Ann Reg Sci (2011) 47:517–541
DOI 10.1007/s00168-010-0393-5

SPECIAL ISSUE PAPER

A practical policy-sensitive, activity-based, travel-demand model

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Received: 7 July 2009 / Accepted: 1 April 2010 / Published online: 15 June 2010

Abstract The development of activity-based models as a tool to analyse travel behaviour and forecast transport demand has been motivated by the growing complexity in activity patterns resulting from socio-economic changes, growing congestion, and negative externalities, as well as the need to estimate changes in travel behaviour in response to innovative policies designed to achieve sustainability. This paper reviews how the trade-off between behavioural realism and complexity, one of the main challenges facing the travel-demand modeler, is made in the best practical activity-based models. It proposes an approach that captures key behavioural aspects and policy sensitivities, while remaining practical with reasonable requirements of computational resources. The three main model elements in this trade-off—model structure, data, and application method—are analysed. Drawing on examples from a model developed for Tel Aviv and from existing US models, this paper shows that behavioural realism and policy sensitivity can be achieved with a reasonable level of model complexity.

JEL Classification R40 Transportation general · R41 Transportation, Demand

Paper submitted for a special issue of Annals of Regional Science of the 3rd Israel-Netherlands Workshop in Regional Science, Jerusalem, November 2008.

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1 Introduction

The growing complexity in travel patterns and the need to estimate changes in travel behaviour in response to new policies call for a better understanding of such issues as the effects of new information and communication technologies on travel behaviour, the effects of land use and growth management on travel behaviour and travellers' response to auto-restraining policies. Understanding such effects, which is essential for an improvement in the design of new policies, is the main motivation behind the development and advancement of activity-based models. The explicit modelling of activities and the consequent tours and trips enable a more credible analysis of the responses to policies and of the subsequent effects of policies on traffic and air quality (Shiftan 2000).

A variety of research methods have been used to study activity behaviour, including duration analysis, limited dependent-variable models, structural equation models and computational processes models (Pas 2002). Different approaches have been used for activity-based models (Henson et al. 2009), but they usually take one of two main approaches: discrete choice analysis (DCA) and rule-based process (Jovicic 2001; Bowman and Ben-Akiva 1997). This paper focuses on the discrete choice modelling approach (Ben-Akiva and Bowman 1998a) as it is the more practical one and therefore the one that is more commonly used in actual regional models.

Based on the DCA approach, Ben-Akiva et al. (1996) proposed a practical activity-based, comprehensive, travel-demand modelling framework that captures the mobility, activity and travel decisions of individuals and households. In addition, a corresponding prototype system of models that can be used for planning and policy analysis was developed by Bowman and Ben-Akiva (1997). Applications have followed and have been demonstrated for policy analysis (Shiftan and Suhrbier 2002). In an effort to enhance behavioural realism, however, and to make the applications sensitive to a wide spectrum of current planning and policy needs, these applications have reached a significant level of complexity, to the point of risking their practical use.

Figure 1 shows conceptually how the move from trip-based (four-step) models to more advanced models increases behavioural realism and computational complexity. As the figure shows, the cost of model complexity increases exponentially. In contrast, the benefits of behavioural realism increase at a decreasing rate. Figure 2 shows the same concept. The difference is that the computational complexity curve has been converted to computational simplicity so that both curves represent model benefits. As Fig. 2 shows, there is an optimal level of behavioural realism that maximizes the benefits of the model.

This paper addresses the issue of incorporating the process of household and individual activity-scheduling into the models and the level of complexity required for travel-demand forecasting and policy analysis. It considers recent advances in research and how these lead to current best practice of activity-based models used or being developed by planning agencies. It discusses the trade-offs between behavioural realism, on the one hand, and complexity and practicality, on the other, made by these models.

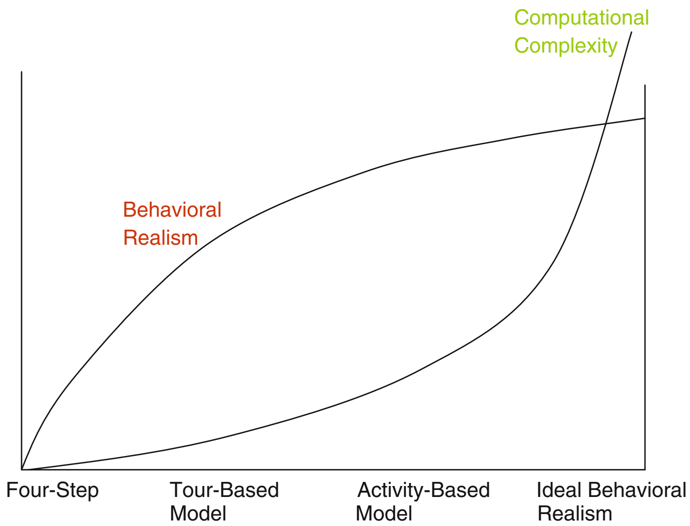

Fig. 1 Behavioral realism and computational complexity in travel-demand models

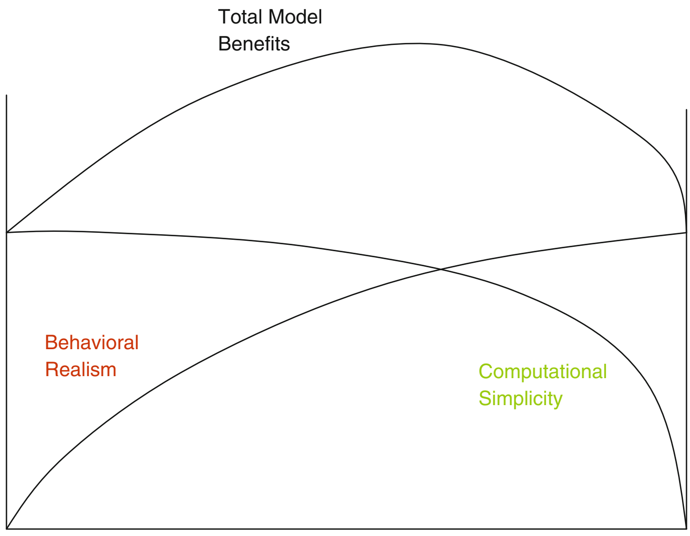

Fig. 2 Benefits from behavioral realism and computational simplicity in travel-demand models

In the next section the paper first further discusses the policy issues that activity-based models should be designed to analyse and the possible trade-offs for increased sensitivity within the barriers of implementation. The paper subsequently analyses the trade-off between behavioural realism and complexity in regard to key concerns in this trade-off, the model structure in Sect. 3, data in Sect. 4 and model application in

Sect. 5. Finally, it suggests on a balanced level of trade-off between model complexity and behaviour realism for good practical policy sensitive models.

2 Policy sensitivity and the desired level of behavioural realism

One of the main motivations for the development of activity-based models is to provide a model that is sensitive to emerging policies. Therefore, the design of the model should take into consideration the types of policies to which the model should be sensitive. Although policy needs can vary from region to region, the minimum set of policies that activity-based models should and can be sensitive to are: (1) *Demand Management* including responses to different demand-management strategies, such as parking restrictions and congestion pricing. (2) *Land-Use Policies* including mixed development, concentrated development in centres or corridors, and pedestrian-friendly site design. (3) *Information Communication Technology (ICT)*, and (4) *Transit Improvements.*

In addition to their greater sensitivity to specific policy measures, activity-based models have two other related important features: inclusion of variable (or latent) demand and sensitivity to equity issues. By using an integrated approach, including logsum variables that bring level-of-service variables up the structure to the activity pattern model, they account for changes in all travel choices including activity participation as a result of changes in level of service. For the model to be able to account for equity considerations, it has to be able to report statistics for different sub-groups in the population. Using the micro-simulation approach, described later in this paper, enables such reporting for any number of demographics. The various impacts can be segmented by income, geographical distribution and other measures. This capability was demonstrated in the San Francisco County Transportation Model (SFCTA) where the impacts were identified for several population groups, such as female heads of household with children (Davidson et al. 2007).

For activity-based models to have the desired behavioural realism, they need to be theoretically sound and at a sufficient resolution to explain policy impacts. An activity-based model should predict activity participation and time allocation, with explicit consideration given to spatial, temporal and social constraints, while accounting for inter-dependency among individuals in a household and among trips. To better understand activity behaviour, we need to analyse the context of the activities, including why, when, with whom, and how long, as well as the sequence of those activities (Bhat and Koppelman 1999; Goulias et al. 2004). An understanding of how households and individuals acquire and process information about their activities and travel options and how this information is used in planning activities and travel is also required as well as proper accounting of the interactions of the household members and of within-person correlations over time (Goulias 2000).

Activity-based models should be integrated with lower-level decisions, such as parking choices or route choice, and higher-level decisions, such as residential location, work location and car ownership (Ben-Akiva et al. 1996). Figure 3 shows the system of models used in travel-demand analysis, with the activity-based model as one of its elements. The upper level of the figure shows aggregate applications, and the

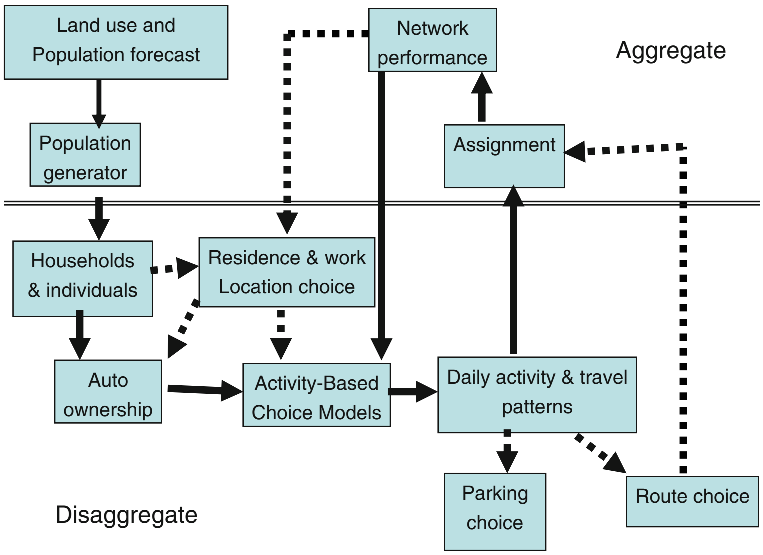

Fig. 3 A combined aggregate and disaggregate model system

lower level disaggregate applications. Full arrows show the current practice of most activity-based models. The dashed arrows show additional required integration at a disaggregate level with higher-level decisions, such as land use and auto ownership, and with lower-level decisions, such as parking and route choice.

Various attempts have been made to develop these types of integration (e.g. Ben-Akiva and Bowman 1998b). Roorda et al. (2009) developed an integrated model of vehicle transactions, activity scheduling and mode choice. Shiftan (2008) integrated activity-based models with residential choice models. Initial efforts have been made to implement integrated land-use and activity-based travel-demand models as shown by Dong et al. (2006), Miller et al. (2004), Salvini and Miller (2003) and Ettema et al. (2006).

From the lower level, most current activity-based models have done little to account for route-choice behaviour and the effects of that behaviour on activity participation and duration and scheduling patterns. Most models use traditional aggregate assignment models instead of utilizing all the benefits of activity-based models. Initial efforts to integrate activity-based modelling with dynamic traffic assignment were presented by Lin et al. (2009).

In the trade-offs between practicality and behaviour realism, emphasis should be placed on aspects of the specific policies of interest. In the Tel Aviv model, great emphasis was on parking pricing and supply and congestion pricing. Accordingly, detailed time-of-day and parking models were developed. A special model of supply, cost, and availability of parking was also developed for San Francisco which also developed a policy variable to measure the potential impacts of improved pedestrian systems and the expected growth that would likely impact future travel demand (Outwater and Charlton 2006).

3 Model structure

3.1 From trip-based to activity-based models

Initial developments advancing from the traditional trip-based/four-step paradigm to activity-based models started with the implementation of tour-based models that captured behavioural interactions across trips within tours (defined as a sequence of trips that start and end at the same location, usually the home), but not across tours. (Adler and Ben-Akiva 1979; Algers et al. 1995; Shiftan 1998; Rossi and Shiftan 1997). The activity-based model, also known as the day-pattern approach, captures interactions across tours. The advantages of behavioural realism in activity-based models outweigh the extra complexities. However, within the activity-based approach, there are different levels of behavioural realism and complexity, and they have increased over time. Early applications include the Activity Mobility Simulator (Kitamura et al. 1996), applied in Washington, DC (Kitamura et al. 1995), and models in the Netherlands (Gunn and Van der Hoorn 1998), Denmark (Algers et al. 1995), Germany (Ruppert 1998) and Italy (Cascetta and Biggiero 1997). More recent applications include San Francisco (Bradley et al. 2002; Jonnalagadda et al. 2001), New York, Columbus, Ohio, Atlanta (Bradley and Vovsha 2005), Dallas/Forth-Worth, Sydney, the Dutch Albatros model (Arentze and Timmermans 2001) and the Travel Activity Scheduler for Household Agents (TASHA) model in Toronto, Canada (Roorda et al. 2008). The following sections discuss some of the variations in the structure of various activity-based models in regard to different aspects of the model design.

3.2 Household interactions

Most existing activity-based models of transport demand are based on individual activity-travel choice instead of household activity-travel choices. While activities in multiple person households need to be coordinated and sometimes synchronized in time and space, most current models neglect this behavioural realism in trying to keep the models simple and practical. Srinivasan and Bhat (2005) showed the complexity associated with studying interactions between in-home and out-of-home activity in the context of intra-household and group decision-making.

Early attempts to deal with the issue include Wen and Koppelman (1999) and Goulias (2000). Scott and Kanaroglou (2002) developed an approach that incorporated interactions between household members and activity setting. Miller and Roorda (2003) allowed for joint activities in the TASHA model. Zhang et al. (2005) developed a household task-allocation and time-use model based on a multi-linear group utility function. Srinivasan and Bhat (2005) studied the role of intra-household interactions on maintenance activities. Pribyl and Goulias (2005) developed CetreSIM, which simulates daily schedules accounting for within-household interactions. Bhat and Pendyala (2005) edited a special issue on the topic for *Transportation*, and Timmermans and Zhang (2009) edited another one for *Transportation Research B*.

Expansion of the discrete choice model of activity-based models to incorporate chauffeuring and other joint activities (Vovsha et al. 2003; Gliebe and Koppelman

2002, 2005) set the basis for their practical implementation. The Mid-Ohio Regional Planning Commission (MORPC) model accounts for explicit modelling of intra-household interactions and joint travel with particular interest in modelling share ride as a travel model. However, it is based on the sequential modelling of household members by a predetermined order of person types. The Atlanta (Georgia) Regional Commission (ARC) model tries to estimate all household members' activities simultaneously (Bradley and Vovsha 2005).

3.3 Tour and activity patterns

In designing the activity-pattern model, modellers have to consider various aspects of the daily pattern: activity purpose, number of tours per day and the pattern of each tour, including the number of stops, the definition of a primary destination and treatment of work sub-tours (tours that start from work and return to work in the middle of the day). Because of the large number of attributes in the activity patterns and the large number of alternatives for each attribute, it is impossible to model all alternatives jointly. To simplify the model, it is common to decompose the structure to three levels, distinguishing among the activity pattern, tour-level models and trip-level models as shown in Fig. 4. The activity pattern predicts the overall daily structure or characteristics of the main activity of the day. Given the activity pattern, it is common to include the tour structure and mode, as well as the destination and timing of the main activity in the tour-level models. In many cases, the location, mode and timing of trips to intermediate stops are applied at the trip level after all other tour-level models are predicted. This is conditional on the tour-level choices, but without feedback from the trip-level models to the tour-level models. Some models, like Portland, have a work-based sub-tour, which is an intermediate level between the tour and trip levels. This approach can significantly simplify the application of the models.

The model should cover all the activity patterns that appear in the data. In practice, 90–95% coverage is considered good. For example, the Tel-Aviv model considers up to two tours per person, a primary tour and a secondary tour. The analysis of the data showed that only 1.6% of the sample made three tours, 0.3% made four tours and only 0.1% made five or more tours (Shiftan et al. 2004). Therefore, by capturing up to two tours per person, 98% of the population's tour generation is covered accurately. When the number of stops per tour is considered, there should be good coverage in terms of Vehicle Miles of Travel (VMT). For example, the number of stops per tour in the Boise model was limited to four. For travellers with more stops, the four chosen were those that make the largest VMT. Ignoring the others had only a marginal effect on the total VMT estimate (Shiftan 1998).

There are various differences in modelling the activity-pattern model. Table 1 shows the definition of main activity types for various models.

In the San Francisco model, the full activity pattern is predicted by one nested logit model (full information), including

- The purpose of the primary home-based tour.
- The trip-chain type (stops on the tour) of the primary home-based tour.
- The number of home-based secondary tours.

Fig. 4 A three-level model system

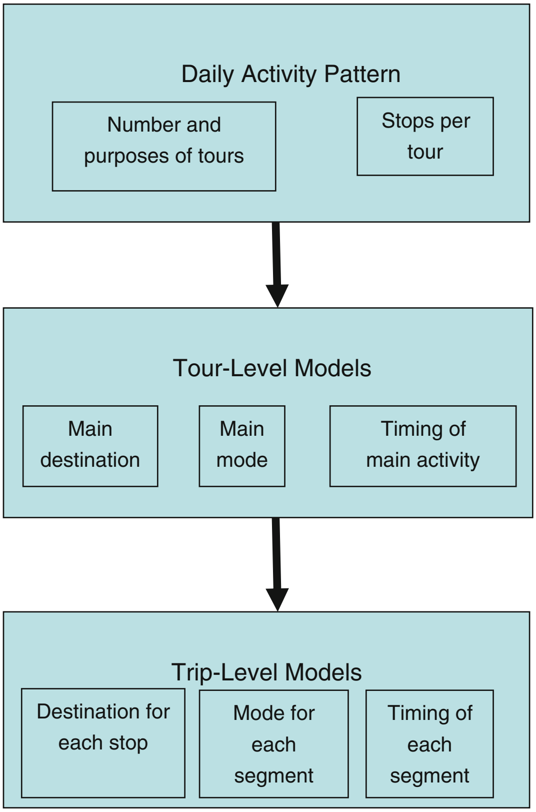

Table 1 Main activity types in several models

San Francisco	Tel Aviv	Sacramento	Portland
Work	Work	Work	Subsistence at home
Education	Education	School	Subsistence on tour
Other	Shopping	Escort	Maintenance at home
Secondary	Other	Shopping	Maintenance on tour
Sub-tour from work	Home	Personal business	Discretionary at home
		Meal	Discretionary on tour
		Social/recreation	

Overall, there are 48 out-of-home activity patterns, composed of 16 primary tour patterns times 3 categories of secondary tour frequencies.

The Portland activity pattern (shown in Fig. 5) determines the purpose of the primary activity of the day and whether the activity occurred at home or on a tour. This allows capturing trade-offs between at-home and on-tour activities. The primary activity is one of six alternatives shown in Table 1. If the primary activity is on-tour, the activity-pattern model also determines the trip-chain type for that tour as defined by the number

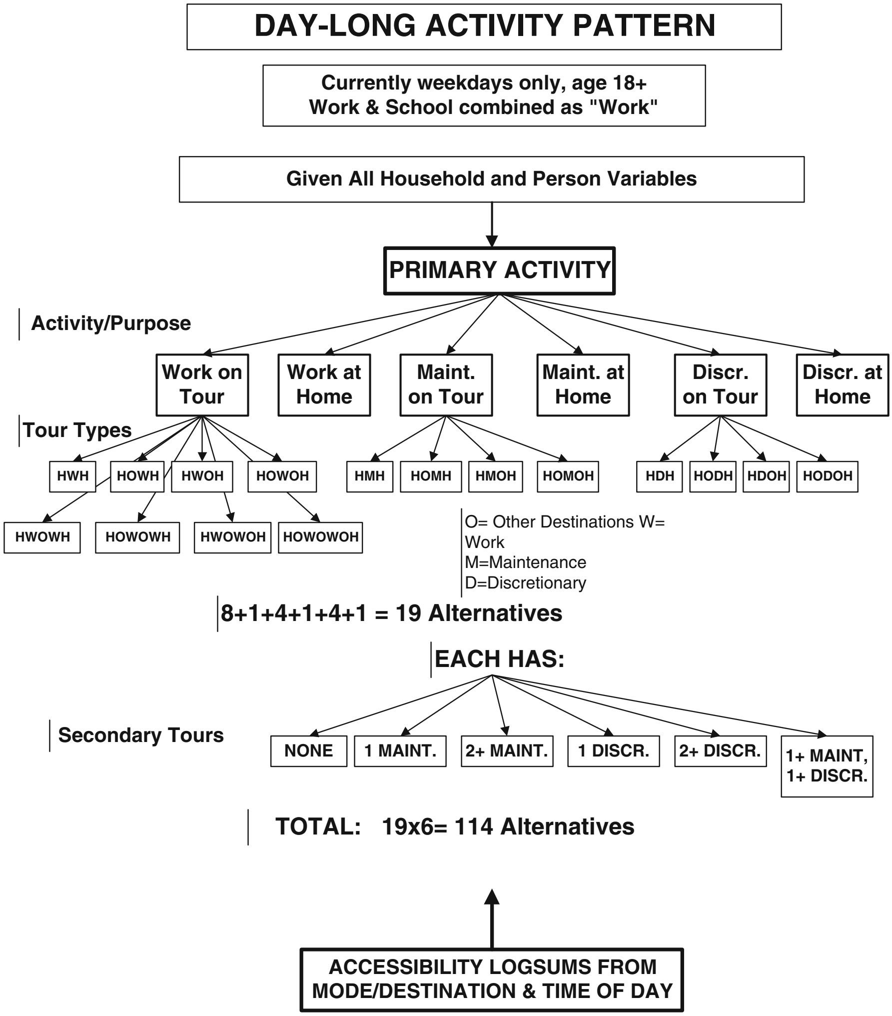

Fig. 5 The Portland daily-activity pattern model

and sequence of stops on the tour. Simultaneously, with primary activity and primary tour type, the activity-pattern model predicts the number and purposes of secondary tours. Overall, there are 19 possible combinations of primary activity/tour types and six secondary tour alternatives possible for each primary activity/tour types to a total of $19 \times 6 = 114$ daily activity pattern alternatives.

Variance exists in modelling the order of the different choices. For example, Portland and San Francisco model the number and purpose of intermediate stops at the activity-pattern level, before any particular tours are simulated. The Columbus, New York and Atlanta models predict the number and purpose of tours only at the activity-pattern level. The number and purposes 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 (Bowman and Bradley 2006). The MORPC model first predicts mandatory activity patterns, including time of day, mode and destination. The subsequent details of the secondary tours are modelled, given the residual time window. The model then estimates a trip-level model to predict stop frequency, trip-mode choice and destination. A similar approach is used in the Florida Activity Mobility Simulator (FAMOS) (Pendyala et al. 2005), in which mandatory activities are predetermined at a higher-level module as part of the Household Attributes Generation System (HAGS).

The Tel-Aviv model presents further variances in model structure (Fig. 6). The destination, mode and time of the primary destination are predicted before details of the full-day pattern are modelled. Modelling the probability of additional stops and of a secondary tour is conditional on the previous decisions. Activity patterns are defined by four primary out-of-home activity types, and for each activity there are four primary tour patterns according to the number and sequence of stops. For each of these 16 combinations, there is an option to have a secondary tour, each of which has a similar structure as the primary tour. This results in 16 alternatives of primary tours plus the alternative of a no-primary tour for a total of 272 (16*17) out-of-home activity patterns. A similar model structure estimates the potential of a secondary tour and the detail of such tour but only after the main tour was determined. The logic is that the duration of the main activity may have an effect on the propensity to undertake a secondary tour. In the San Francisco and Portland models, decisions regarding destination, mode and timing are made after the full-day structure is determined. These examples show that there are many ways to model activity patterns. In designing a model structure, therefore, modellers need to consider the trade-off between more patterns without full information and fewer patterns with full information.

Bhat et al. (2004), in developing the Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) model, defined the start and end time of work as temporal pegs on which the worker's complete activity pattern rests. These pegs, along with commuting duration, determine the departure time to work and the arrival time at home from work. Accordingly, the first set of models determines an individual's decision to participate in mandatory activities. Only then are other activities modelled.

The specific structure for each model is assumed a-priori. Usually modellers do not search for the best structure to fit their data, given the effort involved in such a procedure. Davidson et al. (2007) found that placing the frequency of secondary activities down the hierarchy at the tour level yields better results as was also done in the Tel-Aviv model. Ye et al. (2007) considered three different casual structures: one in which trip-chaining structure is determined first and influences mode choice, one in which the order is reversed and the third in which they are determined simultaneously. Pendyala (1998) suggested that different model structures might suit different segments of the population but no such differentiation has been found.

3.4 Destination choice

Given the large number of TAZ in some regions, it is common to sample zones for model estimation. In the San Francisco model, the sample included 40 zones

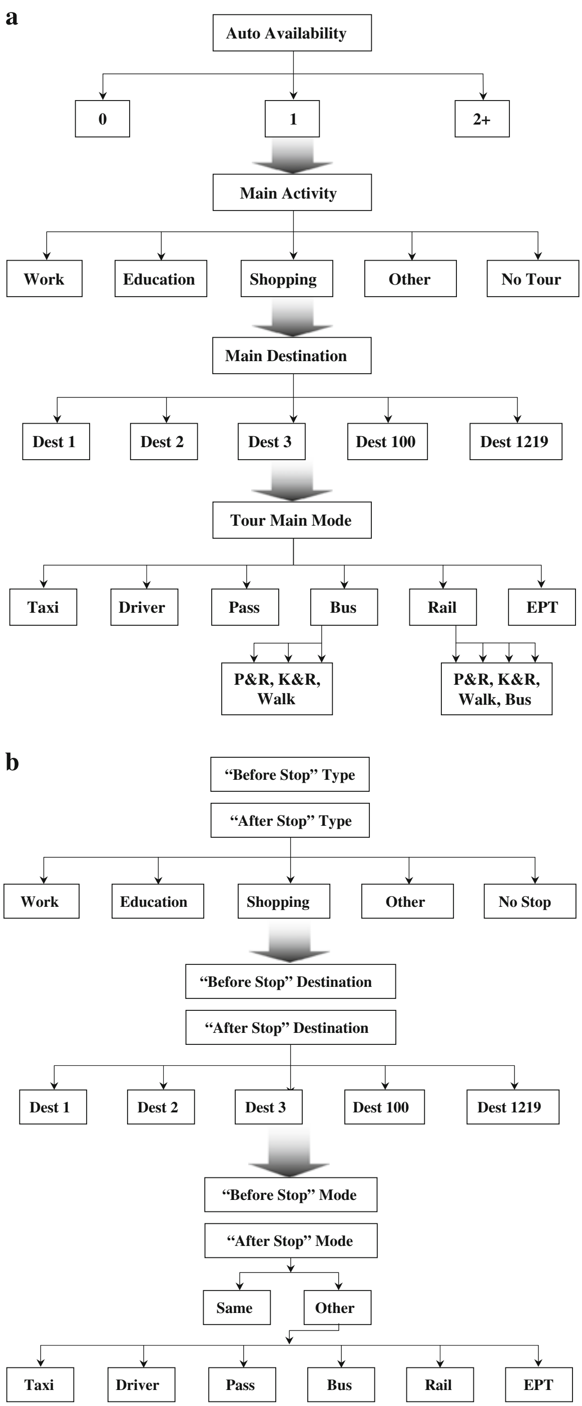

Fig. 6 The Tel-Aviv model structure

(Jonnalagadda et al. 2001), which is similar to the number used in Boise, Idaho (Shiftan 1998), and New Hampshire (Cambridge Systematics 1998). In Portland, the destination and mode choice of the primary activity are modelled simultaneously as a nested structure. A sample of 21 zones, drawn from the full set of 1,244 zones, was used for each tour and estimated together with nine alternative modes.

In Tel Aviv, the full set of 1,244 zones was used for destination-choice models. Using many alternatives does not complicate the estimation task per se and provides more efficient estimates. However, data preparation requires calculation of arrays of the number of zones cubed. This applies specifically to secondary destinations, for which the level of service refers to the additional travel time that the second destination imposes on the already-determined tour from home to main destination. These arrays can be cumbersome to calculate for estimation and application.

None of the models estimate two or more destinations simultaneously. Instead, all models estimate the main destination first. The additional destinations are estimated one by one, given previously determined destinations. While most models predict location choices at the TAZ level, the Sacramento model predicts location at the parcel level. There are more than 700,000 parcels in the region and a sample of 100 parcels was used for estimation.

3.5 Time of day

A behavioural time-of-day model is critical for analysing time-of-day pricing policies, such as congestion pricing or parking policies. Ideally, the time component should be modelled continuously. However, this is probably easier in the simulation/rule-based-type models than in the discrete choice-type models. Even with only a few time periods, the time-of-day model is an element that can highly complicate the model because modelling different time-periods may create a large number of alternatives, given multiple activities and the need to predict start and end time for each activity.

Most activity-based models use the two-level approach for time-of-day modelling. The timing of the main activity is predicted first at the tour level. The timing of other stops is predicted at the trip level in the remaining time window. This approach was used in San Francisco and in Portland. The model simultaneously predicts when the traveller will leave home to begin the primary tour together with the period when the traveller will leave the primary destination to return home at a resolution of five daily time periods. Excluding overnight tours, there are 15 possible combinations. This approach was implemented in the Tel-Aviv model at the activity level. Given the need for more detailed time-of-day information for congestion pricing and parking policies, however, a much more detailed time-of-day model was developed at the trip level.

The detailed time-of-day model for Tel Aviv is based on a model developed by Cambridge Systematics for the US Federal Highway Administration (FHWA) to advance the practice of forecasting individual travel demand by time of day (Cambridge Systematics 1999; Abou Zeid et al. 2006; Popuri et al. 2008). The time-of-day choice model is based on travellers' demographic characteristics, as well as the transportation level of service by period, which represents congestion and pricing levels. Since travel-time data are available from model skims for only a few time periods (three in the Tel Aviv case), a key aspect of this approach is the development of a model that estimates travel time for all time periods to be used in choice models. The basis for developing this model is to relate the reported travel time given in the household survey to the three model travel-time skims and to various other network variables using ordinary least square regression. More specifically, the model relates the ratio of reported speed to network free-flow speed and to various explanatory variables, such as network delay (derived from peak and free-flow speed), trip distance and origin and destination area-types. A cyclical function of time is used to ensure that the travel time corresponding to a given departure time will be the same 24 h later. The Tel-Aviv time of day is modelled at a fine level of resolution using half-hour time periods. This enables to evaluate congestion-pricing strategies specific to a wider range of time segments. The model is applied only to auto trips in order to capture peak spreading and accordingly comes after trip-mode choice and before traffic assignment. This position makes the location (and purpose) of all stops on a tour known (or modelled) prior to time-of-day modelling.

The MORPC model offers a detailed time of day for the tour-level time-of-day choice model at a resolution of 1 h. However, given there are only four network simulations, there are only four different level-of-service variables for the different periods. A similar approach was applied in the ARC model (Davidson et al. 2007). The Sacramento model predicts the time at which each trip and activity starts and ends to the nearest 30 min, using an internally consistent scheduling structure that is also sensitive to differences in travel time across the day (Bowman and Bradley 2006).

In summary, current activity-based models have progressed to the point of simultaneously predicting the start and end times of the primary activity and subsequently determining the timing of other activities in the remaining time windows. However, they are still far from being able to implement a detailed time-use allocation. To this end, a two-tier approach is common. First, a tour-level model captures the behavioural time constraints on individuals by predicting the start and end times of the main activity. Next, a more detailed model, implemented at the trip level with detailed time resolution, can support the analysis of various congestion-pricing policies and their impact on auto-trip time shifts.

3.6 Travel mode

Most mode-choice models in activity-based models consist of two levels: A tour mode choice model that determines the primary tour of the mode and a trip mode choice that determines the mode for each individual trip given the tour main mode. In the Tel-Aviv model the tour's main mode was defined as the mode leaving home and allows for the whole array of modes. The trip-level model is a nested model with a higher level of choice whether to deviate from the main mode. If the person deviates, the lower level determines the other modes, conditional on the main mode of the tour.

In Portland, based on data analysis showing that only 3% of the tours changed in mode from trip to trip within the tour, just the main mode of the tour is predicted assuming all trips within the tour use the same mode. In other cases, such as the

Table 2 Modes in the tour-level models of different model systems

	CEMDAP Commute	Portland	San Francisco	Sacramento	Tel Aviv
Drive alone	+	+		+	
Driver			+		+
Share-ride	+				
Driver		+			
Passenger		+	+		+
Share-ride for 2				+	
Share-ride for 3+				+	
Transit	+				
Transit Walk			+	+	
Premium Drive		+			
Park & Ride					+
Kiss & Ride					+
Premium Bus					+
Premium Walk		+			+
Transit Drive			+	+	
Bus Drive		+			
Park & Ride					+
Kiss & Ride					+
Bus Walk		+			+
Taxi					+
Walk/Bike	+				
Walk		+	+	+	
Bike		+	+	+	
School Bus				+	

San Francisco model, the trip-level model also allows for further detailing of modes. For example, it determines whether the share-ride mode that was predicted in the main model is a share-ride for only 2 or for 3+ persons. Table 2 shows differences in definitions of the modes that appear in the tour's main mode-choice models in several activity-based models.

4 Data

The perfect activity-based model calls for the collection of very detailed time-use data, including the activity diaries of all household members over a period of time, whether in or out-of-home activities; the detailed travel information should contain land-use data and transportation level-of-service data. The detailed time-use data should also comprise spatial and temporal constraints and opportunities, interactions in time and space, as well as interactions among household members. The question is what data are required for a good, practical, policy-sensitive model? In this section we discuss some of the main data issues stemming from activity-based models.

4.1 Activity travel diary

One of the main considerations in developing activity-based models concerns the type and length of the activity and travel diary. Obviously, the Mobidrive data collected in Germany (Axhausen 2000) over a 6-week period may be cumbersome for a planning organization to use in developing a practical activity-based model. A multi-day diary can enable the model to account for inter-day and inter-week interactions, but much can still be achieved with simpler travel diaries. One-day diaries are sufficient for current practice. Even when diaries cover a longer period of time, such as those used in Tel Aviv (3 days) and Portland (2 days), the actual models do not deal with across-day interrelations.

Collecting detailed activity and travel data is problematic and imposes a significant burden on respondents. For practical models, therefore, it is best to keep surveys to a minimum level of required complexity in terms of questionnaire design and to assign appropriate resources for quality control and various logical checks.

The surveys conducted in Portland, Dallas-Fort Worth, Texas and the Research Triangle, North Carolina included in-home activities. The Portland model uses the survey information to capture trade-offs between in-home and out-of-home activities. Since it is impossible to record all in-home activities, guidelines should be developed regarding the types to be included in the diary. Davidson et al. (2007) suggested recording activity duration in addition to time of travels in order to obtain better information on time use.

The size of the sample can affect the number of segments that the model can identify and should be designed together with the model design. These and other issues are dealt with in the literature on surveys and data collection.

4.2 Geographic position systems (GPS)

GPS devices are helpful in collecting more accurate data for activity and travel surveys. Linking GPS data with land-use data at the parcel level can provide a richer data layer to support analyses. GPS traces provide more accurate information on activity locations and durations and minimize under-reporting of short and infrequent trips. GPS can also reduce a respondent's effort by not reporting some aspects of the diary, mainly location and time. The respondent can concentrate on fewer items, such as mode, purpose and occupancy. As GPS devices become cheaper, their use is spreading. Although GPS has the potential to contribute meaningfully to activity-based models and to simplifying data collection, further research and development is needed to make it a better practical tool.

4.3 Combining data sources

Activity-based models contain a larger number of alternative choices and a greater number of unknown parameters than do tour or trip-based models. Therefore, maximum use should be made of travel survey data, which should be combined with other data sources, such as stated-preference data and auxiliary intercept surveys. The

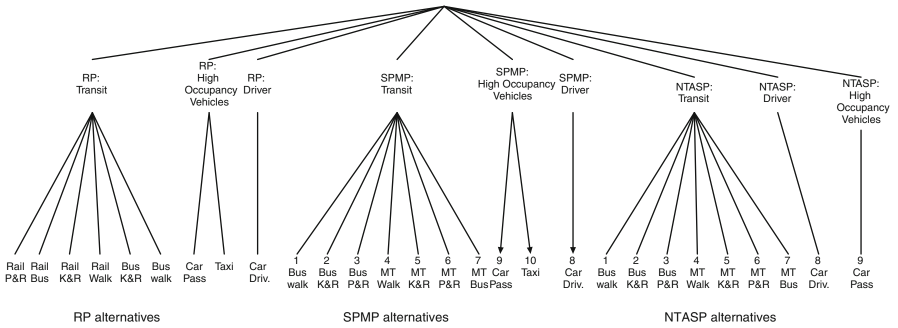

Fig. 7 The Tel-Aviv combined RP-SP model structure

combined analysis of disparate data sources and the integrated application of different modelling methods and approaches that best fit each data set are features that permit cost-effective model development. Ben-Akiva and Morikawa (1990) showed how these features can be used to rigorously account for and reconcile complicated travel behaviour characteristics.

The Tel-Aviv tour-level mode choice model estimated for Tel Aviv is a good example of the efficient use of existing and new data. This model (see Fig. 7) consists of two sets of RP data and two sets of SP data. The RP data include the National Travel Habit Survey and an extension of it conducted specifically for the development of this model in communities adjacent to a rail corridor. The SP data include a previous SP survey conducted for the development of the Tel-Aviv rapid transit system and a new tour-based driver SP survey focusing on drivers' response to parking policing and congestion pricing. The experiment was based on respondents' actual tours and potential alternatives included changes in mode, changes in the time of day and chaining of trips.

For the model to be sensitive to parking policies, special efforts were made to collect meaningful parking data in Tel Aviv. The data, used to estimate parking supply and demand models, consisted of the following elements:

- Parking inventory
- Parking occupancy for street and uncovered parking lots by time of day
- Parking occupancy for selected in-building parking lots.
- Interview with drivers who park in the area (trip purpose, arrival time, search time, walk time, payment and personal data).

The lack of more detailed data collection, specifically more detailed activity and travel diaries, forms a barrier to the research advancement of time-use data and activity participation. Nonetheless, much can still be done with the current practice in data collection. Most activity-based models were developed with the same data sources that are used for traditional trip-based models. The addition of limited main in-home activities can contribute to improved model capability.

5 Model application

Applications of activity-based models offer a complicated task. It is also the task that usually puts the most constraints on the level of behavioural realism achieved in such models. The application consists of several elements, among them an activity-simulation program, the population synthesizer and the transportation networks and assignment procedure.

5.1 Activity-simulation

The application of activity-based models for forecasting normally employs a "sample enumeration" or a "micro-simulation" approach, with a representative sample of households or a synthetic population. In sample enumeration, the probabilities across all possible alternatives are added across all individuals in the sample. In the micro-simulation approach, the probabilities are used in a Monte Carlo approach to predict specific choices for each individual in the sample. The key difference is that the sample-enumeration approach enumerates all possible combinations of model outcomes and multiplies probabilities. The Monte Carlo approach predicts a single outcome per person, drawing randomly from the model probabilities (see Bradley et al. (1999) for more on the differences between the two approaches and Vovsha et al. (2002) and Jonnalagadda et al. (2001) on micro-simulation techniques).

There are various options for short-cuts and run-time reductions. For example, in applying the Portland model with the sample enumeration approach, Bradley et al. (1999) made the following short-cuts:

- Ran the model with only 10% of the sample.
- Applied destination-choice and stop-location models to only a subsample of the 1,244 possible zones.
- Applied the work-based sub-tour and intermediate stop locations at the zonal level using sample enumeration and, therefore, without the use of logsum variables (see also next section).

The Monte Carlo simulation introduces a random sampling error into the forecast. However, this error decreases as the number of simulated households increases. Large samples, as much as the size of the population, should be used to avoid such error. On the other hand, by simulating choices for a specific individual, all that person's characteristics can be retained to provide a wealth of information for other purposes, such as equity considerations. Outwater and Charlton (2006) specified this advantage as the reason for choosing this approach for the application of the San Francisco model.

The consideration for the specific method to apply involves a trade-off between computer run-time on the one hand and geographical coverage and the accuracy of the results, on the other. Sample enumeration was used in some of the tour-based models in combination with Monte Carlo simulations. The problem with sample enumeration is that the more levels there are in the model systems, the more costly it is to store the probabilities of all the possible combinations in the memory. In the Boise model, sample enumeration was used in the high-level models, for which relatively few alternatives were available, such as the tour purpose and patterns. However, for lower-level models with many alternatives, such as destination-choice models, Monte Carlo simulation was used to avoid book-keeping of large numbers of probabilities resulting from multiplying probabilities by the different models (Shiftan 1998). With the move to activity-based models, the number of alternatives significantly increased, and the book-keeping became more cumbersome. The current trend with the applications seems to be Monte Carlo simulation.

The model-application process may require excessive time and computational resources. The main elements in the running time of the application are the model structure and the sample size. Eliminating insignificant interactions or linkages among sub-models may at this stage be considered a way of reducing running time (see next section, on logsums). The required sample size depends on the nature of the application. A flexible application procedure can be used to reduce running time when a lower level of output resolution is required. This can be achieved by allowing the user to select an appropriate sample size.

The literature on model application usually does not report running time. Bradley et al. (1999) reported running time for the Portland model using both the sample-enumeration approach and Monte Carlo simulation. Running the model system with Monte Carlo simulation on the full sample of 600,000 households took 32 h on a 400 MHz Pentium II computer. Running the sample-enumeration approach with the same model on only 10% of the sample also took 32 h. As Bradley et al. (1999) report, 75% of that time was needed to run the zonal enumeration to calculate the distribution of intermediate stop locations between every OD pair in the region. This shows the advantage of the micro-simulation approach from a running-time point of view. Rossi et al. (2009) surveyed various agencies regarding their modelling run time and found it to vary from 2 h in New Hampshire, 10 h in San Francisco, to 1 or 2 days in Sacramento and Columbus.

Although it is always desirable to use larger sample sizes with the micro-simulation approach, it seems that the shorter running time compensates for this disadvantage. Most recent applications, among them MORPC and the generic application of CEMDAP, use the micro-simulation approach.

5.2 The use of logsums

Logsums constitute an integral part of an activity-based model system and its simulation application. However, they impose major computation complexity in model applications resulting from the need to calculate the utility of every combination of the many alternatives (there can be more than a million in the case of the entire daily activity model; see Bowman and Bradley 2006), starting from the bottom of the structure and going up the tree and then calculating probabilities on the way back down. As indicated by Bradley et al. (2002), logsum variables add a great deal of complexity to the process of model application and require much more computer time to run. To reduce this complexity, therefore, it is common to make various shortcuts and assumptions. Thus, in the San Francisco model, the program first applies the work-tour mode-choice model (at the highest level of the model) to calculate a mode-choice accessibility logsum across all modes to each alternative work location. However, since the tour type is not predicted at this point, it is assumed to be an am peak-pm peak work tour with no intermediate stops in either direction. In this model, logsums are also calculated from the main mode-choice models and used in the primary destination-choice models for non-work tours (because work destinations are modelled as the highest decision in the tree).

The Sacramento model uses two methods of approximating logsum variables. First, instead of calculating the logsum for all possible conditional outcomes, the assumed conditional outcome is selected by a Monte Carlo draw, using approximate probabilities. Second, aggregate logsums that approximate the expected utility logsum are calculated by adding up the exponentiated utilities of the multiple alternatives. The amount of computation is reduced either by ignoring differences among decision-makers or by calculating utility for a careful subset or aggregation of the available alternatives (Bowman and Bradley 2006). However, aggregate logsums are not recommended, because of the unknown biases that measurement errors may have on model estimation and that aggregation errors may have on model application.

To simplify the calculation process, simplified logsums were used in the application of the Tel-Aviv model. The logsums were calculated only for four main modes and the calculation used only the in-vehicle and waiting-time components of the utilities from the mode-choice models. This reduced the computation effort significantly because the mode-choice logsums varied only by origin and destination zones instead of by each individual in the estimation data sample. Logsums used in the auto-ownership model were calculated only for work trips at the AM peak hour under the assumption that morning trips to work constitute the main determinant of the number of cars a household needs. Other trips can be more easily accommodated with the number of cars available.

Logsum variables allow for many of the advantageous features of an activity-based model by providing the feedback/accessibility from low-level models to higher ones. Given the role and computational complexity of logsums, one should think about how many and which variables to include in the model. Models should be estimated with as many logsum variables as possible. But one should then carefully consider which ones are the most important to retain for model application, which ones affect specific policy analysis and what kind of simplification can be made without introducing too much error and without excessively hampering policy sensitivity.

5.3 Population generator

Another aspect of the application is the population generator, especially the dimension of the marginal distributions that define the number of segments in the population that are being controlled for. The San Francisco model uses 9 combinations of household size and number of workers, 4 household-income levels, and 3 age categories for head of household for a total of 108 combinations. Portland uses 4 household-size categories, 4 household-income categories, and 4 age-of-household head categories for a total of 64 combinations. This scale of combinations is similar in most models, with some variations in the categories used. For example, both Sacramento and Columbus use 4 household-income categories and 4 number-of-workers categories. But Columbus uses 5 household sizes, whereas Sacramento uses 4 such categories. The Tel-Aviv model uses a slightly different approach, with 12 combinations of age of head of household and gender; it also controls for average household size and average number of workers. Most models find household size and number of workers to be good variables for distinguishing among the main household life-cycle groups.

The sample size generated by the population generator and used in model application directly affects running time as discussed above. Portland uses a sample of 0.6 million households and 1.5 million inhabitants, matching the actual population for the application base year of 1994. However, to save running time, many simulations were run with only a partial sample, usually 10%. Model applications should be designed to provide the user with the option to use a fraction of the complete sample in each run. In this case, initial analysis or sketch-planning levels can be conducted with a smaller sample. Only final analysis would be conducted with the entire sample to achieve better accuracy. For additional comparisons of some of the population generators in use, see Bowman (2004).

5.4 Networks

All practical models use network-assignment procedures with traffic-analysis zones (TAZ) as the basic spatial element. Another aspect that complicates the application of the models is the number of TAZs. Although there has been some discussion on disaggregating destinations, all practical models use the TAZ system. The smaller the TAZ and the more there are, the better spatial resolution they provide. However, every operation has to be performed on more TAZs, thus increasing running time. The San Francisco model has 1,728 TAZs in the metropolitan area; MORPC has 1,805 TAZs, Portland 1,244 and Tel-Aviv a little over 1,200. Overall, it seems common to use between 1,000 and 2,000 zones. It may make sense to consider a two-level zone system, such as alternative transit alignments, which require fine resolution system. Other applications, though, such as an area-wide tax policy, may not require that level of resolution. Finally, as shown in the Destination-Choice Model section, some applications use the entire zone, but sample a subset for specific applications. Some models use a finer zone system to provide more accurate road and transit level-of-service variables, such as land use and parking. Sacramento uses 700,000 parcels, and Portland 20,000 “blocks” for this purpose (Bowman and Bradley 2006).

6 Conclusions

Before undertaking the detailed design of an activity-based model, one should define the planning needs and policy issues to which the model needs to be sensitive. The design of the model should address those needs.

In activity-based models, it is the application procedure that drives the complexity of the model and, therefore, should be kept in mind in designing the model structure. Given that more behavioural realism can be achieved in estimation than in application, it is recommended to design and estimate the model at a higher level of complexity than what is reasonable to apply. In this way, the main features and linkages can be identified and maintained. Other features can be removed during application to obtain a reasonable level of complexity and running time.

Many of the elements of activity-based models can be estimated and applied with data and effort that do not greatly exceed those needed for traditional trip-based models. The Tel-Aviv and San Francisco models were estimated with the same data needed for trip-based models. The San Francisco model was developed and implemented in a relatively short period of time (a little more than a year). These models already provide a big step towards better policy sensitivity than do trip-based models.

With the development of more advanced model systems, such as MORPC and Atlanta, there is need to test their actual contribution to demand forecasts and to analyse their policy sensitivity. Interrelations among household members and among days can clearly contribute to better behavioural realism, but the magnitude of their complexity in practical models raises questions whether their contributions justify this extra level of complexity. For applied planning studies, simpler activity-based models may be used rather than waiting for perfect behaviour-realism models to be feasible. As research advances and various tools, such as generic computer software (Bhat et al. 2004) are developed, it is expected that better behavioural realism will be easier to implement, thereby enhancing practical models.

The sections to follow will summarize the main conclusions and recommendations regarding the three main elements of activity-based modelling: model structure, data and model application.

6.1 Model structure

There are endless options for various model structures. There is also a lack of research into what makes a better structure. However, several general conclusions may be draw, based on the discussion in this paper.

A two-level is recommended for mode-choice and time-of-day decisions. This structure could also be extended to destination choice, in which the main decisions are modelled at the tour level and secondary decisions at the trip level, given the tour-level decision. More details and refined decisions can be modelled at the trip level. A detailed time-of-day model with a resolution of half an hour is recommended for auto trips to support the analysis of various congestion-pricing policies.

Logsum variables better enable capturing behavioural realism. Various logsum variables should be tested in estimation. However, because of their contribution to model complexity, it is recommended to retain only the most important logsum variables for application and consider various appropriate aggregation and approximation of these logsum variables. Further research needs to be conducted to investigate the magnitude of the error introduced by such aggregation and approximations.

6.2 Data

Much can be done in activity-based models with the same data used for trip-based models. A 1-day diary seems sufficient for a good, practical, activity-based model. Given the complexity of diaries, more effort and resources should be invested in quality control. It is recommended to add main in-home activities to diaries. However, further research is required on how to define these main activities. GPS is becoming cheaper and should be used to enhance the accuracy of travel diaries.

6.3 Application

A Monte Carlo simulation approach of large samples, ideally equal to the size of the population, is recommended. Various short-cuts may be considered to reduce complexity and running time in applications. For example, it is reasonable to apply destination-choice models on only a sub-sample of destinations to reduce running time when simulating a single choice by a single individual. Further research regarding the sensitivity of these types of short-cuts is still required. There is also need to further investigate the extent of random-sampling error introduced into forecasts by using the Monte Carlo simulation approach and its geographic coverage.

6.4 Concluding remarks

To better answer the questions posed in this paper, we need to compare predictions and policy forecasts from complex models that capture the full spectrum of behavioural realism with simpler, more practical models. However, opportunities to perform such comparisons are rare. Future research should be conducted to assist in developing guidelines to determine when a more realistic process model is warranted and when a simpler, more practical model will suffice. Although research on activity-based models has a history of several decades, it has advanced significantly only in the past decade. Practical activity-based models have only recently become operational. The time has come to test these models, use them for policy analysis and make the transition toward their wider use.

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