, Vol. 1, No. 3, 1991, pp. 39–46.
3. Allen, W.G. An Analysis of Corridor Traffic Peaking. In *Transportation Research Record 1305*, TRB, National Research Council, Washington, D.C., 1991, pp. 50–60.
4. Purvis, C. *Peak Spreading Models: Promises and Limitations*. TRB, National Research Council, Washington, D.C., 2002.
5. Cambridge Systematics, Inc. "Time-of-Day Modeling Procedures: State-of-the-Art, State-of-the-Practice." DOT-T-99-01. US Department of Transportation, Washington, D.C., 1999.
6. Bhat, C., and J. Steed. A Continuous-Time Model of Departure Time Choice for Urban Shopping Trips. *Transportation Research Part B: Methodological*, Vol. 36, No. 3, 2002, pp. 207–224.
7. Bhat, C. "Duration Modeling: A Methodological Review with Applications in Activity-Travel Analysis." Paper presented at 80th Annual Meeting of the Transportation Research Board, Washington, D.C., 2001.
8. Vovsha, P., E. Petersen, and R. Donnelly. Explicit Modeling of Joint Travel by Household Members: Statistical Evidence and Applied Approach. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1831, Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 1–10.
9. Vovsha P., E. Petersen, and R. Donnelly. Experience, Tendencies, and New Dimensions in the Application of Activity-Based Demand Modeling Systems for Metropolitan Planning Organizations in the United States. Paper presented at 10th International Conference on Travel Behavior Research, Lucerne, Switzerland, 2003.
10. Time-of-Day Choice Model. Technical Memorandum. MORPC Model Improvement Project. PB Consult. (2003). Available by request from the authors.
11. Anderson, R, A. Al-Akhras, N. Gill, and R. Donnelly. Implementation of a Tour-Based Microsimulation Regional Travel Demand Model. In *Ninth TRB Conference on the Application of Transportation Planning Methods* (CD-ROM), Transportation Research Board of the National Academies, Washington, D.C. 2004.
12. Ohio Department of Transportation. *Hourly Percent by Vehicle Type*, 1997–2004.

Mid-Ohio Regional Planning Commission Model Validation Summary

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The new Mid-Ohio Regional Planning Commission (MORPC) model is a disaggregate tour-based model applied with the microsimulation of each individual household, person, or tour. The model area is divided into 1,805 internal and 72 external zones and includes Franklin, Delaware, and Licking counties, and parts of Fairfield, Pickaway, Madison, and Union counties. The primary inputs to the model are transportation networks and zonal data, in which each zone has the standard socioeconomic characteristics that would normally be found in a four-step model. The main differences from the prior four-step model are that the new model accounts for travel at the tour level, as opposed to the trip level, and for each individual household and person, as opposed to zonal and market segment aggregates. This summary shows the highway validation statistics, including some of the standard reports as suggested in the *Ohio Department of Transportation Traffic Assignment Procedures*. It also shows the validation of the work purpose travel distribution compared with the Census Transportation Planning Package.

Travel distribution is one of the most difficult aspects of travel demand to model effectively. As a part of the North Corridor Transit Project, the travel distribution was reviewed with an emphasis on the North Corridor. To explore the reliability of the work component of the distribution model, the simulated year 2000 work-tour distribution was compared with the 2000 Census Transportation Planning Package (CTPP), which captures work journeys. The first step

was to compare the regionwide magnitude of modeled work trip tours with CTPP. On a regionwide basis, the model estimates 660,031 work tours compared with 630,550 CTPP records—a difference of only 4.7%. Next, district-to-district tours were compared with the CTPP (scaled so that regional CTPP records match modeled journeys). Figure 1 shows the districts used for analysis purposes. The modeled work-tour distribution is shown in Table 1. The CTPP journey distribution is shown in Table 2. Table 3 displays the ratio of the modeled to the observed distribution.

Overall, the modeled trip distribution for work purposes appears to be as good as or better than comparable models used elsewhere in the United States. The model is representing trips to the central business district (CBD) very closely, within 1% regionally. Work

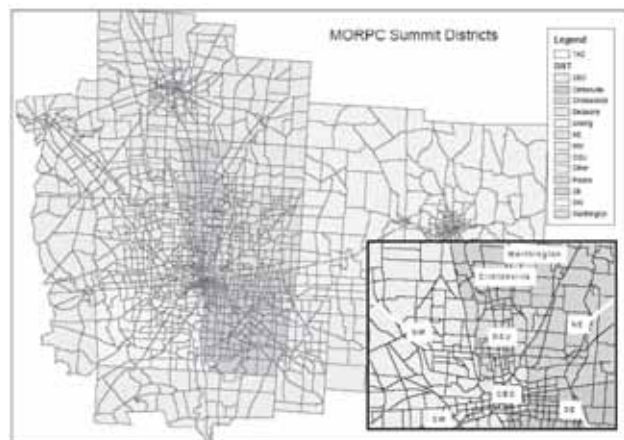


FIGURE 1 Districts used for analysis.

TABLE 1 2000 Modeled Work Tours

District	1	2	3	4	5	6
1 - CBD	277	154	47	34	53	7
2 - OSU	3,646	3,586	1,270	1,077	1,138	200
3 - Clintonville	3,706	2,565	1,612	1,447	1,686	233
4 - Worthington	4,085	1,903	1,434	2,557	3,575	536
5 - Crosswoods	3,197	1,534	1,228	2,086	5,144	1,094
6 - Polaris	625	294	216	382	1,235	464
Corridor Total	15,536	10,036	5,807	7,583	12,831	2,534
7 - Delaware	2,820	1,241	831	1,565	4,431	1,851
8 - NW	15,631	8,178	4,407	3,957	7,360	1,467
9 - NE	11,676	5,134	2,846	4,207	6,472	1,148
10 - SE	17,249	6,414	1,972	1,981	2,496	391
11 - SW	7,265	4,542	1,182	1,025	1,230	234
12 - Licking	2,645	811	407	721	1,094	253
13 - Other	4,877	1,570	615	585	1,173	263
Noncorridor Total	62,163	27,890	12,260	14,041	24,256	5,607
Regional Total	77,699	37,926	18,067	21,624	37,087	8,141

TABLE 2 CTPP 2000 Journeys (Scaled to Modeled Work Tours)

District	1	2	3	4	5	6
1 - CBD	535	243	33	33	47	7
2 - OSU	4,006	6,094	833	1,030	1,023	127
3 - Clintonville	3,609	2,509	2,256	1,120	1,517	311
4 - Worthington	3,761	2,509	1,380	3,745	3,499	505
5 - Crosswoods	3,730	1,633	1,051	1,733	6,194	1,192
6 - Polaris	698	321	240	312	995	995
Corridor Total	16,341	13,801	5,793	7,982	13,275	3,137
7 - Delaware	3,318	1,524	844	1,012	3,887	2,948
8 - NW	16,883	9,268	3,567	2,517	6,983	1,469
9 - NE	11,278	3,910	1,849	3,469	6,704	1,253
10 - SE	16,179	4,264	1,495	1,948	3,585	477
11 - SW	7,637	2,338	1,104	950	2,191	315
12 - Licking	2,437	667	310	642	1,429	268
13 - Other	4,594	1,221	524	621	1,395	283
Noncorridor Total	62,364	23,192	9,693	11,159	26,174	7,012
Regional Total	78,704	36,993	15,486	19,141	39,449	10,149

TABLE 3 Ratio of Model over Scaled CTPP

District	1	2	3	4	5	6
1 - CBD	0.52	0.63	1.40	1.02	1.13	0.96
2 - OSU	0.91	0.59	1.52	1.05	1.11	1.58
3 - Clintonville	1.03	0.85	0.71	1.28	1.11	0.75
4 - Worthington	1.09	0.76	1.04	0.68	1.02	1.06
5 - Crosswoods	0.86	0.94	1.17	1.20	0.83	0.92
6 - Polaris	0.90	0.91	0.90	1.22	1.24	0.47
Corridor Total	0.95	0.73	1.00	0.95	0.97	0.81
7 - Delaware	0.85	0.81	0.96	1.55	1.14	0.63
8 - NW	0.93	0.88	1.24	1.57	1.05	1.00
9 - NE	1.04	1.31	1.54	1.21	0.97	0.92
10 - SE	1.07	1.94	1.32	1.02	0.70	0.82
11 - SW	0.95	1.94	1.07	1.08	0.56	0.74
12 - Licking	1.09	1.22	1.31	1.12	0.77	0.94
13 - Other	1.06	1.29	1.17	0.94	0.84	0.93
Noncorridor Total	1.00	1.20	1.26	1.26	0.93	0.80
Regional Total	0.99	1.03	1.17	1.13	0.94	0.80

7	8	9	10	11	12	13	Total
8	388	167	293	170	5	12	1,565
270	5,846	3,061	2,752	1,854	48	165	24,913
418	5,346	3,281	1,966	1,851	65	165	23,650
929	5,621	5,278	1,842	983	141	213	29,097
1,597	5,883	4,940	1,498	826	178	293	29,498
830	1,478	963	285	146	42	120	7,080
4,052	24,512	17,690	8,636	5,160	479	947	115,803
12,350	7,650	5,210	1,613	865	630	1,634	42,692
3,150	49,480	8,067	6,606	8,857	212	2,895	120,267
2,423	10,431	22,156	10,979	3,146	1,444	906	82,968
705	12,093	17,788	36,222	8,876	1,485	3,228	110,900
436	20,153	4,420	9,439	14,984	113	1,923	66,946
1,202	1,781	6,342	5,713	822	46,456	1,606	69,853
1,536	7,709	4,166	10,641	3,476	2,830	11,161	50,602
21,802	109,297	68,149	81,213	41,056	53,170	23,354	544,228
25,854	133,809	85,839	89,849	46,186	53,649	24,301	660,031

7	8	9	10	11	12	13	Total
15	335	182	195	88	15	24	1,752
296	4,887	2,755	1,778	926	174	104	24,036
416	4,201	2,827	1,695	816	94	99	21,969
542	5,125	4,760	2,107	963	244	182	29,322
1,083	5,255	5,280	1,792	859	210	130	30,142
934	1,340	794	350	170	16	58	7,223
3,286	21,142	16,598	7,917	3,823	753	597	114,444
13,648	6,970	5,695	1,907	789	385	860	43,788
2,256	55,319	8,268	7,483	7,429	561	1,787	123,790
1,925	10,901	29,014	9,764	2,769	1,255	530	84,620
902	14,371	19,233	35,442	7,513	1,340	1,867	108,616
390	19,977	4,790	7,996	18,272	316	1,049	67,365
722	3,111	7,698	5,144	1,010	39,761	716	63,914
574	8,767	5,521	9,164	3,425	1,539	15,868	53,494
20,417	119,416	80,219	76,901	41,207	45,157	22,677	545,587
23,703	140,558	96,817	84,817	45,029	45,910	23,274	660,031

7	8	9	10	11	12	13	Total
0.55	1.01	0.92	1.50	1.93	N/A	0.50	0.89
0.91	1.20	1.11	1.55	2.00	0.28	1.59	1.04
1.01	1.27	1.16	1.16	1.45	0.69	1.45	1.08
1.71	1.10	1.11	0.87	1.02	0.58	1.17	0.99
1.47	1.12	0.94	0.84	0.96	0.85	2.26	0.98
0.89	1.10	1.21	0.82	0.86	2.67	2.08	0.98
1.23	1.16	1.07	1.09	1.35	0.64	1.59	1.01
0.90	1.10	0.91	0.85	1.10	1.64	1.90	0.97
1.40	0.89	0.98	0.88	1.19	0.38	1.62	0.97
1.26	0.96	0.76	1.12	1.14	1.15	1.71	0.98
0.78	0.84	0.92	1.02	1.18	1.11	1.73	1.02
1.12	1.01	0.92	1.18	0.82	0.36	1.83	0.99
1.66	0.57	0.82	1.11	0.81	1.17	2.24	1.09
2.68	0.88	0.75	1.16	1.01	1.84	0.70	0.95
1.07	0.92	0.85	1.06	1.00	1.18	1.03	1.00
1.09	0.95	0.89	1.06	1.03	1.17	1.04	1.00

trips from within the North Corridor to the CBD are underrepresented by 5%. Regionally, the model is over-representing trips to Ohio State University (OSU) by just 3%. There are specific travel markets that are weak, including a 27% underestimation of tours from the North Corridor to OSU. Work-tour productions and attractions are well estimated by the model. Almost all markets are represented within 10% of the CTPP totals.

Figure 2 shows the modeled travel analysis zones with work-tour destinations in the CBD. Figure 3 shows the same for census blocks from the CTPP. While the zones don't match one-to-one, patterns are reflected fairly accurately. The near northwest and the second ring east are two high-income suburbs that are reflected in both maps. The area around the southern circle is OSU, and the small size of the zones in that area potentially obscures the correlation there (also note the above discussion). The model smooths the employment in the

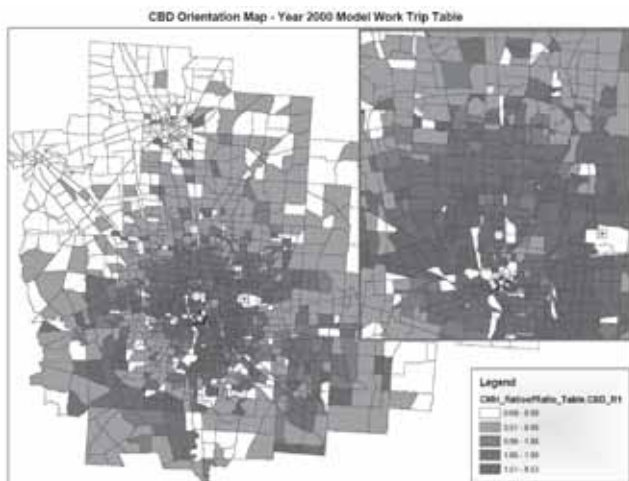


FIGURE 2 2000 model work trips to CBD.

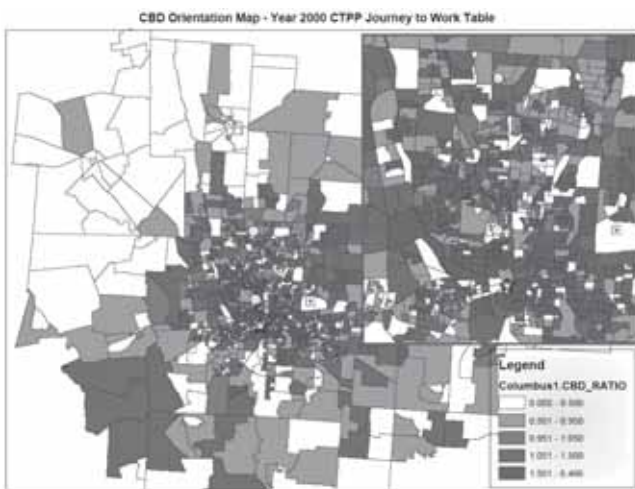


FIGURE 3 2000 CTPP work trips to CBD.

near northeast more than is shown from the CTPP. The far southwest shows a high amount of CBD-oriented workers, while eastern Delaware County shows a fair number of CBD-oriented workers.

HIGHWAY ASSIGNMENT VALIDATION

Model validation refers to the comparison of estimated and observed individual highway link loadings and transit route boardings. The purpose of model validation is to gauge how accurately the model predicts observed base-year travel patterns and to identify potential model shortcomings. The MORPC model was validated against traffic counts that have been processed to represent directional average annual daily traffic for the year 2000. The criteria used to assess the adequacy of the model validation were: percent vehicle miles traveled (VMT) error, percent VMT root-mean-square error (RMSE), and percent volume RMSE, by facility type and volume group. Highway assignment validation was geographically structured by districting schemes—rings, sectors, and super districts.

The validation by volume group is shown in Figure 4 and Table 4. All volume groups, except 0–500, fall below the maximum allowable percent RMSE. (Maximum Allowable %RMSE per ODOT Traffic Assignment Procedures, page 30.)

Table 5 shows validation statistics by facility type. Total VMT is within 1% of the observed data, and total volume is within 2% of the observed volumes.

With respect to the geographic districts as shown in Figure 5, the results demonstrate a validated model with respect to observed counts by each of the three districting schemes—concentric rings, radial sectors, and super districts.

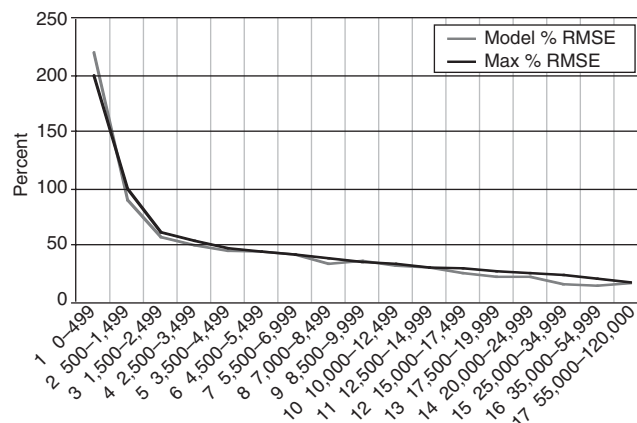


FIGURE 4 % RMSE by volume group.

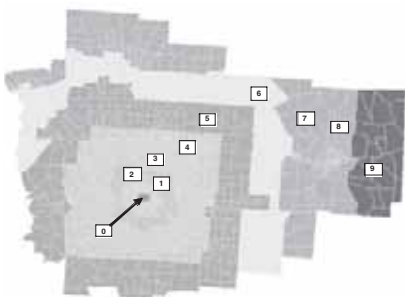
TABLE 4 % RMSE by Volume Group

Volume (Count) Group	Model % RMSE	Max % RMSE	Volume (Count) Group	Model % RMSE	Max % RMSE
1 0-499	220	200	10 10000-12,499	32	34
2 500-1,499	90	100	11 12,500-14,999	30	31
3 1,500-2,499	58	62	12 15,000-17,499	26	28
4 2,500-3,499	50	54	13 17,500-19,999	23	28
5 3,500-4,499	45	48	14 20,000-24,999	23	26
6 4,500-5,499	44	45	15 25,000-34,999	16	24
7 5,500-6,999	42	42	16 35,000-54,999	15	21
8 7,000-8,499	34	39	17 55,000-120,000	17	18
0 8,500-9,999	36	36	Total	40	40

TABLE 5 Counts Versus Model Volume Validation, by Facility Type

FACTYPE	# Links	Observed Traffic		Modeled Traffic		Percent Difference		Max % VMT	% RMSE
		Count	Count VMT	Volume	Model VMT	Volume	VMT		
1 Interstate	144	6,776,143	7,093,162	6,993,800	7,060,835	3	0	7	17
2 Major Arterial	200	3,405,379	2,227,072	3,547,900	2,339,286	4	5	10	22
3 Minor Arterial	843	9,462,496	2,431,483	10,160,500	2,533,349	7	4	10	31
4 Major Collector	1,962	12,341,296	3,743,390	12,031,545	3,485,721	-3	-7	15	31
5 Minor Collector	1,012	3,137,166	1,111,915	2,816,063	990,219	-10	-11	15	55
6 Local	1,050	1,228,257	518,832	1,044,427	464,712	-15	-11	15	93
Total	5,209	36,350,737	17,125,853	36,591,235	16,873,623	1	-1.5	3	40

Rings

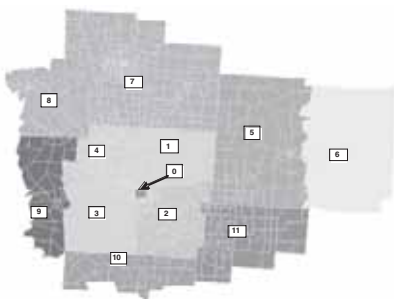


- 0 "CBD"
- 1 "Ring 1"
- 2 "Ring 2"
- 3 "Ring 3"
- 4 "Ring 4"
- 5 "Ring 5"
- 6 "Ring 6"
- 7 "Ring 7"
- 8 "Ring 8"
- 9 "Ring 9"

Min. # of Obs.
5

# Links	Count-Based	Model	# Diff	% Diff	% RMSE
144	11,551	13,249	1,698	15%	34%
581	8,699	10,181	1,482	17%	49%
587	8,850	9,223	374	4%	37%
1,182	9,640	9,119	-521	-5%	32%
987	6,193	5,926	-266	-4%	39%
678	4,273	4,185	-87	-2%	38%
462	4,184	3,983	-201	-5%	40%
271	2,404	2,345	-59	-2%	38%
265	5,038	4,852	-186	-4%	33%
52	2,224	2,504	281	13%	30%
5,209	6,978	7,025	47	1%	40%

Super Districts



- 0 "CBD"
- 1 "NE Franklin"
- 2 "SE Franklin"
- 3 "SW Franklin"
- 4 "NW Franklin"
- 5 "W Licking"
- 6 "E Licking"
- 7 "Delaware"
- 8 "Union"
- 9 "Madison"
- 10 "Pickaway"
- 11 "Fairfield"

# Links	Count-Based	Model	# Diff	% Diff	% RMSE
144	11,551	13,249	1,698	15%	34%
1,042	9,580	9,627	47	0%	35%
902	7,838	7,939	101	1%	37%
669	6,551	6,732	181	3%	45%
724	8,730	8,648	-83	-1%	38%
208	3,593	3,155	-438	-12%	33%
267	4,939	4,852	-86	-2%	33%
705	4,324	4,148	-176	-4%	41%
178	3,385	3,385	-1	0%	36%
110	2,866	2,972	106	4%	33%
52	3,368	3,606	239	7%	30%
208	3,484	3,537	54	2%	41%
5,209	6,978	7,025	47	1%	40%

Sectors



- 0 "CBD"
- 1 "Sector-North"
- 2 "Sector-NE"
- 3 "Sector-East"
- 4 "Sector-SE"
- 5 "Sector-South"
- 6 "Sector-SW (East)"
- 7 "Sector-SW (West)"
- 8 "Sector-NW (South)"
- 9 "Sector-NW (North)"

# Links	Count-Based	Model	# Diff	% Diff	% RMSE
144	11,551	13,249	1,698	15%	34%
942	9,641	9,993	352	4%	35%
763	4,966	4,458	-508	-10%	41%
481	8,464	8,347	-117	-1%	31%
593	5,572	5,671	99	2%	46%
246	5,732	5,875	142	2%	42%
280	5,852	5,568	-284	-5%	32%
453	6,570	7,027	458	7%	50%
650	5,846	5,745	-100	-2%	43%
657	7,028	6,959	-68	-1%	39%
5,209	6,978	7,025	47	1%	40%

FIGURE 5 Counts versus model volume validation, by rings, super districts, and sectors.

REFERENCES

Gaiimo, G. 2001. Traffic Assignment Procedures.

PB Consult. 2005. The MORPC Travel Demand Model: Validation and Final Report.

Schmitt, D. 2006. Application of the MORPC Microsimulation Model: New Starts Review. <http://onlinepubs.trb.org/webmedia/trbweb/austin/schmitt/index.htm>.

BREAKOUT SESSION

THE SECRET IS IN THE SEGUE
Transitioning to a New Model Framework

Lessons Learned from the Implementation of New York Activity-Based Travel Model

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The New York Best Practice Model (NYBPM) has been developed and implemented to meet the demand of regional planners seeking a more accurate way to identify transportation requirements and forecast demand on the transportation system. It has been used on many regional studies to simulate travel patterns including where people travel, their modes of travel (car, subway, bus, ferry, walk and bike, or commuter rail), preferred routes (highway versus local roads), and their trip times.

NYBPM is an activity-based model that attempts to predict the detailed travel patterns of a diverse population using numerous travel modes. It does this by introducing innovative approaches to the traditional travel demand models including the concept of journey or tour as the unit of travel; microsimulation, which is used to simulate the travel pattern of each person in the region and among all other modes of travel; and nonmotorized modes.

NYBPM covers 28 counties and is divided into 3,586 transportation analysis zones. The model analyzes travel patterns by four time periods and eight trip purposes on six highway and four transit modes. The highways of the region are represented in a geographic information system (GIS) with more than 53,000 segments. All available transit modes of the New York metropolitan region ranging from commuter rail to ferries are also coded in GIS.

NYBPM was previewed before a national audience in January 2001 during the TRB Annual Meeting in Washington, D.C., and immediately was in wide implementation throughout the region on various projects in different sizes including:

- Air Quality Conformity Analysis;
- Southern Brooklyn Transportation Investment Study;
- The Gowanus Expressway and Kosciuszko Bridge Study;
- Tappan Zee Bridge and the I-287 Corridor Study;
- Bruckner Sheridan Expressway Study;
- Bronx Arterial Needs Study; and
- Goethals Bridge Modernization Draft Environmental Impact Study.

As one of the first metropolitan planning organizations (MPOs) in the country to develop and implement a new generation of travel demand forecasting models, this paper shares New York Metropolitan Transportation Council's (NYMTC's) experience throughout different stages of development and implementation of NYBPM. Immediately after release of the models in 1992, NYMTC's modeling staff was faced with a series of problems, which are discussed in the following sections.

IDENTIFIED NYBPM ISSUES

Timeliness and Completeness of Data

The development of the regional NYBPM, and the data required for its development, largely occurred in the mid- and late 1990s. Networks were developed to represent a 1996 base-year condition, 6 years after the most recent

decennial census in 1990. In 2002, the model's data were already 10 years old and needed to be updated using new socioeconomic data based on the 2000 census. Also, adjustments needed to reflect the impact of September 11, 2001, on employment and labor force data.

Because of insufficient funding, the Regional Travel Household Interview Survey, which was conducted in 1997 and 1998, did not include the survey of establishments as travel generator or attraction points, so tourist trips were ignored.

Modeling Issues

- Needs for different level of details of modeling documentation not addressed properly.
- Gap between availability of proper documentation and completion of the models.
- Lack of full integration of transit and highway networks.
- Lack of integration of land use model and travel demand model in the NYBPM system.
- Long processing time.

Modeling Environment

- Diversity of the large region: NYBPM is the first regional model of its geographic and functional scope ever implemented successfully in such a large metropolitan region. The New York metropolitan area is unique because of its complex transportation system, diverse population and area type, and its size in both population and area. This diversity adds to the complexity of travel analysis.
- Software issue: It has been a challenge to address the compatibility issues of various NYBPM software versions with various versions of TransCAD as NYBPM's platform. TransCAD is used to manage, edit, and modify the NYBPM transportation highway and transit network databases, and for path building and the development of "skim-tree" matrices of travel times and costs used in the choice models. NYMTC faced some compatibility issues because different member agencies used different versions of TransCAD. Also, compatibility among other software packages used with NYBPM was a problem.
- Hardware issue: The application of the NYBPM model requires an extensive amount of computational resources, as well as careful management of a large number of computer files. Running NYBPM requires a set of special hardware specifications, including dual processors, which could provide an efficient computing application system for NYBPM.

USER TRAINING

One of the daunting tasks facing NYMTC's modeling staff is to provide training to stakeholders who are interested in various NYBPM applications. The stakeholders, based on the levels of technical knowledge and special needs for their applications, require different levels of training, and NYMTC has developed training programs to meet those needs. One-day training is provided to the decision makers; 3- to 5-day training has been developed for individuals who have some modeling background; and a one-to-one training spanning several weeks is being provided to staff of member agencies that need to run the model for specific project analyses.

STAFF RESOURCES

Staffing has been a key issue in NYMTC's model implementation process. Several reasons that attributed to this issue are identified below.

Lack of Trained and Experienced Modeling Staff

There is an inherent shortage of experienced modelers in this country. NYMTC staff, with limited experience at the beginning of the process, needs to work with the stakeholders and the consultants in developing and implementing the complex modeling system. At the same time, NYMTC staff needs to learn all the aspects of model development, including data collection, model methodology, model estimation, calibration and validation, and applications, including project coding, model output analysis, and quality control.

High Turnover Rate

NYMTC also faces the problem of retaining qualified individuals because of organizational constraints. Because NYMTC is hosted by New York State Department of Transportation (NYSDOT)—that is, NYMTC is not a separate legal entity—it must abide by NYSDOT's rules for promotional opportunities. Promotions in NYSDOT are based on examinations that are not closely related to the modeling work, which puts the modelers at a disadvantage for career advancement within the organization.

Hiring Constraints

Hiring in NYMTC is an ongoing struggle. NYMTC's modeling group has lost several staff members over the

years due to retirement or better opportunities. These staff members cannot be replaced in a timely fashion because of the hiring freeze imposed by the hosting agency.

INSTITUTIONAL COORDINATION

As an MPO, NYMTC must take a regional perspective in all of its work and products. NYBPM implementation requires consideration of two important factors: working with stakeholders and getting consensus.

Working with Stakeholders

Throughout the model development process, NYMTC staff work closely with all stakeholders to define the model needs and applications at the beginning of the process. All modeling issues and application support, coordination of data collection efforts, discussion of model calibration and validation results, and issues related to model usage and improvements require close involvement of stakeholders in the complex NYMTC region.

NYMTC staff held 10 sessions with stakeholders throughout the NYMTC region to discuss modeling needs that became the guidance for NYBPM development. NYMTC staff also coordinated with stakeholders on various modeling issues, including data sharing among different zonal systems, consensus building on socioeconomic and demographic forecasts, design and implementation of regional household travel survey, update of regional highway and transit networks, and building the traffic count database for the 2,300 screen line locations. In addition to the complexity involved with the large number of stakeholders, data from stakeholders with inconsistent formats and definitions required the NYBPM project team to spend a lot of resources to reconcile the assembled data into a common database format for use in NYBPM.

Building Consensus

NYMTC staff had to work with stakeholders to reach consensus on all stages of the model development process, including the definition of zonal system, the survey design, the forecasts and calibration results, and so forth.

One of the required inputs to the NYBPM was the socioeconomic demographic data and forecasts. While base-year data were collected from various public agencies in New York, New Jersey, and Connecticut, economic models were run to forecast future years by

county. The future-year forecasts for the four main variables—population, household, employment, and labor force—were shared with local and county agencies to ensure consistency with individual county forecasts.

This was a drawn-out process in which members' suggestions were often divergent, resulting in conflicting forecast numbers. After several rounds of modifications, and numerous meetings and negotiations, the forecasts were finally found acceptable and adopted by the MPO member agencies. Consensus building among the stakeholders is vital in the NYMTC forecasting process. These forecasts are used in all the major investment studies and corridor-level studies in the region.

FUTURE IMPROVEMENTS

With more than 4 years of experience, NYMTC has many ideas on sensitivity tests and improvements of model performance, ease of use, and quality control procedures, to name a few. Those ideas are either under contracts with University Transportation Research Center and consultants to implement, or will be implemented through various model improvements and contracts in the years to come.

One of the problems of NYBPM is its long running times. Previous experiments and new developments suggest massive speedups are possible, however. NYBPM will also try to relax hardware requirements so that more users could use NYBPM, create a full-featured User Interface and a super fast version for production.

To address the data standard issues, NYMTC staff has been working with member agencies through the traffic, transit, and GIS data coordination committees to standardize all data collection in the region. These groups consist of all NYMTC member agencies who are actively working together to collect traffic and transit data in a standardized format so they can be shared among all the agencies. This will avoid duplication and save the region staff time and money. It will also minimize any data reconciliation problems in the variability of data from different sources. A GIS-based traffic data editor and viewer developed by NYSDOT has been used as the traffic data clearinghouse for the NYMTC region.

Other ongoing improvements include:

- Scenario and file management;
- Automated reporting and output manager;
- New user guide with content-sensitive online assistance;
- Improve usability and applicability;
- Move to the latest versions of TransCAD;
- Exploit features of new TransCAD process;
- Streamline and optimize model code;

- New graphic user interfaces;
- Adapt to multiple hardware environments;
- Multithreading and distributed processing; and
- Public, web access to model outputs.

NYMTC has also launched a series of data collections and surveys that will be conducted in the next 3 years. These efforts will include data to update or enhance existing information (regional household travel survey, external survey, regional speed survey, screen line counts, and regional transit on-board surveys), and new data that will improve existing NYBPM deficiencies (regional establishment survey, airport survey, taxi survey, and regional bridge origin–destination survey). Several of the data collections will cover 28 counties in the New York–New Jersey–Connecticut tristate region. This new wave of data collection will provide an up-to-date understanding of travel patterns and behaviors in the region. They will also be used to recalibrate the NYBPM that

will address some of the known issues and bring the NYBPM to the next level.

PROJECT SIGNIFICANCE

This project is significant for a number of reasons. First, it is the first activity-based model that has been used in air quality conformity analysis and many major investment studies in the United States. The experience of NYBPM proves that the concept of activity-based model does work and works very well in the most complex region in the country. Second, throughout the years of experience in various stages of the development and applications, NYMTC staff has worked with stakeholders and gained a better understanding of the modeling system and its improvement needs. The lessons learned will provide other MPOs with valuable insights into future development of activity-based models.

Using Activity-Based Models for Policy Decision Making

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Metropolitan planning organizations (MPOs) are faced with a variety of planning and policy initiatives for which information on travel demand is required. The Denver Regional Council of Governments (DRCOG) is the MPO for the rapidly growing Denver area, which has developed a comprehensive planning process to deal with the issues confronting the area's residents, workers, and visitors.

The regional planning process in the Denver area begins with the plan known as MetroVision, which provides the overall framework within which are developed other key MPO planning elements such as the Regional Transportation Plan, the Transportation Improvement Program, and the Air Quality Conformity analysis. As DRCOG began the design of a new regional modeling system, and given that initial project planning suggested that DRCOG should focus its efforts on the next generation of tour-activity modeling systems, DRCOG management essentially charged the project team to answer the question "What good are these models? Can they better support regional planning, and if so, how?"

MetroVision is composed of six core elements, intended to guide the regional planning process:

- Extent of urban development: promoting a more orderly, compact pattern of development;
- Semi-urban development: minimizing the extent of low-density, large lot development;
- Urban centers: encouraging the development of higher-density, mixed-use, transit- and pedestrian-oriented centers throughout the region;

- Freestanding communities: maintaining as self-sufficient communities several towns currently separate from the larger urban area;
- Balanced, multimodal transportation system: providing environmentally sensitive and efficient mobility choices for people and goods; and
- Environmental quality: establishing a permanent, integrated parks and open space system, and preserving the region's air, water, and noise environments.

INTEGRATED REGIONAL MODEL VISION PHASE

To ensure that the new model developed for the Denver region would address MetroVision and the plans developed under its umbrella, DRCOG conducted the Integrated Regional Model (IRM) vision phase, which involved evaluation of other advanced modeling projects throughout North America and Europe, together with the convening of panels of modeling experts, regional engineers and planners, and regional policy makers who provided overall project guidance. These steps ensured that the model design would be informed by the latest practical efforts in model design and implementation, and, most importantly, by the model's ultimate customers, those in the DRCOG region who will use the results.

During the IRM vision phase, the policy panel developed a list of the top 10 core planning issues that the travel demand model needs to support:

1. Effects of development patterns on travel behavior;
2. Sensitivity to price and behavioral changes;

3. Effects of transportation system and system condition;
4. Need for improved validity and reliability;
5. Ability to evaluate policy initiatives;
6. Better analysis of freight movement;
7. Ability to show environmental effects;
8. Modeling low-share alternatives;
9. Better ability to evaluate effects on specific subgroups; and
10. Reflect nonsystem policy changes (TDM, ITS).

HIGH-INTEREST POLICY ISSUES

These issues were boiled down in the vision process to keep the list short. More specific, high-interest policy issues in the Denver region include:

- The Colorado Tolling Enterprise (CTE): Established 2 years ago by the state legislature, the CTE has been working to identify a set of corridors with the potential for toll facility establishment. The CTE has identified about six corridors in the Denver area and is conducting an evaluation of these corridors, which is expected to be submitted to the regional planning process for inclusion in the regional plan. These efforts also have caused planners conducting several environmental impact statements in the region to take a harder look at toll options in their alternatives' analyses.
- The effects of MetroVision urban centers and other transit-oriented developments: Support of such development patterns is intended to foster a more balanced transportation system, reduce the number and lengths of trips, foster additional bicycle and pedestrian use, and so forth. The MetroVision 2030 update developed in 2004 included approximately 70 such centers, and the evaluation of the effects of these centers is a key aspect of the regional model's usefulness. These will be evaluated again during the MetroVision 2035 process.
- Effects of the MetroVision urban growth boundary: The extent of the urban growth boundary or area currently is set at approximately 750 sq mi for the year 2030, and the extent to which it may need to be expanded for 2035 will be a key part of the MetroVision 2035 process.
- Reexamination of lower-density development, referred to as semi-urban: Issues include defining semi-urban, estimating how much of it there is, how much should there be, and its transportation and air quality effects.
- The FasTracks ballot initiative of 2004: Passage of this initiative kicked off a project to build about 130 mi of rapid transit to all parts of the region by 2017. The ability to evaluate the effects of such a system will be critical over the next decade.

- Air quality: As always, evaluation of the effects on air quality of various policy and transportation initiatives will continue to be a key issue in regional planning.
- Highway project planning: This also will continue to be a core focus of the planning process in the region.

ACTIVITY-BASED MODELING APPROACH

In addition to providing guidance concerning the needs that a new model must address, the vision phase validated DRCOG planners' initial impression that an activity-based modeling approach would best meet those planning analysis needs for the region. While it is clear that activity-based modeling as it can be implemented now cannot fully address all of the issues discussed above, it is superior to conventional four-step modeling in many respects. DRCOG and its consultant team have concluded detailed design of an activity-based model, considering the region's planning needs and resource constraints, and model development is now in progress.

The activity-based modeling approach chosen by DRCOG is based on that used in the model developed for the San Francisco County Transportation Authority in 2000–2001, but includes enhancements informed by the capabilities of some of the activity-based models implemented more recently in other areas. The approach includes microsimulating the daily activity patterns of individuals in a synthetic population; determination of "regular" workplaces and school locations in relation to the home location; the modeling of the times of day, destinations, and modes of tours and trips; and the use of conventional static highway and transit assignment procedures. The model design is described more completely by Cambridge Systematics, Inc., et al. (1).

In general, the activity-based modeling approach would be expected to produce more accurate results for policy testing because it can consider a wider range of variables and interactions than a conventional trip-based model. Trip-based models tend to be relatively insensitive to many input data changes (such as transit-oriented, development-related land use changes) because they usually do not include enough detail (geographic location, demographic variables, trip-tour relationships, and so forth) to permit them to respond fully to such changes. Trip-based model users often resort to adjustment factors to account for behavior that cannot be analyzed by these models, with varying degrees of reliability and success; activity- and tour-based models are expected to provide considerably improved forecasting for all types of policy analyses. Of course, the level of increased accuracy may depend on how much the analysis of the specific policy depends on the factors that are considered in the activity-based approach but not in the trip-based approach.

ADDRESSING POLICY ANALYSIS NEEDS

The following discussion summarizes some specifics of how the proposed modeling approach would address some of the specific policy analysis needs described above.

Pricing Analysis

The traffic forecasting procedures for toll facilities and managed lanes have been a topic of considerable discussion recently. Various aspects of existing procedures have been criticized, including the assumed values of time for various market segments of travelers, the aggregate nature of the process (which requires fixed values of time for each segment), the difficulty in modeling time of day outside a tour-based approach, and the static nature of the traffic assignment process, which ignores the effects of the buildup and dissipation of queues.

Activity-based approaches present some advantages over conventional modeling procedures in addressing some of these issues. One major advantage is that modeling individuals in the synthetic population provides an opportunity to use distributed values of time rather than fixed values for a relatively small number of market segments. For example, say that it would take a value of time of \$12/h for a certain geographic market to find using a particular toll road segment desirable. If the average value of time for the market segment were \$10/h, then the model would estimate that no one from that segment would use the toll road. However, if a value of time distribution were used with an average value of \$10/h but with a 20% probability of having a value of time of greater than \$12/h, there would be demand estimated for the toll road within this market segment.

Another major advantage is that demand for roadways where tolls vary by time of day can be modeled much more accurately. Time-of-day decisions for activities must consider not only the time when the trip to or from the activity takes place, but also the trip in the other direction and the duration of the activity itself. For example, if someone wishes to consider shifting his departure time for a work trip to avoid a high-peak-period toll, he or she would likely also need to consider the amount of time needed to be spent at work and whether the time shift for the trip to work might shift the departure time from work to or from a peak period with a high toll. Obviously a model that treats individual trips independently cannot include such considerations.

Urban Centers and Transit-Oriented Development

There are several advantages to modeling travel by residents, workers, and visitors in these types of develop-

ments using the proposed activity-based modeling approach. First, many variables in an aggregate, trip-based model must be introduced through the use of segmentation, which significantly limits the number of variables that can be included in the model. Adding further segmentation to a typical cross-classification trip production model (likely with only two or three dimensions) to account for different trip-making characteristics in denser, transit-oriented areas would require the household survey data to be segmented by additional dimensions, often beyond the ability to obtain statistically significant estimates of trip rates given the limitations of the existing sample. The activity-based modeling approach, where individual daily activity patterns are simulated, permits description of individuals using a much richer set of variables.

Planning judgment and travel behavior data also support the expectation that having a variety of attractions located in close proximity in the urban centers, including workplaces, other businesses, and shopping and entertainment opportunities, would have an effect on trip chaining, as individuals might choose to combine activities that can be accomplished in the same vicinity. Obviously, a tour-based approach is required to capture the effects of trip chaining.

Finally, data also suggest that persons living or working in higher-density transit-oriented areas should have greater opportunities to use transit and nonmotorized modes. However, properly reflecting these opportunities in the model requires a combination of capabilities: modeling travel in tours so that, for example, secondary tour trips, stops, and modes can be shown to be compatible with transit as the primary mode of the tour (as they will sometimes be within walking distance); destination choice models that can operate at sufficient geographic detail so as to locate some secondary stops within the transit-oriented development; and fine geographic detail on stop locations so that walk distances can be accurately calculated (so that walk choices in the mode choice models are accurately estimated).

Transportation Project Analysis

The use of disaggregate microsimulation of individuals provides some advantages to the analysis of new transportation projects, particularly the extensive transit investments planned for the Denver area. One of the key questions involved in the analysis of transit investments involves the identification of how specific groups of the population (for example, persons from low-income households) benefit from the investments. In conventional models, demographic market segmentation is not carried through beyond the mode choice step, so some model results cannot be differentiated by market seg-

ment. In addition, the market segmentation is limited to a single variable (usually income) in conventional models whereas all characteristics of the simulated individuals can be retained in the activity-based approach.

Another way in which transportation project analysis is improved compared with the use of conventional models is that the effects of new projects on travel demand (i.e., induced travel) can be modeled directly. Conventional trip-generation models consider only demographic variables and do not consider transportation level of service. The magnitude of the effects of improved transportation level of service stemming from new projects on the amount of travel demand can be estimated through the incorporation of level-of-service variables in all steps of the demand modeling process. The use of logsum variables from subsequent model steps provides a way to do this while maintaining consistency among the level-of-service data for all model components.

It is worth briefly discussing some of the ways in which the proposed activity-based modeling approach fails to address some of the planning analysis needs. One of the most significant is that a conventional static traffic assignment process will be used. Although it would be desirable to consider traffic microsimulation or dynamic traffic assignment (DTA) procedures, the ability to implement and validate such procedures when they are applied at a regional level (at least in a region as large as the Denver metropolitan area) has not yet been proven. Lack of a fully disaggregate or at least DTA procedure will limit the model's ability to analyze the effects of queuing of traffic and to examine variations in traffic flow within peak periods. This inhibits the full exploration of the effects of tolling options and other highway operations analyses.

Another issue is that, despite its use of microsimulation of individuals, the model will still have some aggregate elements. The region will still be divided into

analysis zones, which will be used as the basis for highway travel time and some other level of service network skims. This means that aggregation error will still exist in the model (although to a lesser extent than in a conventional model). However, current model design anticipates storing each household and job at the point level, mitigating some aggregation errors by allowing detailed calculation of walk skims.

IMPROVING THE MODELING PROCESS

In conclusion, it is clear that existing modeling tools come up short in their ability to address the planning analysis needs of the Denver region. While the proposed activity-based approach is not a panacea for all of the shortcomings, it does provide many improvements to the modeling process that specifically address some of the issues. These include the ability to introduce distributions for the value of travel time in road pricing analyses, the use of a more accurate tour-based time-of-day-modeling procedure in road pricing and other analyses, the use of additional segmentation variables in such analyses as the development of urban centers and transit-oriented development, the ability to directly model trip chaining, and the use of transportation level-of-service variables in all steps of the model to estimate the effects of induced travel demand. These advantages led DRCOG to begin development of an activity-based model as the main travel demand estimation tool for future planning analyses.

REFERENCE

1. Cambridge Systematics, Inc., M. Bradley, and J. Bowman. Model Design Plan for the DRCOG Activity-Based Model. January 2006.

Hardware Requirements and Running Time for the Mid-Ohio Regional Planning Commission Travel Forecasting Model

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In October 2001, the Mid-Ohio Regional Planning Commission (MORPC) contracted with PB Consult to develop a set of regional travel forecasting models. The new model is a disaggregate tour-based model applied with the microsimulation of each individual household, person, or tour. The new modeling system was completed in late 2004 and refined throughout 2005. The new model is being used by MORPC for conformity analysis, transit alternative analysis, and for highway Major Investment Study projects in the Columbus region.

The model area is divided into 1,805 internal and 72 external zones and includes Franklin, Delaware, and Licking counties, and parts of Fairfield, Pickaway, Madison, and Union counties. The primary inputs to the model are transportation networks and zonal data, where each zone has the standard socioeconomic characteristics that one would normally find in a four-step model. The main differences from the prior four-step model are that the new model accounts for travel at the tour level, as opposed to the trip level, and for each individual household and person, as opposed to zonal and market segment aggregates.

MODEL FORMULATION

The forecasting model consists of nine separate linked models and other network processing steps. The nine models are

1. Population synthesis: A synthesized list of all households and population for the entire area is gener-

ated, consistent with the household and workforce variables in the zonal data. The output from the population synthesis model is a file with a record for every person in the area containing various attributes attributed to that synthesized person.

2. Auto ownership: The number of vehicles available for each household is simulated.

3. Daily activity pattern: The daily activity pattern for each person and the number of mandatory tours each person with a mandatory activity pattern makes during the day are simulated.

4. Joint tour generation: Generation of tours undertaken by members of the same household.

5. Individual nonmandatory tour generation;

6. Tour destination choice: Logit-based choice model (applied with Models 7 and 8).

7. Time-of-day choice: Logit-based choice model (applied with Models 6 and 8).

8. Tour mode choice: Logit-based choice model (applied with Models 6 and 7).

9. Stops and trip mode choice: This model determines if any stops are made on either the outbound (from home) or inbound leg of the tour and the location of those stops.

The core choice models (1 through 9 as described above) are applied in a disaggregate manner. Instead of applying aggregate fractional probabilities to estimate the number of trips, the new model is applied with the microsimulation of each individual household, person, or tour, mostly using Monte Carlo realization of each possibility estimated by the models, with use of a ran-

dom number series to determine which possibility is chosen for that record.

The new model is implemented with three global feedback loops for consistency between highway travel times that are both used as inputs to, and as forecast outputs of, the model.

The main model application package is Cube, with TP+ being used for network management, assignment, external, and commercial vehicle models and other processing. The core tour-based choice models described above are written in Java with access to the TP+ skins. The custom programs are designed to take advantage of the numerous opportunities for parallel processing in the model chain, multi-threading of tasks, and to readily accommodate the addition of computers in the distributed processing framework to optimize processing.

After the networks and initial skins are generated in TP+ and all input files are created for a particular scenario, the custom Java programs are executed to implement the tour-based microsimulation models. A pre-assignment processor step aggregates the microsimulation results and integrates the commercial and external models to produce standard TP+ trip tables for four time periods. After the final trip tables are generated, vehicles are assigned with a multi-class (SOV, HOV, medium truck, and heavy truck) equilibrium assignment utilizing 21 volume delay functions by facility and area type for each of four time periods (a.m., midday, p.m., and night). Transit assignments are also performed in TP+ for the a.m. and midday time periods, with standard reports generated to support analysis and evaluation of the alternatives tested (Anderson et al. 2003).

HARDWARE CONFIGURATIONS

There are three operational systems that can run the MORPC travel forecasting model. The two systems that are currently installed at MORPC are the topic of this paper. The initial system was built in December 2004 with one server computer and three worker computers. The specifications for the computers are below.

- Server
 - Dual 64-bit Xeon 3.6 GHz 1MB L2 800MHz FSB Processors
 - 4 GB PC3200 ECC Registered DDR Memory
 - 4 - 36GB SCSI 15K U320 RAID-5 Array
 - Dual Gigabit network interface cards
 - Windows 2000 Server Operating System (OS)
- Worker (3–4)
 - Dual Xeon 3.06 GHz 512KB L2 533MHz FSB
 - 2 GB PC2100 ECC Registered DDR Memory
 - 120 GB IDE HDD
 - Gigabit network interface card

- Linux 32-bit OS
- Networking Specifications
 - 5 port 10/100/1000 Gigabit network switch
 - CAT6 Ethernet cable

The workers are directly networked and are isolated from the general MORPC network to make them less susceptible to viruses. The workers are not running anti-virus software every time a file is accessed, unlike the rest of the MORPC network; it was found that running anti-virus software imposed a 15% penalty on the run time. In December 2005, a fourth worker was added to the cluster. This first system is running 32-bit OSs and Java.

The second system was purchased by the Central Ohio Transit Authority (COTA) in support of its North Corridor Transit Project DEIS. This cluster consists of one server and four workers all running 64-bit Windows and Java. The specifications for this cluster are below.

- Server
 - Dual 64-bit AMD Opteron 2.2 GHz 1MB L2 Cache Processors
 - 4 GB PC3200 ECC Registered DDR Memory
 - 4 - 73GB SCSI U320 10K RPM RAID-5 Array
 - Dual Gigabit network interface cards
 - Windows 2003 Server 64-bit OS
- Worker (4)
 - Dual 64-bit AMD Opteron 2.2 GHz 1MB L2 Cache Processors
 - 4 GB PC3200 ECC Registered DDR Memory
 - 160 GB SATA NCQ HDD
 - Dual Gigabit network interface card
 - Windows XP Professional 64-bit OS

MODEL RUNNING TIMES

Table 1 shows the running times of the MORPC Travel Forecasting Model for 2000 and 2030 on the various computer systems. MORPC 3 is the MORPC system with three Linux workers running 32-bit OSs, MORPC 4 is the MORPC system with four Linux Workers running 32-bit OSs, and COTA is the COTA system with four Windows XP Workers running 64-bit OSs. The 2000 model has 1.5 million synthetic people making 2 million tours; 2030 has 2 million synthetic people making 3 million tours. All runs include only two transit modes (local and express bus). The core model running time does not include the time to generate the four-period highway networks, two-period transit networks including support links, or the time to generate the initial travel skins, which is similar to the time to generate the travel skins during the model run. Overall, the time for these excluded tasks is about 2 h of running time on a 32-bit Windows computer.

TABLE 1 2000 and 2030 Running Times of the MORPC Travel Models (Hour:Min)

	2000			2030		
	MORPC 3	MORPC 4	COTA	MORPC 3	MORPC 4	COTA
Households	610,774	610,774	610,774	872,919	872,919	872,919
Population	1,435,389	1,435,389	1,435,389	1,956,660	1,956,660	1,956,660
Tours	2,074,618	2,073,659	2,075,797	2,997,507	2,997,214	2,996,117
Core model total (3 iterations)	35:43	31:20	20:55	48:35	41:23	26:43
Iteration 1	11:27	10:08	6:51	16:18	13:28	8:30
Iteration 2	11:26	9:55	6:28	14:59	12:48	8:06
Iteration 3	12:49	11:16	7:36	17:17	15:06	10:06
Iter 1 - Population synthesis	0:02	0:02	0:01	0:02	0:02	0:01
Iter 1 - Sending files to workers	0:20	0:20	0:12	0:19	0:20	0:14
Iter 1 - Auto ownership	0:01	0:01	0:00	0:02	0:02	0:01
Iter 1 - Mandatory tour generation	0:53	0:53	0:39	1:15	1:15	0:39
Iter 1 - Mandatory DTM	4:01	3:14	1:59	6:07	4:48	2:50
Iter 1 - Joint tour generation	0:12	0:12	0:08	0:14	0:14	0:08
Iter 1 - Joint tour DTM	0:08	0:06	0:04	0:08	0:07	0:05
Iter 1 - Individual tour generation	0:05	0:05	0:05	0:07	0:07	0:05
Iter 1 - Individual tour DTM	0:54	0:41	0:23	1:15	0:56	0:30
Iter 1 - At-work subtour DTM	0:08	0:07	0:06	0:12	0:10	0:07
Iter 1 - Mandatory stops model	0:49	0:38	0:21	1:14	0:59	0:32
Iter 1 - Joint stops model	0:07	0:06	0:04	0:08	0:07	0:05
Iter 1 - Individual stops model	0:54	0:43	0:24	1:11	0:54	0:31
Iter 1 - At-work stops model	0:06	0:05	0:04	0:09	0:08	0:05
Iter 1 - Writing files and trip tables	0:13	0:13	0:10	0:35	0:34	0:26
Iter 1 - Commercial vehicle +	0:00	0:00	0:00	0:01	0:01	0:01
Iter 1 - Commercial vehicles +	0:02	0:02	0:01	0:02	0:02	0:01
Iter 1 - IE trips +	0:00	0:00	0:00	0:00	0:00	0:00
Iter 1 - Highway assignment - 2 period +	1:08	1:14	1:07	2:03	1:31	1:16
Iter 1 - Highway and transit network skimming +	1:17	1:17	0:53	1:04	1:03	0:44
Iter 3 - Highway assignment - 4 period +	2:14	2:18	1:51	3:11	3:07	2:19
Iter 3 - Transit assignment - 2 period +	0:16	0:16	0:10	0:12	0:12	0:07

Times for the individual model components are shown for Iteration 1. At the end of Iterations 1 and 2, the a.m. and midday highway trips are assigned and the congested networks are then skimmed for feedback to the next iteration. Afternoon and night skims are the transposed a.m. and midday skims. At the end of the third iteration, all highway and transit trips are assigned to the appropriate network.

As seen from Table 1, 2030 takes longer to run than 2000 due to the additional population and tours. The addition of the fourth worker on the MORPC system improves the running time on the DTM and Stops models. The COTA system shows the most significant improvement in running times due to 64-bit computing and runs substantially faster than the 32-bit MORPC system. Therefore, any future installations of the MORPC model system would almost certainly involve 64-bit computing.

All runs are based on Cube Version 3.2. All TP+ programs are run on the server in sequential order. It has been found that Windows will only allocate a maximum of 50% of its CPU power to any application. Therefore, if the TP+ scripts were run in parallel, a significant time savings could result. Future upgrades include installing Cube on the systems of the COTA workers and

sending TP+ scripts to run in parallel. This is not possible on the MORPC system as the workers are running Linux.

MORPC MODELING STAFF

MORPC employs three staff members who use the travel forecasting model directly. Responsibilities are broken down roughly as follows:

- **Senior Engineer:** This person manages the model development and is familiar with the theory behind the model. This person runs the model for projects when needed and would proffer new features to be added to the model. This job includes model validation and calibration and script writing in support thereof.
- **Associate Engineers (2):** These people run the model for project-level analysis and air quality conformity. They maintain and upgrade the highway and transit networks.

In addition to the staff above, MORPC employs five staff members who maintain and forecast the socio-economic variables and two others who use the model results.

The Ohio Department of Transportation (ODOT) provides assistance for model development and running the model upon request by the MPOs. ODOT also runs the model for its own studies and projects.

POSTSCRIPT

The ODOT system is expected to be in operation in mid-to late 2006. Run times will be made available in late 2006 upon request.

REFERENCES

- Anderson, R., and R. Donnelly. 2005. Comparison of the Prior and New MORPC Travel Forecasting Models.
- Anderson, R., A. Al-Akhras, N. Gill, and R. Donnelly. 2003. Implementation of a Tour-Based Microsimulation Regional Travel Demand Model: Mid-Ohio Region.
- PB Consult. MORPC Travel Forecasting Model: Systems Documentation. Draft, December 2004.

BREAKOUT SESSION

**THE FUTURE OF TRAVEL BEHAVIOR
AND DATA COLLECTION**

Data-Oriented Travel Behavior Analysis Based on Probe Person Systems

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Planning methods, like most methods in science and engineering, evolve within the confines of the technologies available at the time of development, and travel survey methods are not an exception. It took a leap of conceptualization before roadside surveys, which addressed car trips, were replaced by household travel surveys, which addressed person trips. The conceptualization of urban passenger travel was then formalized to be what is known to be four-step procedures. With what now appear as extremely limited capabilities of data processing and statistical analyses in the 1950s and 1960s, the four-step procedures adopted the approach of aggregating the rich information available from travel surveys at household and individual levels to the level of traffic zones. Likewise, trip ends were coded by using traffic zones. Trip starting and ending times reported in the surveys were not well utilized, other than perhaps for estimating the duration of each trip, and many of the analyses in the four-step procedures were performed disregarding the time-of-day dimension. The problem today is that many of these weaknesses remain, when many of the technical constraints have disappeared.

Researchers became aware of the statistical inefficiency of aggregating information to the zone level as early as the 1960s, and estimation of trip generation models at the level of household was proposed. At the time, however, storing and processing of data were quite a challenge. Fast computers, inexpensive data storage media, and easy-to-use statistical and econometric software packages now available have made the analysis of large-scale household travel survey results possible at the desktop of a researcher or planner. Household travel survey results have been used to analyze a wide range of

behavioral aspects, not just trip generation, distribution, modal split, and network assignment. Examples include trip chaining, time use, daily activity scheduling, and group behavior. In fact, the last three decades have shown that the information contained in results of conventional household travel surveys can be used in analyzing a rich spectrum of behavioral aspects as the evolution of the activity-based analysis field has demonstrated (Jones et al. 1990, Kitamura 1990). Spatial elements, however, have continued to be the weak link, and geocoding trip ends to the point in a transportation study is rather an exception than a norm even now. Another weakness is the error in reporting trip beginning and ending times (Kitamura 1990).

Recent developments in information and communications technology, however, are changing this situation by making possible acquisition of precise time and location information from survey respondents. A Global Positioning System (GPS) unit integrated into a cellular phone transforms a survey respondent into a “probe” (subsequently called “probe person” rather than “probe vehicle”) whose trajectories in space and time can be recorded with levels of accuracy unimaginable from the conventional questionnaire-based surveys. When these are supplemented with web-based data acquisition on the contents of activities (what type, with whom, etc.), opportunity characteristics (facility types), and trip attributes (cotravelers, parking facilities and charges), one can obtain every type of measurement that has traditionally been used in travel behavior analysis and demand forecasting. In addition, attempts have been made to acquire unconventional measurements, such as

monetary expenditures and types of commodities and services purchased at commercial establishments. These kinds of data will make survey results applicable to a wider range of planning studies.

This paper summarizes the results of several pilot surveys conducted in Japan by using probe person systems. It shows technical requirements for new travel behavior surveys that are based on the results of these pilot surveys and discusses the possibility of data-oriented travel behavior analysis.

TECHNICAL REQUIREMENTS FOR TRAVEL BEHAVIOR SURVEYS

An individual's activity and travel vary from day to day. To capture day-to-day variations in travel behavior in urban space through surveys and to develop and evaluate alternative transportation policy measures, one would desire to

1. Implement a long-term survey,
2. Determine space-time coordinates with high resolution and accuracy, and
3. Automatically and accurately measure detailed activity contents.

First, to capture more accurately the diverse patterns of travel behavior that vary day to day, it is necessary to implement a long-term, detailed travel behavior survey and observe day-to-day variations in travel patterns. A one-day survey would be sufficient if one wishes to acquire information on highly repetitive travel such as commuting. Travel patterns vary from day to day for various reasons, as noted above, and one's knowing the patterns of variation is a prerequisite for determining the causes for, and revealing the mechanisms of, day-to-day variations in travel. This knowledge obviously requires long-term observation of travel patterns.

Second, it is desirable to determine the space-time coordinates of an individual's trajectory in urban space along the time axis. Gathering this information calls for identifying—with high accuracy—activity locations, activity durations, trip starting and ending times, and the like. In some planning contexts, one would also desire to determine travel routes, transfer locations, public transit waiting times, and the beginning and ending times and locations of the respective trip segments typically involved in a public transit trip. (Even an automobile trip involves access and egress walking, yet the exact location of parking is often ignored in conventional travel surveys.) A survey method aimed at capturing the total daily demand volume between zones is incapable of providing the information necessary to evaluate planning measures intended to manage travel demand by fine-tuning a range

of factors that influence service levels. A survey method that provides time-space coordinates of an individual's movement trajectory with high resolution is desired.

Third, there is a fundamental issue of whether trip measurements obtained from conventional travel surveys may be inadequate to represent an individual's travel pattern in time and space. For example, accurate measurement of travel behavior calls for the recording of short trips. Yet, in addition to the fact that conventional questionnaire surveys have a problem with reporting omissions, it is often difficult or costly to geocode trips accurately on the basis of the information available from conventional questionnaire surveys, and errors can be excessive in the case of short trips. Moreover, the accuracy of measurements that are based on survey respondents' memory may be inadequately low in relation to the current planning analysis requirements.

IMPLEMENTATION OF SURVEY TECHNIQUES

This section covers the characteristics and problems of the following five survey methods as tools to collect data for travel behavior analysis:

1. Questionnaire surveys,
2. Web surveys,
3. Mobile phone surveys,
4. Probe-person surveys, and
5. Surveys using multiple sensors.

A questionnaire survey can be administered in many ways, each having advantages and disadvantages. For example, it is relatively easy to collect data at a low cost per completed survey but with a low response rate and a lower quality of data in the case of mail-out-mail-back surveys. These problems may be overcome when a survey involves home visits (either just to deliver-collect questionnaires or to conduct home interviews) but with the much higher costs and difficulties of visiting households. Moreover, either method requires data coding, which consumes monetary cost and time in proportion to the sample size.

Computer-aided telephone interview (CATI) surveys have become a standard procedure in household travel surveys in the United States. It has many advantages (e.g., data coding is automated, branching is automatic and error free, and questionnaires can be easily customized) as well as disadvantages (e.g., it takes an excessive amount of interview time in case of a large household). As with conventional surveys, trip records are obtained on the basis of the respondents' abilities to recall travel events on the survey day. The quality of the data also rests on the respondents' understanding of what exactly a trip is and how its attributes, including

the purpose, should be reported. Interacting with the interviewer, however, should aid in improving the data quality attainable by telephone surveys.

In recent years, Internet-based interactive survey methods have been proposed by Lyons and McDonald. Web surveys have the advantage of quick implementation and cost reduction in survey administration, and, like CATI, the need for data coding can be eliminated. The obvious advantage is the absence of sampling frames and no control of respondent self-selectivity. Yet improvement in the accuracy of data records can be expected by providing a graphical user interface (GUI) that uses maps, graphic illustrations, and the like. For these interactive surveys, as with all the other methods mentioned so far, however, the accuracy of data on travel route and time is low because the surveys rely on respondents' memory (Hato et al. 1999).

To solve some of these problems, survey procedures based on probe vehicles using GPS units have been developed by Murakami and Wagner (1999) and Zitto et al. (1995). The ability of automatically recording the position of a vehicle over time has made it possible to observe travel speed and path for a long period. In contrast, a method has been proposed in which sensors are incorporated into spaces of travel to record human travel behaviors rather than attaching measuring instruments to transport modes for travel. For travel of pedestrians, a survey method using integrated circuit (IC) tags has been proposed. Hato and Asakura (2001) have developed a system that allows the measurement of migration behaviors of subjects in which interactive information is pro-

vided by subjects touching or passing readers for contact-type passive radio frequency identification (RFID) tags and active RFID tags installed in specific spaces in the Matsuyama metropolitan area.

However, although such measurement methods have high accuracy for determining space-time positions, they can be said to be survey methods for limited transport modes and spaces of travel. It is difficult to record travel seamlessly to analyze travelers' travel behaviors trip by trip. There is a common problem that the system cannot measure trips that use other means of transportation than specific transport modes or such trips as transfers. Moreover, the purpose of a trip needs to rely on questionnaire surveys.

To solve such problems, a survey method using an automatic position and time recording system on the basis of mobile phones has been proposed by Hato and Asakura (2001). A travel behavior survey method that uses personal handset system automatically measures position data, and several methods have been proposed for recognizing human travel-activity patterns and determining paths on the basis of position data alone. The numbers of observable trips are larger—and long-term surveys are possible by these methods—than with conventional survey methods that rely on subjects' memory (Figure 1). However, complete automation will increase estimation errors in behavior patterns and paths if the accuracy of position determination is low (Hato et al. 2006). Therefore, it is necessary that the investigator perform data correction. Because there is a limit to the automatic recognition of the facilities of stay by using a

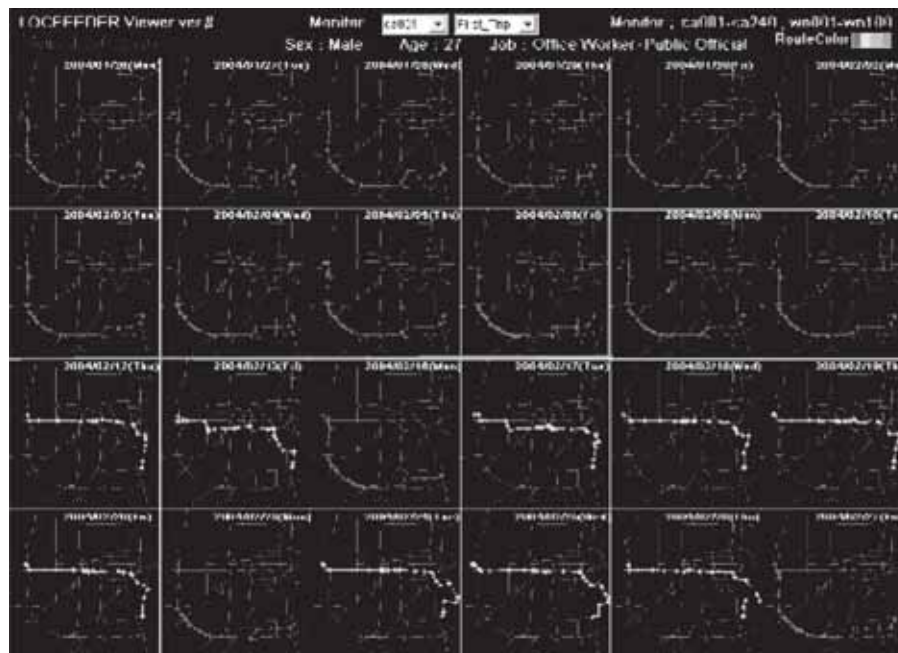


FIGURE 1 Day-to-day path selection activity patterns for one individual.

geographic information system, it is necessary to survey the contents of trips through ancillary questionnaire surveys and other means.

The probe person survey system is one that, on the basis of the advantages and problems to be solved for such existing studies, aims to achieve the goals of (a) ensuring accurate travel records through space–time position determination functions of high accuracy, (b) reducing recording omissions through timely travel behavior recording functions, and (c) ensuring improved efficiency of data coding by the investigator and improving the sense of participation in surveys of subjects through a system that emphasizes real-timeness and interactivity.

A survey system of high timeliness is constructed that allows travel records to be input anywhere through the use of both mobile phones and the web as input media. This process allows subjects to record travel in a timely manner while they have a clear memory and to check and correct the travel records. Moreover, in a long-term survey in which mobile phones with position determination functions are used to establish space–time position, it is necessary to obtain data of high accuracy while reducing the burden on subjects. To this end, it is important to have a GUI that allows subjects to check visually and to edit both the data they recorded through the information input and the travel records obtained through mobile communication systems, which complement each other. An example of such a survey is a successive diary survey of about 3 months.

A survey has been proposed in which the contents of individuals' behaviors are identified by using accelerometers, barometers, and sound sensors rather than implementing questionnaire surveys as a complement to a behavior survey that uses mobile phones and a GPS. In such a survey, transport mode is identified by the magnitude of acceleration; the floor of a subject is identified by atmospheric pressure; and the behavior content is identified by variability in acceleration and sound. It is aimed at automatically recognizing the behavior content by preparing sensor signal sequence data corresponding to behavior patterns, such as transport mode and activity content, as training data. Survey methods using multiple sensors can be said to allow a long-term behavior survey of high quality to be achieved by reducing the burden of input on subjects in the survey.

APPLICATIONS OF SURVEY TECHNIQUES

Wide Area: Probe Person Survey

The most versatile survey technique of those described in the previous section is the probe person survey, in which subjects are asked to carry GPS mobile phones, which

are in wide use in Japan. It is possible to record the travel path and departure and arrival times by using the phones as well as to correct input data and implement various ancillary surveys through a web diary in combination with them. Hato et al. (2006) implemented a successive day-to-day survey for several months on the same individuals as a three-wave panel survey (Figure 2).

The survey was composed of agent-type application software for GPS mobile phones, a web diary system, and a position data management server. Test subjects were asked to carry mobile GPS phones and to press the start or stop button at the time of departure or arrival, respectively, through the agent-type application software. Doing so determined origin–destination data and departure and arrival times for the trip. Position data were recorded every 20 s while the subject was traveling, and position data of about ± 5 to 10-m accuracy was transferred to the data management server if outdoors. By a series of such processes, path data were automatically determined. The results of trips were instantly reflected in a blog-type web diary system that could be viewed, with corrections being possible for any omissions related to the purpose of the trip and means of transportation. Furthermore, correcting the web diary was also possible from mobile phones by using their Internet function.

Long-term recording became possible in a diary-like sense for test subjects because they could verify what was recorded about their trips via a map on the Internet. Through input via mobile phones, the agent application software transmitted transportation data. A mechanism to prevent omissions was made possible by using the transmitted traffic data as an incentive. Furthermore, this survey system proved to be stable with existing mobile phone systems and capable of supporting large-scale studies.



FIGURE 2 Outline of probe person systems.

With mobile activity loggers (MoALs) and the adoption of an agent-type system, a system in which input from a mobile phone was easy, and viewing, recording, and correcting trip records was made possible for subjects anywhere was developed by instantly sharing data via the web diary. Figure 3 shows travel-activity data from a subject that was collected by MoALs. It is clear that the trip-activity and path-selection patterns that varied daily were simultaneously measured. In GPS-based probe vehicle surveys, it is possible to collect successive day-to-day activity data for a long period, if only for the path variations. However, it is difficult to collect trip-activity data and analyze activities after trips that are related to path changes at the same time.

However, simple web or paper questionnaires can be a great burden in successive surveys, and it has been surmised that simultaneously collecting path data is difficult even when diary data can be obtained. As shown in the Figure 3, MoALs enable the observation of perturbation phenomena such as path changes and rechanges that can occur over the long term, along with concurrent time variations for the trip-activity patterns. It suggests that the collection of individual trip-activity data is possible over a long period by combining mobile phones and a web diary.

To verify the validity of MoALs, the Matsuyama probe person (MPP) survey was implemented for 3 years starting in 2003. The MPP survey is a panel-type survey, and a successive diary survey was implemented for the same subjects by using MoALs for about a month. A new panel was added each wave. The rate of subject withdrawal in the course of the survey by using these methods was 2% and 9.3%, respectively, for MPP2003 and MPP2004. The rate was higher for MPP2004 than for MPP2003. In implementing the survey, measures to protect personal information were taken and included the preparation of a privacy policy that documented the

limited methods of personal information usage and the like and its presentation to subjects to obtain a data provision contract. The survey results were compared with those from both the national transportation census and a person trip survey implemented within the same region in the past. The survey periods for the national transportation census and person trip survey were both a day long. Upon comparison of the average number of trips, it is clear that MPP showed a larger value. In addition, the average number of trips for one day drastically increased when compared with the conventional national transportation census or person trip survey. It has been surmised that trip omission occurs less frequently with this method than with conventional surveys that use paper.

Furthermore, the number of trips for one use on 1 day increased from 3.61 in MPP2003 to 3.80 in MPP2004. Trip omission was considered to decrease due to the reduction in the reply-flow burden on test subjects. The system configuration varied in MPP2003, MPP2004, and MPP2005. Because MPP2003 had no facility registration function, the reason for omission may have been test subject reluctance. Moreover, there were no facility attributes, transportation means, or purpose of trip omissions in MPP2004. The reason for this seemed to be the system's preventing of test subjects from completing editing work if any of the report is blank when editing the web diary. The cost for converting the information into data in MoALs is negligible. In contrast, data coding costs can be enormous for censuses or person trip surveys if implemented on a large scale, as it can take from 1 to 10 min per slip.

In such a system, attempts are made to enhance the function of making subjects themselves complete activity records by using a blog function, as well as by simply asking them to record trip data.

Interactive Surveys: Applications of Survey Techniques by Using RFID Tags

In the probe person survey, the origin and destination of travel behavior in a wide area are collected by means of GPS information. Because the accuracy of position information from a GPS is about 5 to 15 m, it cannot be said that the origin and destination are accurately and reliably authenticated. In particular, it is difficult to acquire indoor position information, and there are such problems as the inability to identify with accuracy travel to different facilities in the same building and the difficulty of identifying an automobile and a bus traveling the same path.

However, in a behavior survey using RFID tags, subjects are asked to carry a card with an IC chip that transmits weak radio waves, and the radio waves are transmitted by RFID tags to readers installed in specific locations, making it possible to record an individual's



FIGURE 3 Incentive systems for pedestrians based on probe person systems.

position with arbitrary position accuracy. The accuracy can be changed from 10 cm to 50 m by changing the type of RFID tag, and various behaviors can be authenticated. Unlike conventional questionnaire and GPS surveys, in which the authentication of precise behavior spaces was difficult due to low position accuracy, reliable authentication of transport mode is made possible by installing RFID tag readers in buses and in bicycle parking lots or by attaching RFID tags to bicycles. And the collection of data on purchase behaviors of individuals is made possible by installing readers at cash registers.

Applications of survey techniques are shown Figures 2 and 3. This survey system has been implemented with passive- and active-type RFID tags, adds points according to the content of individuals' history of town walking, and transmits the content in real time, through cooperation with the e-mail system of mobile phones. The granted points become the incentive compensation for the subjects.

Three major characteristics of such a survey system are as follows:

1. It is possible to capture detailed migration behaviors of subjects in a small area.
2. It is possible to revitalize the commercial activities in the target area by introducing (a) purchase incentives according to migration patterns and (b) advertising distribution according to location.
3. Subjects will come to provide accurate behavior data to obtain these incentives.

Although the investigator only unilaterally observed and surveyed the behaviors of subjects in conventional survey systems, the real-time collection and accumulation of behavior data of subjects who used such communication functions enable interactive marketing analysis and make it possible to induce various life behaviors in a planned way by distributing information on the basis of the results of analysis.

Figure 3 shows the overview and results of the social experiment on town-walking points. In this social experiment, an RFID tag-based survey system was implemented in a commercial mall in the urban center of the Matsuyama metropolitan area. A system was prepared by installing passive tag readers (with an effective range of 10 cm), which authenticate people who have put a card over a reader, and active tag readers (with an effective range of a 50-m radius), which tell the locations of passage and personal IDs of passers without their cards being put over a reader, in several locations in a town.

By using this system, more points were granted to people whose duration of stay was longer and who migrated to specific stores rather than having points uniformly assigned to people who have simply visited a commercial mall. A longer duration of stay in a commercial mall has

a greater tendency of producing purchase behavior and revitalizing a town. In addition, an attempt was made to increase the number of visited stores and the number of purchases by granting more points to people who successively migrated to highly associated commercial facilities.

The experiment was implemented for 1 month. The number of participants in the experiment was 260; the number of samples for only passive tags was 130; and the number of samples for active-passive tags was 130. Analysis of the results shows that the visit frequency to the city center was 1.5 times per week before the experiment was started, but it increased considerably to 2.5 times per week, on average, after the experiment began. Moreover, the duration of stay in the city center increased from 100 to 120 min, and the average purchase increased from 2,000 to 2,700 yen by the introduction of the incentives. The introduction of this system, called a town-walking point system, to shopping malls and similar locations will make possible analysis of the migration patterns specific to the commercial malls in real time and the design of the incentives.

An important point is that the implementation of results of travel behavior analyses and behavior models that have conventionally been used in this field as an information system will directly help the revenue management of commercial areas. Modeling of the reactions to incentives for each segment that are predicted by behavior models will enable the construction of an optimum online-type revenue management system. Furthermore, the accumulation of such longitudinal behavior data on town walking, which are collected in real time, will lead to a better understanding of travel behavior, such as (a) the differences in duration of stay, purchased items, and purchase frequency between shoppers who have visited the central urban area by car and by public transportation and (b) the extent to which behaviors are related to daily activity patterns and their day-to-day perturbations.

Example of Behavioral-Context Addressable Loggers in the Shell

Both questionnaire surveys and the probe person survey, which is aided by GPS mobile phones and a web diary, can be said to be survey methods that try to obtain more accurate behavior data by requesting subjects to perform some kind of operation for recording. Such recording methods as completing questionnaire forms, responding to web questionnaires, pressing a button of a GPS at the time of departure, or putting a card incorporated with an RFID tag close to a reader at the time of arrival require the subjects themselves to perform an act of recording, and therefore these methods tend to result in

recording omissions when people forget to do that. Such recording omissions inevitably become noticeable when a survey is implemented for a longer period and in more detail. However, recording detailed travel behavior for a long period is indispensable for better understanding of travel behavior and analyzing the dynamics of that behavior. To solve such problems, Hato (2006) proposed a method for identifying travel activities by using information from multiple sensors, with the aim of enabling the achievement of long-term observations by completely eliminating the act of recording by subjects.

Hato has already developed a small, portable travel-activity measuring instrument that requires no entry by subjects. Conventional surveys have collected identification information such as facility type, transport mode, and activity content through the operation of instruments, questionnaires, and the like. However, these complicated surveys burden the subjects and rely on their memory, problems often leading to recording omissions or incorrect records. Hato proposed a method for estimating behavioral contexts by using behavioral-context addressable loggers in the shell (BCALS), a wearable, behavioral-context information-measuring instrument, for reestimating label information, such as facility type and transport mode, from ecological and environmental sensors that are based on learning models. Figure 4 shows the BCALS used in the present study, and Table 1 lists the data to be acquired. Acceleration information is used for identifying the transport mode. Atmospheric pressure is used in combination with ultraviolet rays for judging the floor level and whether the person is indoors or outdoors. Sound and temperature are used for identifying the behavior content.

Here are some examples of measurement results from the sensors. Figure 5 shows the changes in acceleration of each transport mode. Walking has the largest variability in acceleration and is followed by bicycling, motor-bike, and automobile. It shows the possibility of identifying transport modes on the basis of the magnitude of acceleration without asking subjects. Figure 6 is



FIGURE 4 Exterior view of BCALS.

TABLE 1 Data to Be Acquired

Data (Numerals Indicate Geographic Points of Observation)	Bytes
X-axis acceleration (32 Hz)	2
Y-axis acceleration (32 Hz)	2
Z-axis acceleration (32 Hz)	2
Atmospheric pressure sensor (32 Hz)	2
Angular velocity (32 Hz)	2
Ultraviolet ray (32 Hz)	2
Direction (32 Hz)	2
Sound (10 Hz)	2
PS location (latitude, longitude, altitude, velocity, direction) (1 Hz)	23
Elliptical error of GPS location measurement	15

NOTE: 88-day continuous recording (battery duration: about 3 days). OS is TRON (activity identification programs can be embedded or rewritten in C).

a record of acceleration variability of subjects in coffee shops and CD shops. It shows that, in coffee shops, subjects move only when the menu is given by a waiter or waitress or when they try to drink water in a cup, and the accelerations at these occasions have been recorded. In contrast, in CD shops, subjects often move around looking for CDs, and the variability in acceleration has been observed. Most of the cases that show no variability in acceleration probably indicate that such actions include listening to a CD at a set location or paying at the cash register. Thus, it is possible to record detailed behaviors of subjects.

Furthermore, Figure 7 shows changes in atmospheric pressure. Every time a subject changes floors or visits a different facility, the atmospheric pressure changes considerably. The floor of an activity can be identified from data on atmospheric pressure.

A small logger equipped with multiple sensors has been introduced. Acceleration and sound are effective for identifying activity content and location. (They also enable capturing the number of steps and are effective for evaluating walking environments.) Moreover, atmos-



FIGURE 5 Measurement results of changes in acceleration and noise.

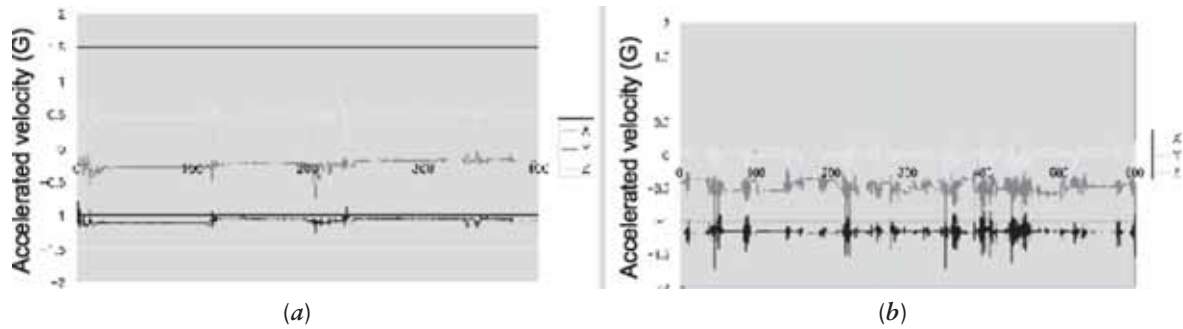


FIGURE 6 Measurement results of changes in acceleration at (a) coffee shop and (b) record shop.

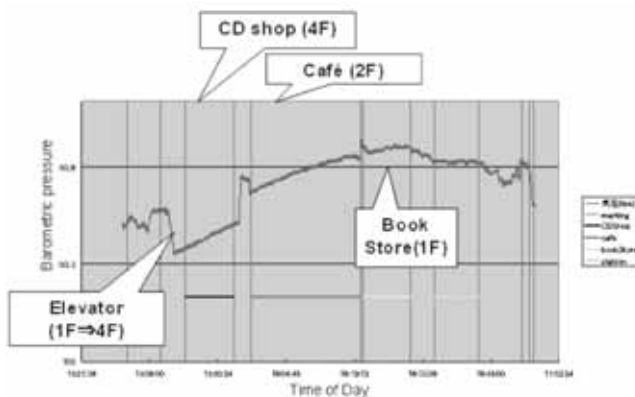


FIGURE 7 Ranges in atmospheric pressure.

pheric pressure sensors are effective for identifying indoor floors that are outside the range of GPS radio waves. It also seems possible to construct, from such information, an automatic estimation model for behavioral contexts without forcing subjects to perform any action, by using a hidden Markov-type model.

DATA-ORIENTED APPROACHES

Such techniques that enable long-term online observations of travel-activity patterns may also have a great influence on the usage of behavior models. Such monitoring techniques will significantly affect the design of fares for public transportation, central urban area planning, and transportation planning in real time. It is because the behavior databases, in which data continue to be accumulated through IT-based monitoring techniques, themselves will contain travel behavior models and activity models, making possible simultaneous searches for and viewing the findings on various travel behaviors.

Both techniques for measuring travel behavior and computer techniques are ceaselessly progressing. It is impossible to create a program on a computer when the object to be calculated is not clear, and theoretical stud-

ies, which allow calculation only with paper and pencil, have been considered superior in such cases. However, expectations are that enormous amounts of travel behavior data will continue to be stocked in databases as a result of progress in survey techniques, which has been shown in this paper. In that case, an effective analysis method will be data mining, which directly mines strategies effective for transportation policies from a large amount of data, unlike conventional approaches, which try to validate assumptions and reproducibility of models by using data.

A well-known application of data mining is the diapers-and-beer episode of Wal-Mart, the largest U.S. retailer. A correlation rule analysis, a typical method of data mining, was performed on an enormous amount of purchase data, which were being instantly collected through a point-of-sale system, and it revealed a rule that customers buying diapers on Friday evening tend to buy cans of beer as well. Wal-Mart immediately placed cans of beer beside the diaper section, and beer sales doubled.

This episode indicates that it is possible to directly draw causal relationships of consumer behaviors, which are difficult to obtain by intuition of analyzers, from a large amount of data. This method is already in use for various business data analyses, such as those for inventory control, new product planning, securities valuation, stock valuation, and medical diagnosis, and it is delivering remarkable results.

Unlike conventional analysis approaches, which have poor flexibility in policy evaluation because of too much emphasis on consistency and reproducibility of models, data mining captures transportation policies in a marketing sense, on the basis of a large amount of data, and focuses on discovering effective relationships from the data.

In fact, such a method based on data science is not considerably different from conventional approaches, which consist of the steps of data sampling, analysis, modeling, validation, and then solution of real problems. The only difference is that such a method tries to make data themselves reveal many relationships. Such a

method requires a technique for accumulating and operating accurate data, as well as for mining significant relationships of certain traffic phenomena by using the large amounts of accumulated data. A method for efficiently accumulating data and a methodology for uncovering such treasures are required for data mining.

Data mining is a method for uncovering the true nature of the structures or phenomena behind data. Whether any treasure is buried in the mountain of data to be mined depends largely on how data themselves are prepared. The following paragraphs will summarize problems to be solved for constructing a behavior database.

Transportation data mining requires a large amount of accurate data. In an additive-type database, such as those for traffic data, both the number of records and the number of attributes will continue to increase. Parallel processing and incremental processing are indispensable for handling data that range in size from gigabytes to terabytes.

Data obtained under the pervasive computing environment, which consists of GPS, mobile phones, multiple sensors, and the like, cannot be analyzed as they are. To make the data sharable, the interfaces of devices must be normalized. For example, vehicle speed data are usually measured and internally processed as pulses (hertz), and it is difficult to recognize them as speeds if they are published as they are. To share vehicle speed pulses as traffic data, they must be published as speeds, not as pulses, to the outside. The usage of data in the entire system must be envisioned to some degree and, on the basis of that envisioned usage, the data structure standardized and the data published. Moreover, to extract from the data the knowledge appropriate for the objective of the analysis, the spatial data, such as data on land use, and economic data must be prepared simultaneously and their mutual use enabled through XML or other means.

Privacy and security are also major issues to be addressed. If personal travel data (identification number, time, latitude, and longitude) are recorded at intervals of 1 min for 1 year in a city with a population of one million, a large personal database of 100 TB or more will be constructed. Although the introduction of a large personal information system has been hoped for since September 11 from the standpoint of homeland defense, there is a persistent concern over a panoptic on society from the standpoint of privacy, and a technique for ensuring anonymity is necessary.

CONCLUSIONS

This paper has shown the possibilities of new survey techniques for travel behavior through GPS mobile phones, a web diary, and multiple sensors. The crucial

difference between such survey techniques and conventional survey methods is the resolution of behavior observation. Although conventional questionnaire surveys have allowed only zone-by-zone behavior observations that rely on subjects' memory, the use of a GPS enables the measurement of detailed behavior paths and spatial dispersion in destination without relying on subjects' memory. The use of multiple sensors makes possible observation of variables conventionally difficult to observe, such as detailed activity contents at the locations of stay and the number of steps of the staircase at a transfer.

Such data will have a great influence on models. Researchers will be able to obtain a realistic knowledge of the set of choices that a traveler is actually considering, and the use of detailed path selection data, which have conventionally been difficult to obtain, will enable the development of path selection models of higher accuracy. Furthermore, it will become possible to perform modeling by using actual data on transfer resistances, such as the steps of staircases, and service levels, such as whether a traveler is sitting on a train or standing because it is crowded.

Unlike longitudinal surveys, such as panel surveys, which observe year-to-year changes in behavior, these survey techniques make possible collective observation from day-to-day to year-to-year changes in behavior in real time. They will enable real-time data mining and model analysis of an enormous amount of accumulated data on systematic changes in behavior. It is thought that the contributions of travel behavior analysis will expand from transportation plans set up on a several-year basis to transportation management that manages transport demand on a several-minute basis.

Data mining allows easy acquisition of various contents by following hyperlinks without previously having a format for analysis. Such an approach may be called an Internet-based approach, and the database, in which data continue to be accumulated, may be compared with aerial photographs in precision. In either case, models that are validated on the basis of enormous amounts of accurate data and mechanically derived knowledge may be highly beneficial for travel behavior analysis.

Which are more beautiful, paintings or aerial photographs? An aerial photograph precisely expresses an object. However, it does not tell where to look or where to proceed in the long run (although it helps decide where to proceed). The author believes that nothing can be a match for the beauty of theoretical models, which are the paintings of data mining. The results of efforts condensed on a planar canvas brilliantly express the true nature of an object. However, paintings may be replaced by aerial photographs someday if the painter and the viewer fail to improve the technique of painting, to extract true natures, and to feel the beauty.

REFERENCES

- Hato, E. 2006. Probe Person Monitoring: Intrapersonal Variability of Activity Pattern. In TRB 85th Annual Meeting Compendium of Papers (CD-ROM), Washington, D.C.
- Hato, E., and Y. Asakura. 2001. New Approach for Collection of Activity Diary Using Mobile Communication Systems. In TRB 80th Annual Meeting Compendium of Papers (CD-ROM), Washington, D.C.
- Hato, E., Y. Asakura, M. Kashiwadani, and S. Katsuki. 1999. The Simulation Study of Traffic Information Strategies Using the Computer for Data Collection on Drivers' Response to ATIS. *Urban Transport and the Environment for 21st Century*, pp. 131–142.
- Hato, E., S. Itsubo, and T. Mitani. 2006. Development of MoALs (Mobile Activity Loggers Supported by GPS-Phones) for Travel Behavior Analysis. TRB 85th Annual Meeting Compendium of Papers (CD-ROM), Washington, D.C.
- Jones, P., F. Koppelman and J.-P. Orfeuil. 1990. Activity Analysis: State-of-the-Art and Future Directions. *Developments in Dynamic and Activity-Based Approaches to Travel Analysis* (P. Jones, ed.), Gower, Aldershot, United Kingdom.
- Kitamura, R. 1990. Panel Analysis in Transportation Planning: An Overview. *Transportation Research A*, Vol. 24, No. 6, pp. 401–415.
- Murakami, E., and D. P. Wagner. 1999. Can Using Global Positioning System (GPS) Improve Trip Reporting? *Transportation Research C*, Vol. 7, No. 3–4, pp. 149–165.
- Zitto R., G. D'este, and P. Taylor. 1995. Global Positioning Systems in the Time Domain: How Useful a Tool for Intelligent Vehicle-Highway Systems? *Transportation Research C*, Vol. 3, No. 4, pp. 193–209.

ADDITIONAL RESOURCES

- Hatipkarasulu, Y., B. Wolhon, and C. Quiroga. 2000. A GPS Approach for Analysis of Car Following Behavior. Presented at 79th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Koutsopoulos, H. N., A. Polydoropoulou, and M. Ben-Akiva. 1995. Travel Simulators for Data Collected on Driver Behavior in the Presence on Information. *Transportation Research C*, Vol. 3, No. 3, pp. 143–159.
- Lyons, G. D., and M. McDonald. 1998. Traveler Information and the Internet. 1998. *Traffic Engineering and Control*, Vol. 38, No. 1, pp. 24–31.