Advanced Activity-Based Models in Context of Planning Decisions

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Travel demand modeling today is undergoing a transition from the conventional four-step models to a new generation of advanced activity-based models. The new generation of travel models is characterized by such distinctive features as the use of tours instead of trips as the base unit of travel, the generation of travel in the framework of daily activity agendas of individuals, and the use of fully disaggregate microsimulation techniques instead of the aggregate zonal calculations. Although the theoretical advantages of activity-based models—in particular, behavioral realism and consistency across all travel dimensions—are well known, the practical advantages in the context of planning decisions have rarely been discussed and documented. Experiences to date are summarized for application of activity-based models for various planning purposes in metropolitan regions of New York City; Columbus, Ohio; Atlanta, Georgia; San Francisco, California; and Montreal, Canada. The focus is on the practical planning questions and policies that were analyzed with these models and their relative strengths and advanced features compared with the four-step models. The planning questions and policies include congestion pricing schemes, high-occupancy-vehicle facilities, parking policy, testing impacts of demographic scenarios, and so on. It is shown that activity-based models are capable of treating these planning and policy issues at the level at which four-step models become inadequate.

Theoretical advantages of activity-based models are well-known and accepted by the research community and model developers. They include internal consistency, behavioral realism, and greater detail in typological, spatial, and temporal terms (*1–4*). However, these arguments are not tangible for a wider community of planners and model users. They need documented validation and testing, clear demonstration of practical advantages, as well as explanation of the quality of the outcomes rather than quality of the model structure (*5*).

This paper addresses some of these issues on the basis of first applications of activity-based models. These include applications in San Francisco, California, for a major highway investment study and new light rail transit (LRT) line study (*6*); in New York City for air quality (conformity) analysis and congestion pricing (*7*); in Montreal, Canada, for a large-scale toll road traffic and revenue study (*8*); and in Columbus, Ohio, for a new LRT line study (*9, 10*). In San Francisco and Columbus, activity-based models were used for the user benefit analysis required by FTA for new starts.

The following planning and policy issues were identified as focused communication points with a wider community of planners:

- Congestion pricing and toll facilities,
- High-occupancy vehicle (HOV) and high-occupancy toll (HOT) policies and facilities,
- Parking policy and facility development,
- Transit fare policies,
- Impact of demographic changes,
- Implications of a shorter workday, and
- Impact on land use development.

In the subsequent sections, advantages of activity-based models are highlighted in conjunction with the corresponding issue.

CONGESTION PRICING

Modeling traveler responses to toll strategies and pricing schemes has always been a vulnerable point of four-step models. There are some rules of thumb frequently applied in practice that the elasticity of demand to the toll value should be between –0.1 and –0.4.

Conventional models can predict shifts of departure and arrival times only within a particular time-of-day period and cannot predict daily schedule changes. The placement of a time-of-day choice model and its interaction with the other models have never been fully established for four-step models. Also, a four-step model operates with three or four broad time-of-day periods while congestion pricing is intended to spread traffic more evenly across specific hours of the peak and adjacent off-peak periods.

In the framework of improvements for the New York model, the authors have analyzed a rich database of the Port Authority of New York and New Jersey on the last time-of-day pricing initiatives for several bridges and tunnels around Manhattan (*11*). A significant variability across facilities was observed, and the average elasticity proved to be much lower than expected—between –0.05 and –0.2.

It is important to understand the sources of price elasticity in the model structure. The price elasticity can be estimated as a function of underlying time coefficient in the time-of-day choice utility function and value of time (VOT). With some realistic assumptions about the base time-of-day choice distribution between peak and off-peak periods, the following typical elasticities were arrived at, shown in Table 1 (upper part), for a case in which a value of $1 was added to the toll in the peak period but travel time was assumed unchanged.

The results appear consistent with the rule of thumb. For most of the reasonable values of the time coefficient and VOT shaded in Table 1 (upper part), the elasticity ranges from –0.124 through –0.322. Extreme values of either time coefficient or VOT outside the shaded area are normally rejected because they produce unrealistic mode or time-of-day shift in response to a small travel time improvement. Thus, the question remains of why the observed elasticity is systematically lower than that.

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TABLE 1 Demand Elasticity, $1 Additional Toll, Fixed Time Versus 5 min Saved

Time Coefficient	Value of Time, $/h 5	10	15	20	25	30
$1 additional toll, fixed time						
–0.01	–0.124	–0.061	–0.040	–0.030	–0.024	–0.020
–0.02	–0.254	–0.124	–0.082	–0.061	–0.049	–0.040
–0.03	–0.391	–0.188	–0.124	–0.092	–0.073	–0.061
–0.04	–0.534	–0.254	–0.166	–0.124	–0.098	–0.082
–0.05	–0.682	–0.322	–0.210	–0.156	–0.124	–0.102
–0.10	–1.468	–0.682	–0.438	–0.322	–0.254	–0.210
–0.15	–2.232	–1.069	–0.682	–0.498	–0.391	–0.322
$1 additional toll, 5 min saved						
–0.01	–0.071	–0.010	0.010	0.020	0.026	0.030
–0.02	–0.145	–0.020	0.020	0.040	0.051	0.059
–0.03	–0.221	–0.030	0.030	0.059	0.077	0.088
–0.04	–0.299	–0.040	0.040	0.078	0.101	0.116
–0.05	–0.379	–0.051	0.049	0.098	0.126	0.144
–0.10	–0.809	–0.102	0.098	0.190	0.243	0.277
–0.15	–1.268	–0.156	0.144	0.277	0.351	0.398

Three major reasons were identified to explain the relatively low observed elasticity of the demand to congestion pricing:

1. Equilibrium time offset,
2. Highly differential VOT across population and travel segments, and
3. Entire-work-tour and entire-day-schedule considerations.

These three factors are crucial for a proper price sensitivity analysis. The first factor is equally relevant for both four-step and activity-based models. The second and third factors can be effectively addressed only within the activity-based modeling framework.

Equilibrium time offset occurs as a result of the congestion relief. Since some drivers switch from the peak period to the off-peak period as a response to (higher) tolls, the travel time is improved, and this attracts some drivers back. This equilibrium mechanism reduces elasticity to congestion pricing to the extent the improved travel time compensates for extra cost. The lower part of Table 1 illustrates this effect. It is organized in the same way as the upper part; however, when the responses were calculated, a fixed travel time saving of 5 min was added.

Since 5 min saved is equivalent to $1 of extra cost at VOT equal to $12/h, the entries with VOT higher than $12/h have obtained a positive elasticity. For VOT lower than $12/h, there is still a negative response, but the elasticity is close to zero in many cases in the shaded area. In reality, positive elasticity can be observed only if congestion pricing is accompanied by improvements to the level of service. If there is no improvement, the sensitivity to extra toll will be negative but lower than the sensitivity calculated with fixed travel times because of the equilibrium time offset.

The second important factor relates to travel segmentation by VOT. Different travel population groups exhibit different VOT values. For example, in the New York model, VOT values were differentiated by six travel purposes (*7*):

- Work—$15.8,
- School—$6.5,
- University—$11.7,
- Maintenance—$12.4,
- Discretionary—$10.7, and
- At work—$40.0.

In the Montreal model, since toll revenue forecast was the focus of the study (*8*), VOT was specifically estimated for three relevant travel purposes with additional segmentation by gender, income group, and time of day (see Table 2).

Detailed travel segmentation can be incorporated effectively only in the activity-based microsimulation modeling framework. Conventional models are limited in treating detailed segments and operate with crude average VOTs that result in significant aggregation biases. Detailed segmentation tends to dampen the price sensitivity (or stated otherwise, aggregation across different segments tends to overestimate sensitivity) since a typical sigmoid response curve

TABLE 2 Summary of VOT Estimates for Toll Road Users in Montreal Model

Gender	Income	Time of Day	VOT by Purpose Work	Maintenance	Discretionary
Male	Low	Off-peak	$7.3	$4.0	$3.0
		Peak	$10.3	$4.0	$3.0
	High	Off-peak	$10.2	$4.0	$3.0
		Peak	$10.2	$4.0	$3.0
Female	Low	Off-peak	$7.3	$6.4	$6.0
		Peak	$10.3	$6.4	$6.0
	High	Off-peak	$10.6	$7.3	$7.6
		Peak	$10.6	$7.3	$7.6

(such as logit model) has the steepest part in the middle while the ends are quite flat.

The third important factor relates to the entire-work-tour and entire-day-schedule framework. When travelers change outbound commuting time in response to a.m. congestion pricing, they consider consequences for the subsequent schedule. In general, work schedule considerations can be broken into the following three groups:

- Departure time from home, including flexibility of work arrangements, congestion avoidance, household errands associated with the outbound commute (giving a child a ride to school or having breakfast together), and so on;
- Arrival time back home, including flexibility of work arrangements, congestion avoidance, household and personal errands associated with the inbound evening commute, postwork maintenance or discretionary activity, and so on; and
- Duration of the work activity, including workplace regulations (8-h workday for full-time workers) as well as some particular work arrangements that happen on the given day (for example, working extra time to finish an urgent project), and so on.

Any decision to shift the departure time to a later or earlier hour not only can violate some of the arrangements associated with morning commute but also can trigger a chain of changes in the evening commute and postwork activity as well as can conflict with the necessary work duration. Conventional models operate with trips, not tours; thus their time-of-day choice submodels (or peak spreading models) cannot incorporate entire-tour effects and linkages. Conventional peak spreading models are focused on one period (frequently a.m. peak) or have separate models for a.m. and p.m. peaks. In both cases, the a.m. peak spreading analysis is isolated from the other periods.

Ignoring entire-tour and entire-day schedule considerations may eventually hamper the effectiveness of the policy. For example, an a.m. peak spreading policy intended to move traffic from the peak hour to the late shoulder or midday period may result in worsening congestion in the p.m. period. Consider a typical work commuter who leaves home at 7:30 a.m. and arrives back home at 6:00 p.m. Most of the commuters with this schedule do not have significant additional travel-related activities before 7:30 a.m. They undertake almost all nonwork travel in a relatively narrow residual time window between 6:00 p.m. and 11:00 p.m. By shifting the work schedule by 1 h later (making it from 8:30 a.m. to 7:00 p.m.), one cannot expect significant redistribution of nonwork activities from the postwork to prework period. Thus, almost the same amount of activities and travel would be compressed in a narrower residual window (from 7:00 p.m. to 11:00 p.m.). Moving the late threshold for nonwork activities (from 11:00 p.m. to 12:00 p.m.) that one would argue should follow the work schedule shift is problematic because of the intrahousehold interactions (children still go to school with the same early schedule and the second worker may not be affected by the policy).

Activity-based models show a consistent response of commuters on different toll strategies by time-of-day periods. They also capture interlinkages between work and nonwork activities. Activity-based models normally exhibit a reasonably low sensitivity to congestion pricing applied in a single period (a.m.); however, they explicitly capture impact of a.m. peak spreading policies on the p.m. peak (reverse commuting) and other periods, which a four-step model would ignore.

HOV FACILITIES AND POLICIES

Travel decisions of persons who travel together are naturally linked across such dimensions as mode, destination, and time of day. This fundamental aspect is missing from the four-step model, in which each trip is modeled for each person independently. This limitation of the four-step models is especially critical for such planning decisions as HOV lanes, HOT lanes, and differential-by-occupancy toll strategies.

Conventional models treat HOV as mode, assuming that each individual traveler may choose this option, along with driving alone or riding transit, on the basis of the relative time and cost. There is no explicit linkage of the joint travel choices made by different household members in the modeling procedure. As a result, conflicting choices of mode, destination, and time of day may be produced for the same household. Inclusion of the HOV option as a mode alternative obscures its true availability, which depends on the household composition and the possibility of synchronizing the activities and trips of different persons. Attributing choice of HOV solely to network level-of-service characteristics can lead to a significant overestimation of the number of users of HOV and HOT lanes.

Joint travel statistics for different regions such as New York, Columbus, and Atlanta show several commonalities. First, roughly 40% to 45% of tours proved to be either fully or partially joint. This statistic was normally lower for elemental trips (25% to 30%); it was higher for tours since having one joint trip between two tours is enough to make them partially joint. Another important commonality is that about 75% to 80% of joint tours related to members of the same household while only 20% to 25% related to interhousehold carpools. Of the intrahousehold joint tours, approximately 50% related to shared nonwork family activities (such as visiting a shopping mall), and another 50% related to partially joint travel arrangements for nonshared mandatory activities (such as escorting children to school). Most intrahousehold travel arrangements are predetermined by the household composition and alternative modes available for children. They are less sensitive to HOV policies and incentives compared with interhousehold carpools.

Activity-based models have a clear advantage in that they can incorporate explicit modeling of joint travel by household members, which significantly improves the accuracy of HOV forecasts. Travel models developed in New York and Columbus, and being developed in Atlanta, already have included several major types of joint activities and travel (*7, 9*).

PARKING POLICY

Parking is an inherent and important aspect of transportation. It includes many interrelated planning issues such as land allocation, construction of parking facilities, provision of space for street parking, parking restrictions and regulations, parking cost strategies, and so on. Parking lots can be public or private, and the corresponding decisions require tools for demand and revenue forecasting.

Conventional models provide a little help in forecasting parking demand or assessing the related policies. They do not model parking duration explicitly. Consequently, four-step models do not explicitly generate demand for parking. Only crude estimation of parking demand by broad time-of-day periods can be done on the basis of the modeled auto trip attractions and average activity duration. Also, it is normally assumed that the parking lot for each trip coincides with the destination zone, and cases in which the vehicle is parked in a different zone (followed by a walk to the final destination) are not modeled. Parking constraints, restrictions, and regulations are difficult to introduce in the four-step framework.

Conventional models operate with flat zonal parking charges per trip (as a variable in mode and destination choice) that cannot be directly related to parking charge schemes and policies. In combination with the limited model segmentation, this creates a significant aggregation bias illustrated by the following example. Consider a realistic logit-type curve for probability of using auto versus transit as a function of parking cost with the following pivot points:

- Parking cost $0—auto 90%, transit 10%;
- Parking cost $4—auto 85%, transit 15%;
- Parking cost $8—auto 70%, transit 30%;
- Parking cost $12—auto 30%, transit 70%;
- Parking cost $16—auto 15%, transit 85%; and
- Parking cost $20—auto 10%, transit 90%.

Assume that in the "before" scenario, 50% of travelers do not pay any charge since they either are eligible for free parking or have a full reimbursement from their employer. Another 50% have to pay $16. Average parking charge before is $8.

Consider now an additional area pricing strategy "after" of $4 that would affect both segments of travelers. Those who did not pay now will be paying $4. Those who paid $16 before will be paying $20. Average parking charge after is $12.

With average values of $8 (before) and $12 (after) with the curve, a high elasticity is obtained. The auto share change will be from 30% to 70%. However, by considering two segments, it can be concluded that the auto share for the first segment with values of $0 (before) and $4 (after) will change from 90% to 85%, while the auto share for the second segment with values $16 (before) and $20 (after) will change from 15% to 10%. As a result, the total auto share will change from 52.5% to 47.5%. This significant difference is typical for behavioral response models. Aggregate calculations tend to overestimate elasticity because the average values of explanatory variables fall into the steepest part of the curve. Reasonable segmentation helps avoid aggregation bias and frequently produces a more conservative forecast.

Many practitioners express reasonable skepticism about the validity of the whole four-step demand modeling procedure because it fails to handle such important components as parking. Ability of activity-based models to address parking policy lies in the nature of consistent simulation of daily schedules for all individuals and vehicles used. This allows for keeping track of all vehicles arrived in or departed from the parking place and associated parking durations with a fine temporal resolution (1 h, ½ h, or even less if necessary). This forms a basis for detailed analysis of each parking lot.

Individual parking lots and their locations can be distinguished from the final destinations of trips with explicit modeling of parking lot choice and walk to the final destination. The longer-term direction of the activity-based models is to move down to grid cell or parcel level for trip ends, and that will open up new possibilities for parking models.

Activity-based models can realistically incorporate various parking charge schemes including hourly rates and daily rates. They also can include various individual discounts. The Columbus model incorporates three interrelated submodels that capture the current parking conditions in the central business district (CBD) and allow for testing various policies:

- Parking cost model, sensitive to the buffered zonal density and parking capacity;
- Person free parking eligibility model formulated as binary characteristic for each worker (whether he or she has to pay for parking in CBD or not); and
- Parking location model for primary destination of each tour that is a nested logit structure—at the upper level, binary choice between parking in the destination zone versus parking elsewhere is modeled, and at the lower level, choice of the parking zone is modeled for those who did not park in the destination zone.

TRANSIT FARE POLICIES

Transit fare is an important component of mode choice and (through mode choice log sums) of destination and time-of-day choice. When multimodal transit combinations are considered, transit fare policies become one of the key issues. Transit fare policy is also an integral part of travel demand management.

Cost of an individual transit trip is a function of three major factors:

- Path-dependent mode-specific base fare associated with a single ride from the origin to the destination with possible line-to-line transfers;
- Mode-specific and intermodal payment options, including monthly pass, multiple-ride cards, two-way ticket, parking cost for park-and-ride, and so on; and
- Person-specific discounts, including such categories as children, students, seniors, employer-provided reimbursements, pretax transit checks, and so on.

Conventional models are characterized by an extremely simplistic approach to modeling transit fares. They normally operate with zone-to-zone base transit fares scaled down by crude average discounts based on the observed proportion of various payment types and person discounts. As a result, a four-step model is of little help when transit fare policies are evaluated. Implications of such policies as "free transfer between bus and subway" or "single monthly path" including all transit modes (bus, subway, LRT, and rail) are difficult issues to handle with a four-step model.

Activity-based models can help in better modeling transit fare policies, especially with respect to the payment option and person discount. For the path-dependent base fare, both four-step and activity-based models are still bound to transit path-building algorithms built in to the software packages. Though individual microsimulation offers some new opportunities for transit path-building algorithms (better accounting for individual locations and associated walk access and egress components), it has not yet been essentially exploited by the software developers.

Payment media type can be included in microsimulation. It can be done either by applying predetermined distributions or by choice models that would relate probability of choosing each payment media type to person, household, or travel characteristics (including daily frequency of transit use across all travel purposes).

Person-type discounts can be applied in activity-based models in a relatively straightforward way through explicit person segmentation. For example, the Columbus model has included actual transit discounts for schoolchildren and university students that directly correspond to the policies applied in the region. This improved the mode choice model for school and university tours tremendously. The technique can be extended further to incorporate senior discounts (through the age variable), pretax transit check programs (through employment status), and so on.

DEMOGRAPHIC CHANGES

Another important advantage of activity-based models is associated with explicit microsimulation of synthetic households and persons that allows for testing effects of demographic changes as well as singling out detailed population subgroups for analysis.

Conventional models are not suitable for testing demographic scenarios since they allow for only a small set of demographic segments. This stems from the matrix-based structure of the core trip-distribution and mode choice models. This structure requires that each socioeconomic variable be associated with a set of fully segmented origin–destination matrices. Traditionally, four-step models have been based on three or four major socioeconomic variables (household size, number of workers, income group, car ownership, etc.), and little has been done to extend this set of variables since it would result in an infeasible number of trip matrices to handle.

Principally different, activity-based microsimulation models can accommodate a virtually unlimited set of person and household attributes in both estimation and application. However, for many practitioners, the advantages of greater detail of individual behavior remain unclear. The ultimate purpose of travel models is to provide aggregate forecasts for transportation projects and policies. This pragmatic purpose has not changed with the new generation of models. Thus, it is important to demonstrate how activity-based models can help in making aggregate forecasts more realistic and how additional socioeconomic variables contribute to this improvement.

The key point in inclusion of additional socioeconomic variables is their association with significant observed tendencies in travel. Two examples are provided of additional socioeconomic variables that are in many respects more important that the traditionally used variables and show their impact on the aggregate travel forecast. These variables include worker status (full-time versus part-time) and presence of a preschool child (under 6 years old) in the household. Both variables traditionally have been ignored in the four-step framework.

Consider simple binary classification of workers into full-time and part-time status. Full-time workers are normally characterized by 35 to 40 work hours a week (7 to 8 h a day) and predominantly daily commute. Part-time workers represent a group with a wide variation of work arrangements that result in less than 35 work hours a week. Some part-time workers have a shorter workday but still commute every day while others work less than 5 days a week. There are several important travel-related differences between full-time and part-time workers illustrated by a comprehensive household travel survey undertaken in the Atlanta region in 2001 (8,069 households surveyed during 2 consecutive days):

- Number of work commute tours per day—0.85 for full-time worker, 0.56 for part-time worker;
- Average commuting distance (miles)—13.1 for full-time worker; 9.9 for part-time worker; and
- Commuting mileage per day—22.3 for full-time worker, 11.1 for part-time worker.

In addition to the lower work tour frequency, part-time workers are characterized by a significantly shorter commuting distance. As a result, each full-time worker contributes twice as much to the commuting mileage compared with a part-time worker (calculated as a round-trip distance multiplied by the work tour frequency). While there is a certain positive impact of the part-time worker status on non-work travel, the work-related travel segment is of primary importance for congestion-related policies and transit projects.

The proportion between full-time and part-time workers is an important determinant of the level of congestion in the peak period. Consider four possible regional scenarios with respect to the proportion between full-time and part-time workers and corresponding peak hour mileage (relative to the highest-mileage scenario with the highest proportion of full-time workers).

- High scenario—10% part-time, 90% full-time, 100% mileage;
- Atlanta 2001 scenario—14% part-time, 86% full-time, 97% mileage;
- Columbus 1999 scenario—21% part-time, 79% full-time, 93% mileage; and
- Low scenario—25% part-time, 75% full-time, 90% mileage.

Two scenarios correspond to the observed proportions in the Atlanta and Columbus regions. The Columbus region is characterized by a comparatively aging population with a higher share of part-time workers in the regional labor force (21%) while the Atlanta region has a generally younger population with a lower share of part-time workers (14%). Also considered are two additional scenarios with an even higher share of part-time workers than in Columbus (25%) and a lower share than in Atlanta (10%) correspondingly. These hypothetical scenarios are realistic and should be considered in the future, especially for regions with a dynamic socioeconomic mix.

There is a significant 10% leeway in the peak hour vehicle miles traveled (VMT), depending on the scenario. This becomes a non-trivial issue for a long-term forecast. An assumption that the existing proportion will hold for 20 to 30 years on can lead to a significant underestimation of future travel for regions such as Columbus with a high share of part-time workers today if there are reasons for this proportion to change.

Another example of an important socioeconomic variable that cannot be used in the four-step structure is the presence of a preschool child in the household. It was included in the Columbus activity-based model and proved to be one of the important factors influencing household behavior.

To show the impact of this variable in a simple form, several regressions for household tour generation were run with the Atlanta survey data. The following basic independent variables were defined in line with the prevailing four-step modeling practice:

- Dummies for household size (1, 2, 3, 4, 5+);
- Dummies for number of workers (0, 1, 2+);
- Dummies for three household income groups (low that is less than or equal to $20,000, medium, and high that is $100,000 or higher); and
- Dummies for car ownership (0, 1, 2+).

These dummies together define 135 segments, and many practitioners would think that a model with these variables should be robust enough for practical purposes. In addition to these variables, however, another dummy was added—the presence of a preschool child in the household. The dependent variables represented number of tours generated by the household per day by primary tour purpose (work, school, and other). The results are presented in Figure 1. The bars in the figure are associated with a direct contribution of each dummy to the household number of tours per average workday.

For work tours, presence of a preschool child proved to be the strongest negative factor, much stronger than any impact of income or car ownership. With the presence of a preschool child, household workers (especially the female spouse) frequently have days off or temporary changes in the work arrangement. In particular, for a single-worker household, presence of a preschool child reduces work activity by about 20%. It should be noted that a single-adult household is a growing group representing almost 30% of households in both the Atlanta and Columbus regions.

For school tours, presence of a preschool child proved to be an even stronger negative factor. Unlike schoolchildren who normally go to school every day, preschool children may either stay at home or have a flexible day-care arrangement.

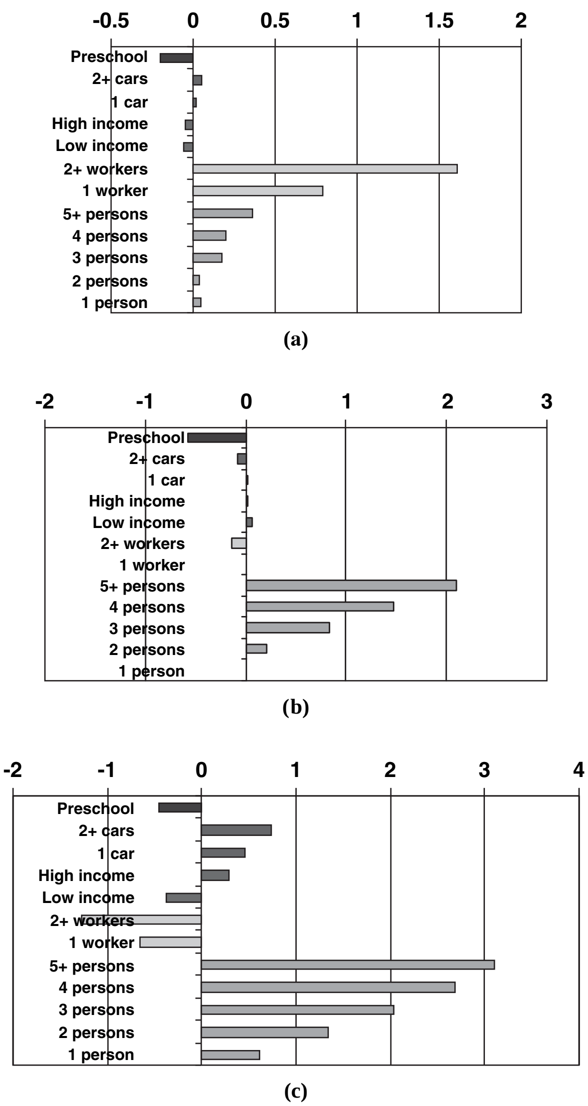

FIGURE 1 Impact of socioeconomic variables on tour generation: (*a*) work tours, (*b*) school tours, and (*c*) nonwork tours.

For nonwork tours, presence of a preschool child also proved to be a significant negative factor (stronger than the income impact). A systematic structural shift in nonwork activities was also observed in households with a preschool child. While there was a significant drop in discretionary activities (especially for the household heads), it was partially offset by a growth in escorting and other trips related to child care.

There are many more socioeconomic variables that could significantly add an explanatory power to travel models. They include changing proportion between age groups (older versus younger population), growing share of nontraditional households (singles, households without children), structural changes in occupation types (in particular, more specialized occupations for most workers), and so on.

Conventional models in general produce conservative long-term forecasts that are driven mostly by the population growth. The observed general tendency of travel growth by 2% annually, as confirmed by the last National Household Travel Survey, is quite contradictory to most forecasts. One of the major reasons is that the traditional set of socioeconomic variables is not nearly enough to explain the observed tendencies.

Activity-based models with a richer set of socioeconomic variables can help capture structural changes and produce more reasonable forecasts. It is also believed that by adding socioeconomic variables, the model structures will become more transferable spatially and temporally.

SHORTER WORKDAY

In four-step models, peak factors applied for work trips do not include any duration variable. Nonwork trip generation and peak factors are independent of work peak factors and also do not relate to work duration. As a result, a four-step model is not sensitive to the work duration and cannot serve as a tool for analyzing such policies as shortening a workday.

Models of the new generation are capable of testing such policies. The advantageous feature of activity-based models is that activity–travel generation and scheduling are tied together by means of tracking available time windows at the individual level. Thus, any time savings on mandatory activity or travel has a realistic impact on nonmandatory activity generation and scheduling.

Consider a worker who has a work tour scheduled from 7:00 a.m. (departure from home) to 5:00 p.m. (arrival back home). Since the work tour has been scheduled, this person has two residual time windows open for other tours. The morning window starts at 5:00 a.m. (the most common early temporal frontier) and ends at 6:59 a.m. The evening window starts at 5:01 p.m. and ends at 11:00 p.m. (the most common late temporal frontier). Any subsequent tour can be generated and scheduled only within one of the residual windows. In this example, the evening window is wide enough to generate a discretionary tour and schedule it from 7:00 p.m. through 11:00 p.m. After the second tour has been scheduled, the evening window is reset from 5:01 p.m. through 6:59 p.m. This process continues until the time is exhausted. With this procedure, generation and scheduling of nonwork activities become realistically sensitive to the work duration.

To illustrate the impact of the work duration on nonwork activity generation, first the relevant tabulations with the data from the Columbus survey (5,555 households) were implemented. The observed patterns are presented in Figure 2.

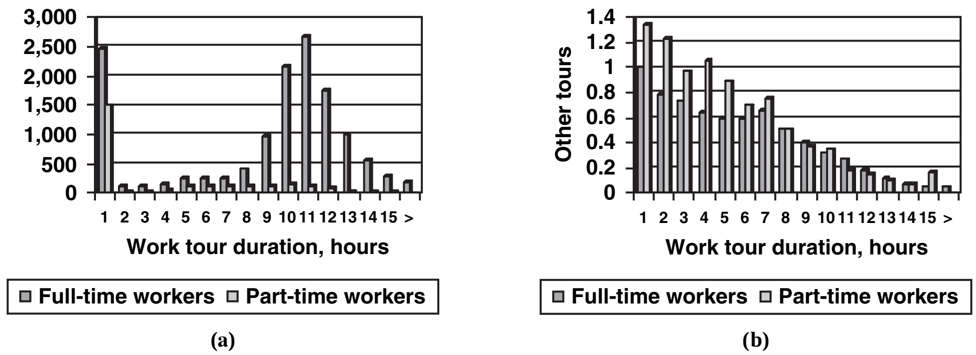

FIGURE 2 Impact of work duration on nonwork travel: (*a*) frequency distribution of work tour durations and (*b*) number of nonwork tours as function of work tour duration.

Figure 2*a* shows the observed distribution of work tour durations. Work tour duration includes both work activity duration (including lunch break or any business activity or travel during the workday) and travel time to and from work. Thus the mode of the distribution is between 10 and 11 h. The distribution for full-time workers has a clear bell-shape form. The distribution for part-time workers is scattered and does not have a distinct mode. Approximately 20% of full-time workers and 50% of part-time workers did not have a travel tour to work on the surveyed day for various reasons (vacation, day off, sickness, work at home, less than five workdays a week, etc.).

Figure 2*b* shows the observed impact of work duration on the number of nonwork tours. For relatively short durations (7 h or less), there is a clear status-based difference. Full-time workers do not behave like part-time workers, even occasionally having shorter work duration. There is a strong correlation between worker status and gender (80% of part-time workers are female). Thus, the difference in nonwork activity levels can be attributed partially to the gender roles in a household. For longer work durations when time–space constraints come into play, there is no significant difference between full-time and part-time workers.

Considering the observed cross-sectional differences in nonwork activity levels across different work durations, one can expect that shortening a normative workday from 8 h to 7 h should add approximately 20% of nonwork tours for workers, which should result in about 10% more nonwork tours overall since workers represent roughly 50% of the population. However, one can also reasonably expect that intrahousehold interactions and various satiation effects probably would mitigate growth of the nonwork travel.

The corresponding test was implemented with the Columbus model for the base year 2002. The results proved to be different from the simple cross-sectional tabulation, with a clear indication on the following behaviorally realistic tendencies.

- Growth of 8% in nonwork activities for workers. It was a combination of several very different travel components:
  - The biggest growth of 12% for joint activities since these activities are conditional on residual time window overlaps (after scheduling work tours);
  - A significant growth of 7% for individual home-based tours but much lower than for joint activities; and
  - A certain reduction of –2% for at-work activities since the shorter workday narrowed the possible window for these activities.
- Reduction of –1% of nonwork activities for nonworkers as the result of intrahousehold interactions between workers and nonworkers. Again, two quite different components should be mentioned:
  - A significant growth of 5% for joint activities undertaken with (now more available) workers and
  - A certain reduction of–2% for individual travel because of the reallocation of some maintenance activities from nonworkers to workers.
- Overall, by totaling all person types, a 4% growth in travel was modeled. This is a logical result, though it is less than half of what one might expect on the basis of a simple cross-sectional tabulation. Since the Columbus model includes various forms of intrahousehold interactions and time–space constraints, it was able to capture various direct and compensatory effects of shortening work duration.

Shortening workday duration is a realistic factor that should not be ignored for long-term forecasts of 20 to 30 years. A shorter normative workday of 7.5 h already has been adopted in Canada and many European countries. It is suggested that a shorter workday should be included, at least as a sensitivity test, for long-term scenarios.

LAND USE DEVELOPMENT

One important feature of a travel model is its compatibility with a land use model. It is of special importance for long-term planning when effects of the transportation system and land use development on each other become significant and closely intertwined.

Conventional models traditionally have been combined with land use models in an iterative fashion (frequently referred to as "integrated" model though it never assumed a real integration). Transportation and land use models were applied iteratively for each target year and were linked by a small number of input–output components. A land use model provided zonal population and employment inputs for the transportation model. The transportation model provided zone-to-zone travel times and cost as inputs for the land use model. In most formulations, both models had numerous duplicating components such as spatial interaction in the land use model and trip distribution in the transportation model.

Activity-based models offer a different approach to (real) integration with land use models. In this approach, both models have a mutual core component that corresponds to the activity simulation at the individual level: generation, scheduling, and location of activities for each household and person (*12*). The transportation model then includes various network-related procedures (tour formation, mode choice, route choice, traffic and transit simulation, etc.) that put the simulated activities into a "physical layer" for implementation. The land use model includes various activity supply-side procedures (land use development, household location, associated prices) that provide location attractors and constraints on the individual activity agendas. Transportation simulation provides individual location choices and preferences that serve as drivers, developing pressure on the land use development side. Land use development provides location factors and constraints (available housing, jobs, and services) for the activity–travel simulation.

CONCLUSIONS

Activity-based model applications for several planning and policy issues were discussed, and other possible practical aspects were mentioned in which these models can help and provide information that cannot be obtained from four-step models. Activity-based models offer numerous significant advantages in supporting various planning decisions and policies, especially related to travel cost (congestion pricing, parking policy, HOV and HOT facilities, transit fare policy, etc.). Activity-based models also are more sensitive to changing demography or land use, and through this sensitivity they allow for better capturing travel growth factors in long-term planning. For these reasons, moving activity-based models into practice represents the most important direction in improvement of travel demand models.

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