Agent-Based Activity/Travel Microsimulation: What's Next?

Eric J. Miller

Abstract This chapter briefly summarizes and reviews the current generation of operational activity/tour-based model systems. These model systems are developed to varying degrees within an agent-based microsimulation (ABM) framework. ABM provides an extremely flexible, powerful, and efficient means for modelling complex spatial-temporal, socio-economic behaviour such as travel. A high-level definition of microsimulation in general and agent-based microsimulation in particular is presented. Overall, currently operational activity/travel model systems represent a sound "first generation" of such methods, but they are far from realizing the full potential of the ABM concept. A wide range of issues and challenges in advancing the ABM-based activity/travel modelling state of the art are discussed, leading to a few suggestions for key "next steps" in model development.

1 Introduction

Activity/tour-based models of urban travel demand are increasingly being used in operational planning practice (Castiglione et al. 2015). These are generally implemented within a microsimulation framework, in which out-of-home activity participation and the associated travel are modelled for individual trip-makers (agents). These operational model systems are the product of over 40 years of research and development, dating back at least to calls in the 1970s for an activity-based approach to modelling travel demand (Jones 1979; Hensher and Stopher 1979; Axhausen and Gärling 1992). They are also built upon the tremendous advances that have been made over this same time period in disaggregate, random utility choice modelling, computer hardware and software, and GIS-based spatial-temporal datasets, among other factors.

The rapidly growing availability of "big data" concerning travel behaviour from a variety of sources, continuing growth in computing capabilities, and ever-changing

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(and increasingly challenging) policy issues (autonomous vehicles, new mobility services, increasing emphasis on active transportation, etc.) create both the opportunity and the need to continue to develop more advanced, robust travel demand modelling methods to help guide the continuing explosive growth of urban regions worldwide along more sustainable paths (Miller 2017).

Section 2 of this chapter briefly summarizes and reviews the current generation of operational activity/tour-based model systems. These model systems are developed to varying degrees within an agent-based microsimulation (ABM) framework. ABM provides an extremely flexible, powerful, and efficient means for modelling complex spatial-temporal, socio-economic behaviour such as travel (Kreibich 1979; Clarke et al. 1980; Mackett 1985; Goulias and Kitamura 1992; Ettema et al. 1993; Miller 1996, 2003). Section 3 provides a high-level definition of microsimulation in general and agent-based microsimulation in particular. Overall, currently operational activity/travel model systems represent a sound "first generation" of such methods, but they are far from realizing the full potential of the ABM concept. Section 4 discusses a wide range of issues and challenges in advancing the ABM-based activity/travel modelling state of the art. Section 5 concludes the chapter with a few suggestions for key "next steps" in model development.

2 Modelling Activity and Travel

2.1 Introduction

Many "activity-based" travel models currently exist worldwide. These can be loosely divided into two primary types: *tour-based* models and *activity-scheduling* models. These two classes of models are briefly discussed in the following two sub-sections.

2.2 Tour-Based Models

Tour-based models are the most common form of currently operational models. As their name implies, these models focus on predicting the most common forms of daily tours made by individuals. A *tour* (also often referred to as a *trip-chain*) is a connected set of trips in which the origin of each subsequent trip is the destination of the previous trip, with the origin of the first trip being the destination of the last trip. Figure 1a illustrates a simple tour consisting of three trips: from home to work, work to shopping, and shopping back home again. Tours generally are assumed to be *home-based* (as in Fig. 1a), with home being the start and end point of the tour (or the tour's "anchor point"), but non-home-based sub-tours are, of course, possible in which a non-home anchor point exists within the overall home-based tour. Figure 1b

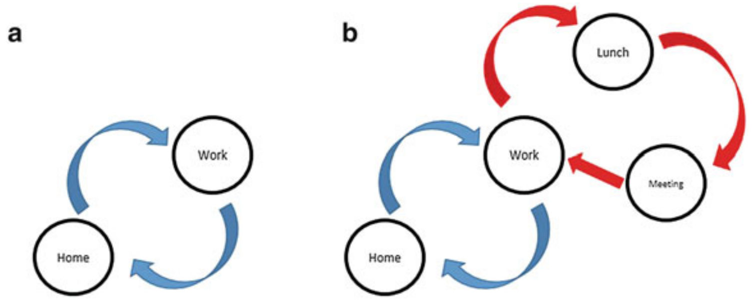

Fig. 1 Examples of tours. (**a**) A simple 2-trip home-work-home-tour. (**b**) 5-Trip home-based tour with a 3-trip work-based sub-tour

provides an illustration of this, in which a work-based sub-tour (work-lunch-meeting-work) exists within the overall home-based tour.

Tour-based models represent a major advance over conventional trip-based models in several important respects. Most fundamentally, they allow the logical interconnections between individual trips to be explicitly accounted for. Important examples of this include:

- The decision to drive to work in the morning is not independent of the decision to drive home in the evening. It may be, for example, that it would be feasible for a worker to take a commuter train to work during the morning peak period, but the worker is planning on staying at work late that evening and will miss the last train home. In such a case, the worker will drive to work so that she has the car available to drive home again that night. More generally, if a "car leaves the driveway", it must return again at some point.[1] Only a tour-based approach can ensure that this "tour-level" constraint is imposed on the individual trip mode choices.
- The existence of other trips in the tour may influence mode and/or location choices for other trips. Again consider a worker who might take the train to and from work if these are the only two trips being made that day (i.e. a simple home-work-home tour). But if he needs to do some shopping on the way home from work, and it is only feasible to execute this shopping trip by car (i.e. transit does not serve the shopping mall), then he will use the drive mode for the entire tour. Conversely, given that he has decided to drive to work he may choose to drive to a nearby mall to do his shopping on the way home, whereas, if he did take the train to/from work he might then do his shopping by taking the car once he had returned home to drive back and forth to this mall (or maybe he walks to and from a neighbourhood shopping street instead), in either case generating a second

[1]The same holds true for bicycles, which are also, in principle a "tour-based" travel mode.

home-shop-home tour by a different mode and perhaps to a different shopping location.

- In trip-based models, *non-home-based trips*, in which home is neither the origin nor destination of the trip, are notoriously difficult to model in any defensible way since little logical explanation for such trips exist with the model: why is this trip going from here to there by this mode at this time? In a tour-based formulation, as illustrated above (e.g. the work-shop trip), these trips sit within a logical/causal framework that considerably improves one's ability to model them in a sensible way.
- The "auto-drive to transit" ("park and ride") "mixed-mode" type of trip is also intrinsically a tour-based mode choice. The decision to drive to the train station in morning commits the commuter to return to that train station in the evening to retrieve the parked car and use it to drive home again from the station. The trip-maker in the model needs to "remember" at which station her car is parked and arrange her tour so that she returns at the end of the day to pick it up. The model can only be internally consistent in its prediction of auto access and egress trips to/from transit (and the transit trips originating and destined for each park and ride station) if the logical connections between the trips within the tour are explicitly maintained.
- As all of the examples above illustrate, a 24-h travel day can only be modelled in a logical, internally consistent way if a tour-based approach is used.

In order to model tours, a microsimulation approach must be adopted in which the tours (and their constituent trips) are explicitly modelled for each individual trip-maker. Aggregate, matrix-based approaches simply cannot deal with tours. As is discussed in Sect. 3, many reasons exist for adopting a microsimulation modelling approach, but, over and above these reasons, microsimulation is simply the only feasible means for modelling tours.

Within this microsimulation framework, many approaches are conceivable for modelling tours, including the activity-based models discussed in the next sub-section. In current operational practice, however, tour-based models very typically make use of random utility theory-based (deeply) nested logit models for their implementation. While details vary from one model to another, Fig. 2 presents a

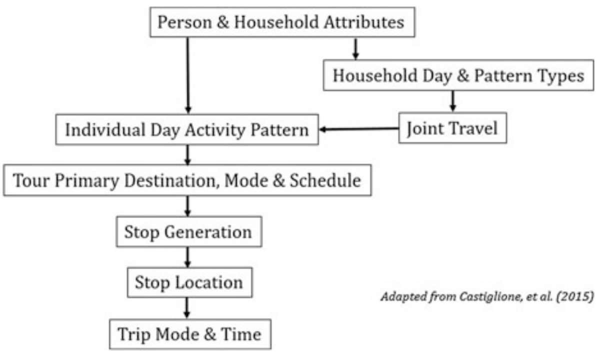

Fig. 2 Example Tour-Based Model Structure. Adapted from Castiglione et al. (2015)

high-level representation of a typical tour-based model, which includes the following key components or steps (Castiglione et al. 2015):

- Given the synthesized attributes of persons within a given household, a daily activity pattern for each individual is predicted (e.g. number of tours).
- A primary destination, mode and overall timing for each tour is determined (e.g. a "mandatory work" tour, with auto drive as the travel mode).
- Additional stops by purpose and location may be added to each tour.
- Given the selected primary mode for the tour, modes for individual trips within the tour are assigned, as well as time of day for each trip.
- Optionally (in some models), household-level joint trips may be generated that influence the activity patterns for the individual household members involved.

This model structure derives in large part from the seminal work of Bowman and Ben-Akiva in Portland (Bowman and Ben-Akiva 1997). For a more complete discussion of such models, see Castiglione et al. (2015).

Operational tour-based model implementations are particularly increasingly common in the USA, usually involving the use of relatively standardized software developed by a handful of leading transportation consulting firms. Urban regions with currently operational or near-operational models include San Francisco, Columbus, Ohio, Atlanta, Denver, Sacramento, Los Angeles, and Jerusalem, among others (Bradley et al. 2010; Paleti et al. 2017; Vovsha et al. 2011).

2.3 Activity-Scheduling Models

This class of models focusses on predicting out-of-home activities and the associated travel required to execute these activities. That is, the primary focus is on predicting the start time, duration, location, and purpose (or type) of the out-of-home *activity episodes* in which a given person decides to engage in the day (or other time period) being modelled. Trips are then the emergent outcome of the need to travel from one activity location to another. Indeed, trips can themselves be thought of as another, special type of activity episode. Activity episodes and their associated trips need to be *scheduled*, generating a daily *activity pattern* for each person being modelled. Tours clearly emerge out of this scheduling process as a travel linkage among a sequence of out-of-home activity episodes.

Given this explicit focus on generating activity episodes, it is argued that these models are more truly "activity-based" than the tour-based models discussed in the previous sub-section, since these still focus on directly predicting trip-making, rather than activity participation. At some point, this distinction may be largely semantic in nature. What is more important is the extent to which an *activity-scheduling* approach may be a more behaviourally fundamental and/or more flexible/extensible one than the tour-based approach.

As with tour-based models, activity-scheduling models must use microsimulation, since it is impossible to develop a daily (or other time period) activity pattern for individuals in any other way, and the notion of somehow modelling activity patterns in some sort of aggregate, matrix-based way is simply inconceivable.

A much wider set of approaches are used in activity-scheduling models than for tour-based models, with no dominant method being apparent at this time. Random utility models (RUM) are often used, but examples of rule-based ("computational process") approaches, and hybrid RUM-rule based, also exist. Examples of fully operationally implemented activity-scheduling models are relatively rare compared to tour-based models. Many have been "quasi-operationally" used in various policy studies, but are not yet generally in day-to-day use by mainstream planning agencies.[2] Important examples of activity-scheduling models (in alphabetical order) include:

- ADAPTS (USA; Auld and Mohammadian 2012).
- ALBATROSS (The Netherlands; Arentze and Timmermans 2004).
- CEMDAP (USA; Bhat et al. 2004).
- C-TAP (Switzerland; Märki et al. 2014).
- CUSTOM (Canada; Habib 2018).
- FAMOS (USA; Pendyala et al. 2005).
- FEATHERS (Belgium; Arentze and Timmermans 2004).
- MATSIM (Multiple applications; Balmer et al. 2006).
- PCATS (Japan; Kitamura and Fuji 1998).
- TASHA (Canada; Miller and Roorda 2003).

3 Agent-Based Microsimulation Modelling

3.1 Introduction: Simulation and Complexity

Simulation is a widely used method for implementing models of a wide variety of systems and behaviours. It provides a computational/algorithmic mechanism for modelling such systems when simpler, typically analytical-based, methods are not able to deal with the complexity and/or detail of the process to be modelled. Simulation is a procedure for evolving a "system state" over time as a function of both exogenous and endogenous factors. It can also be thought of as providing a computer-based "laboratory", within which experimental investigations of a system's behaviour can be undertaken. Key characteristics of a simulation model include:

- It is a numerical algorithm (as opposed to analytical approach) for modelling the system or behaviour in question.

[2] A notable exception to this general statement is the TASHA model, which is the operational travel demand forecasting model for the City of Toronto.

- Dynamic changes in system behaviour are modelled over time, i.e. time is an explicit dimension within the model.
- The model is usually stochastic, i.e. random elements exist within the processes being modelled—"state outcomes" are not known with certainty.[3]
- The forecasted end state of the system being modelled is "evolved" rather than "solved for". Again, simulation involves the iterative stepping through time, with the system state incrementally evolving in each time step, rather than the end state being determined by, for example, analytically solving for an equilibrium state.

Simulation is used to model complex systems that cannot be modelled adequately by other means. Complexity arises due to combinations of:

- Dynamics
- Stochastic elements
- Complex (non-linear) behavioural processes
- Path (and initial condition) dependencies
- Multiplicity of heterogeneous actors/agents

Travel behaviour (as with most other urban socio-economic processes) clearly displays all of these characteristics.

Complexity theory has emerged over the past 50+ years as a new paradigm for understanding and modelling complex phenomena. The emergence of this new science is tied directly to the widespread access to high-speed digital computing that first occurred in the late 1950s and early 1960s, which allowed scientists and mathematicians for the first time to gather and analyse data concerning complex behaviours (weather patterns, stock market prices, fluid flows, etc.) in new and much more powerful and insightful ways (Gleick 1987). Also, the ability to simulate complex system behaviour within the computer as a means for exploring and understanding this behaviour was also integral to the emergence of this "complexity revolution". As illustrated in Fig. 3, Downey (2012) argues that complexity theory has led to a shift in the nature of models from analysis to computation and from equation-based to simulation-based in a variety of "dimensions" in terms of our representation of processes, populations, and spaces from:

- Homogeneous to heterogeneous/composite
- Linear to non-linear
- Deterministic to stochastic
- Continuous to discrete and so on.

Although not generally discussed in these terms, the evolution of, first trip-based, and, more recently, activity-based travel demand modelling has displayed at least some elements of this shift towards a "complexity paradigm". Travel demand modelling also emerged as a recognizable discipline in the mid-1950s with the advent of high-speed digital computing and the emergence of first-generation four-

[3]Although deterministic simulation models also exist.

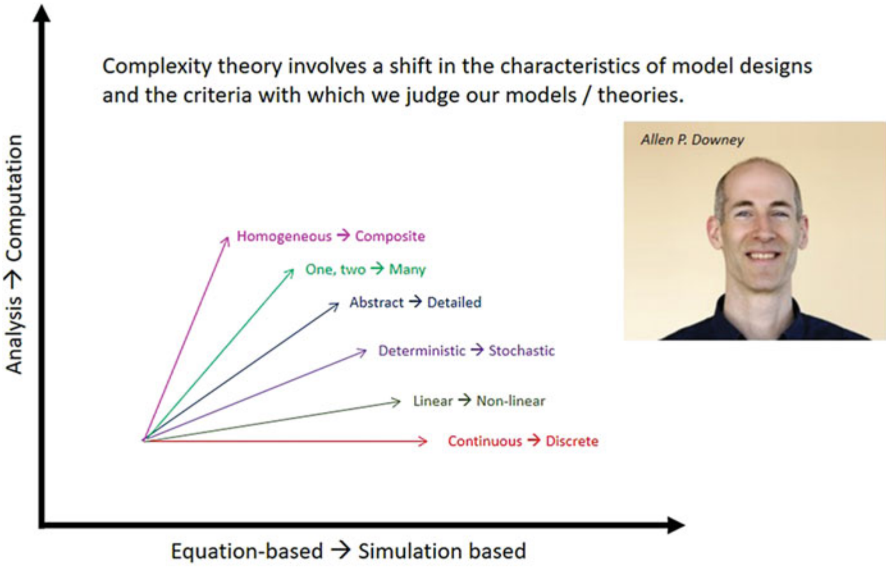

Fig. 3 Complexity Theory: A New Kind of Science. Complexity theory involves a shift in the characteristic of model designs and the criteria with which we judge our models/theories

step travel demand models in Detroit, Chicago, and elsewhere, and its evolutionary development has always been tied to computing capabilities and associated data availability (Meyer and Miller 2013). Since the early 1970s, it has grown increasingly discrete, stochastic, non-linear, and heterogeneous in its modelling approaches. This trend is continuing (and, indeed, accelerating) today as the availability of "big data", ever-increasing computing power and software, and new modelling methods, such as machine learning, continue to push the evolution of the field.

As already discussed in Sect. 2, activity-based travel demand modelling has also moved firmly into a microsimulation computational framework. Section 3.2 defines microsimulation and briefly discusses key motivations for its use in the construction of activity/travel demand forecasting model systems. Many of these model systems are also agent-based in their design. Section 3.3 defines what is meant by an agent-based microsimulation model system and why it is a useful approach to modelling activity and travel.

3.2 Microsimulation

O'Donoghuel (2014) defines microsimulation as "a simulation-based tool with a micro unit of analysis that can be used for ex-ante analysis. It is a micro-based methodology, utilizing micro units of analysis such as individuals, households, firms, and farms, using surveys or administrative datasets. It is a simulation-based methodology utilizing computer programmes to simulate public policy, economic or social changes on the micro population of interest". "Micro" implies simulating a system in a highly disaggregated way spatially, temporally, socio-economically (representation of actors), and in the representation of processes. Microsimulation modelling of socio-economic processes such as travel date at least to the seminal work of Orcutt in the late 1950s (Orcutt 1957, 1960).

Many important reasons exists for microsimulating travel demand (Miller 1996, 2018; Miller and Salvini 2002):

- Heterogeneity in trip-makers (attributes, preferences, contexts, history, behaviour, etc.).
- Identification of detailed impacts of policies across people and locations.
- Modelling complex behaviour. In addition to the modelling of tours and mixed-mode trips discussed in Sect. 2, this includes inter-personal interactions: within-household members (resolving competing demands for car usage, joint activities, etc.); among non-household alters (social network interactions, carpooling, etc.); and market interactions (buyers and sellers interacting within a market).
- Potential to capture memory, learning, and/or adaptation.
- Efficiency in data storage and processing.
- Emergent behaviour.

3.3 Agent-Based Modelling

Once one is microsimulating a socio-economic system it is a (relatively) small step to adopting a full agent-based microsimulation (ABM) approach. An agent is an "intelligent object" that:

- Perceives the world around it (monitors and receives information concerning its environment)
- Is able to control its actions in response to its environment, usually based on goal-oriented decision-making
- Acts into the world in an attempt to achieve its goals and objectives, thereby altering the world's state and its own environment

Persons, households, firms, etc. are obviously agents. Within the context of this chapter, they make decisions about their daily activity/travel patterns based on their personal goals and their perceptions of the transportation and urban activity systems (Manheim 1978). And by travelling through the transportation system, they interact with other trip-makers, change network congestion levels, etc.

While it has been noted that all tour/activity-based travel demand models are disaggregate microsimulation models that simulate the travel behaviour of individual trip-makers, it can be debated the extent to which the various models are "truly agent-based" or not. One need not get bogged down into too detailed a semantical debate about this, but the working assumption in this chapter is that an ABM is one in which the individual trip-makers are explicitly modelled as agent "objects" within which information concerning their attributes, their experiences in the system and their decision-making processes are encapsulated. Advantages of an explicit ABM formulation include:

- Agents are clearly a very natural, "high fidelity" representation for implementing any model of individual decision-making: as noted above, we are, literally, agents.
- Encapsulation of data and processes within the agent makes for "clean" coding and well-defined interfaces for information flow, agent interactions, etc. within the software.
- Facilitating model system modularity and extensibility.

Agent-based modelling is a very practical approach to decomposing the enormous complexity of modelling a system involving the multiple decisions and interactions in time and space of literally millions of heterogeneous agents with non-linear, context-dependent decision processes. Each agent is literally the "container" within which is stored all information concerning that agent, as well as the knowledge that the agent needs to make its daily activity/travel decisions, and wherein these decisions are made. In particular, as illustrated in Fig. 4, each agent is able to monitor its own context/environment, retain its memory of past events, its tastes and preferences, etc., keep track of its relationships and interactions with other agents, and make decisions about (and eventually execute) its daily activity/travel patterns. Within the confines of an individual agent, these decisions may be relatively simple and straightforward to model, given that the agent's decision-making context, memory, etc. are all explicitly "known" (at least within the virtual world of the simulation model). Complexity within the overall travel market still exists,

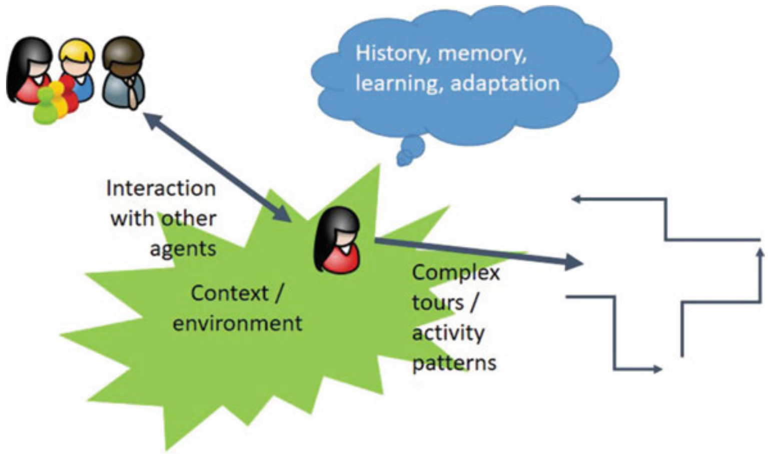

Fig. 4 Agent-Based Modelling

largely in terms of the interaction of all the trip-makers as they actually execute their activity/travel plans and compete for road space, seats on the bus, etc. But modelling the decisions of millions of individual trip-makers is, in principle, no more difficult than modelling a single individual.

4 Towards Next-Generation ABM Activity/Travel Models

4.1 Introduction

It is argued that ABM is a "logical", powerful, and practical approach to modelling the complexities of travel behaviour. But adopting an ABM approach does not automatically solve all modelling problems. ABM is a computational framework for modelling behaviour, rather than a model per se. Issues of model formulation, information flow, interactions among agents, data requirements for model construction and usage, computational practicality, etc. all remain to be addressed.

Indeed, there may be limitations in data, theory, or computational practicality that may limit the capabilities of ABM models in a variety of ways. Whether other modelling methods might better deal with at least some of these issues remains to be seen. It is arguable that ABM is the currently best available approach, but this remains to be demonstrated, especially as we try to expand beyond our current capabilities.

Research issues/challenges in developing improved activity-based model travel demand model systems include:

1. Dynamics and information flows (memory, inertia, state dependencies, adaptation, etc.)
2. Heterogeneity in both trip-makers and choice contexts
3. Issues in modelling spatial choice (activity episode locations)
4. Multi-dimensionality and sequencing of activity/travel decisions
5. Inter-agent interactions (within and between households; individual- vs. household-based models)
6. Activity episode utility (why do we travel?)
7. Modelling in-home activity
8. Moving beyond daily travel:
   (a) Modelling intercity (long-distance) travel
   (b) Multi-day (week-long) models
9. Computational efficiency
10. Statistical representativeness of microsimulation results
11. New/big data sources—how will these change our models?

The first eight of these issues all deal with modelling various elements of agent behaviour. Behavioural representation is the primary focus of this chapter, and so these issues are briefly discussed in turn in the following sub-sections. The remaining three issues are generic, technical issues with which all models (ABM or otherwise) must deal. They are largely "implementation issues" although they can never be totally excluded from the discussion of behavioural representation. The point is that these issues are "always with us" and act as constraints on what can/cannot be done, rather than as primary criteria for what we would "like" or "need" to do in terms of modelling activity/travel behaviour.

In the following sections, the intent in the discussions is not to solve problems in building activity/travel demand models, but simply to raise them in sufficient detail to show:

- Why there is a concern/need/issue.
- Identify major challenges/obstacles to model improvement, which inevitably involve some combination of limitations in data, theory, methods, and/or computational requirements
- Possible approaches for investigation (where this can be identified).

4.2 Behavioural Dynamics, Information, and Attitude Formation

In "real life", each person has memories of past experiences which provide an "information base" for current decisions as well as help shape our tastes, preferences, and attitudes. Our information and interactions with our social networks, media, etc. also shape our knowledge and our attitudes over time, and, hence, our current decision-making. We develop habits over the course of time (mode to work, favourite grocery store, etc.) that, once formed, are often not re-evaluated/changed over possibly considerable periods of time. The length of time that we have lived in a given neighbourhood affects our "awareness set" of potential destinations for shopping and other activities, as well as our experience with the transportation services connecting this neighbourhood to the rest of the urban area. People adapt to the circumstances within which they find themselves, which means that their preferences and behaviours evolve over time in response to their environment and their day-to-day experiences.

Memory/experience, inertia/habits, and adaptation are all examples of dynamic (temporally varying/evolving) factors that influence our day-to-day activity/travel behaviour. Essentially all activity/travel models, however, are static in that they model behaviour on a single, arbitrary "day in the life" with no consideration of memory or past experience. This massive "left censoring" is seemingly inescapable given that these models are inevitably built using similarly "left-censored" cross-sectional data collected from a 1-day survey.

Panel surveys are sometimes used to try to observe changes in behaviour over time. But these traditionally have consisted of conducting a conventional one- or two-day travel survey once a year. Arguably, this does not help much: observing a person's behaviour on one arbitrary day a year misses virtually all of the variability in day-to-day travel experience, trends in behaviour and evolution of habits that are actually of interest.

It is not clear, of course, how people actually do "internalize" their day-to-day travel experiences to evolve their "cognitive map" of the transportation system and their tastes/preferences over time, and, hence, how to model these processes. Much/most of this is likely to be intrinsically unobservable (latent), at least at a sampling scale that would be sufficient for generalized modelling purposes, i.e. beyond small sample, focussed research efforts, which are not easy/possible to generalize. Observing trip-makers over extended, continuous periods of time, however (from a minimum of 1 week up to several weeks) would, however, certainly be extremely beneficial in terms of observing both what behaviour varies over time and what is more stable, as well as providing valuable insights into at least short-run activity/travel dynamics.

"Outer loop" iteration/equilibration in all operational models arguably represents a crude form of "learning" in which agents' information concerning modal service levels is iteratively updated until they reach an equilibrium state in which their (aggregate) behaviour is consistent with (aggregate) service levels. While this may (very loosely) approximate the learning process of commuters, who undertake approximately the same set of trips each weekday, it clearly is not really representative of how people actually learn, gather information and evolve their behaviour over time. It also typically assumes that trip-makers are fully aware of the attributes of all feasible destinations, service levels for all modes for all trips to all destinations, etc., which clearly is not correct.

Another temporal-related problem with current modelling practice is the merging of survey travel records from different weekdays (i.e. Monday through Friday) into a single pooled dataset that is used to develop a model of travel on a "typical weekday". This represents a classic example of aggregation bias (in this case temporal aggregation), since it is clear that travel patterns vary by day of the week (Dianat et al. 2018a, b), and, hence, the "typical" day being modelled with the pooled data actually never occurs. Ideally travel on each day of the week should be modelled and then statistics useful for planning purposes (weekly averages, peak loads, etc.) could be computed. These would provide a far more realistic representation of "typical" system usage and travel behaviour for planning and decision-making purposes than the current biased pooled-data models.

The universal focus on weekday travel while ignoring weekend travel is also problematic. While planning for weekday peaks still dominates planning analyses, weekends also experience significant travel flows, which are quite different in their spatial-temporal patterns than weekday patterns and so pose their own challenges for the transportation system. Total greenhouse gas and air pollution emissions should include weekend effects in their calculation. And weekday–weekend trade-offs exist in activity episode scheduling, especially for shopping and other non-work/school activities.

While, as noted above, dynamically modelling trip-makers' tastes, preferences, and cognitive maps over time is an extraordinarily difficult task, it is arguable that activity-based models could be improved by:

- Collecting activity/travel participation data over extended periods of time, ranging from at least one full week up to several weeks. In the past, this has been an almost impossible thing to do, except for small-sample surveys involving considerable effort on the part of both surveyors and respondents. The emergence of smartphone apps and other large, continuous passive data streams concerning travel, however, makes multi-week, continuous tracking of travel by large samples of trip-makers an increasingly feasible proposition. Although not without their own issues, such new data sources offer exciting new possibilities for building more dynamic activity-based models (Habib 2018).
- Moving from conventional 1-day models to 1-week models offers the potential for significantly improved models. It is very arguable that 1 day is too limited a time period to fully exploit the potential of the activity-based paradigm for improved travel modelling. Too much day-to-day variability in activities and, perhaps more importantly, too many trade-offs within the week concerning when activities can be scheduled (especially for non-work/school activities, but the argument also holds for many workers and students as well), exist for a 1-day snapshot to be adequate. As noted above, week-long models would eliminate the aggregation bias of "typical day" models based on pooled data, capture weekday–weekend activity-scheduling trade-offs, and permit more complete accounting with respect to emissions, VKT, transit ridership and revenues, and other system performance measures of planning interest. Historically, week-long models were simply not practical due to lack of data and computational limitations. Again, new large data streams may address the data issue, while advanced high performance computing (HPC) capabilities (notably cloud computing) effectively eliminates computational constraints.
- In all surveys, asking how long the respondents have lived in their current residence, and, ideally, briefly gathering key retrospective information concerning their housing and labour market histories would provide some insight into where in "the learning curve" respondents are with respect to information about and experience with their neighbourhood and the local transportation system.

4.3 Heterogeneity

Over and above the dynamics/information issues discussed above, different people will tend to have different tastes and preferences due to their socio-economic characteristics. At least this is what we conventionally assume. It is an open question, however, how much of this heterogeneity in tastes and preferences is literally attributable to socio-economic factors (e.g. rich people behave differently than poor people simply because they are rich) and how much it is due to different dynamic/information contexts (rich people have different social influence networks than poor people and different experiences)? Certainly income, in particular, is a resource which enables/constrains what is feasible for people to do, and so it changes the context for decision-making in a very direct way. This then leads to different experiences, etc. A similar argument undoubtedly holds for age, and probably at least some other socio-economic attributes. Thus, experience (and hence, learning, memory, and preference formation), in general, is conditioned by socio-economic attributes, thus confounding the roles played by socio-economics *per se* versus the dynamics of social network information flows, day-to-day experience, etc. Perhaps as a result of this, in the absence of generally being able to dynamically model information acquisition and preference formation, modellers lean heavily on using socio-economic attributes to condition their choice models. This is certainly a practical approach, but it generally "locks into" the model current average behaviour by socio-economic category. Thus, the problem of allowing for changes over time in these behaviours is not solved in what remains a static model formulation.

Decision-maker heterogeneity is usually handled by some combination of categorization (different models for different socio-economic groups), inclusion of socio-economic attributes as explanatory variables in the model (e.g. dividing cost by income in mode choice models to allow for values of time to vary by income), and/or mixed-logit models (in which at least some parameters are allowed to vary randomly from person to person as a means of accounting for heterogeneity in these parameters across the population). Classification methods can include *ad hoc*, exogenously imposed categories (e.g. simply imposing a classification scheme on the model), a wide variety of statistical classification methods to find a "best-fit" classification scheme given the data, and latent class models (in which the allocation of agents into groups is performed by a statistically estimated stochastic model), among others.

To the extent that the classifier is a parameterized model with explanatory variables that can change over time, at least some dynamics are introduced into the model, since such classifiers permit agents to change category as their attributes (and/or their choice context) changes over time. The categorization scheme itself, however, remains static and can be susceptible to over-training to base case conditions (Badoe and Miller 1998).

Stochastic models such as mixed-logit and latent class models are not easy to apply in forecasting and have seen almost no application in operational applications to date. Latent class models are also generally computationally burdensome to estimate. Mixed-logit models indicate when significant variance in a parameter appears to exist in a population, but usually do not provide direct explanation of who is likely to have a greater or lower value of a given parameter. Hierarchical models of various kinds, in which utility function parameters are themselves parametric functions of explanatory variables, would generally appear to be a better approach to addressing heterogeneity in a more systematically forecastable manner.

Heterogeneity, of course, also exists in any practical characterization of activity alternatives, as well as in the attributes of these alternatives. "Shopping", for example, is often an activity type in both trip-based and activity-based models. But there are many different types of shopping (shopping for groceries is a very different activity than shopping for a new washing machine), with very different activity rates, costs, and feasible locations. Regardless of how detailed an activity categorization one might adopt, it is clear that these categories will always be aggregations of the myriad activities actually available in a complex economy/ society. Thus, significant heterogeneity in choice alternatives and their attributes is inherent in the problem. This issue is discussed further in the next section.

Better data, advanced econometric modelling methods and, increasingly, machine learning methods applied to activity/travel modelling can all help address heterogeneity issues. Access to very large samples of trips over extended time periods, in particular, should be extremely useful in obtaining a much better understanding of both the spatial and temporal variability in travel. Despite this, it is highly arguable, however, that heterogeneity as a modelling challenge is "here to stay": it is inherent in the complexity and diversity of the modern urban systems that we are attempting to model. Put another way, a fundamental "social Heisenberg Uncertainty Principle" exists, in that we are inevitably limited in our ability to accurately and completely observe a complex socio-economic system and to deterministically determine its behaviour. We are working in an inherently stochastic "world". This reinforces the case for microsimulation as the method of choice for modelling this world.

But this also means that we need to take the stochastic properties of this world and of our models' results more seriously. We need to work towards having the capability of routinely running many model replications for a single policy scenario to better account for this stochasticity. We also need to be able to "aggregate" over these replications to generate useful depictions of both the "average" predicted outcome and the "variance" in predictions around this average. Given the huge multidimensionality of even a single day's travel in a large urban area, such a "meta-simulation" approach is a non-trivial task. Current and ever-improving (and increasingly cost-effective) HPC hardware and software, as well as advanced visualization capabilities, however, make this a practical possibility.

4.4 Issues in Modelling Spatial Choice

A particularly important weakness in arguably all travel demand models is modelling location choice for non-work/school activity locations.[4] The predictive accuracy of such models is typically quite weak (Wang and Miller 2014). Many reasons for this exist, but, as noted in the previous section, considerable heterogeneity is inherent in the process in two ways:

[4]Work and school location choices/allocations for workers and students are also a major modelling challenge. For the purpose of this chapter, which is focussing on modelling day-to-day activity/ travel, we assume that work and school locations are determined exogenously to the activity/travel model, through longer-term labour market (place of residence—place of work) and school participation (place of residence—place of school) models.

1. There are a very large number of competing destinations for any given activity, with varying attributes: the choice set is very heterogeneous. Historically, data concerning the attributes of competing destinations has also often been limited.
2. Activity episode types (purposes) are very heterogeneous. In any practical model, we are all always dealing with broad classes of activities ("shopping", "recreation", etc.). Therefore, describing the attractiveness of one location versus another for a given episode (even if the attributes of the locations are known in great detail, which they usually aren't) is very difficult due to the aggregation of the episode types.

Time-space prisms are routinely touted as the "solution" to the first of these problems, and they certainly help, but they come with a host of practical problems:

- Prism calculation requires prior and posterior time-location "anchor points". This means that the set of feasible locations varies depending on what "gap" in the current (provisional) schedule is being considered for executing the given activity episode. Thus, location choice is interconnected with "gap" or episode start time choice.
- Episode duration inevitably also influences feasible prism calculations (and hence the location choice set), but durations may depend on the location chosen.
- Prisms are mode specific, so mode and location choices also become intertwined.
- Episode start/end times and durations are often somewhat flexible (fuzzy) and may be modified from originally desired or nominal values during the scheduling process in order to accommodate addition episodes or for other reasons. As a practical matter, we always observe realized episode start times and durations that are the outcome of the scheduling process, never possible "prior" nominal/desired start times and durations that may have been originally envisioned by the trip-maker at the time the "idea" of a given activity episode is first "generated".
- Even with crisp, well-defined prisms, the "feasible" choice set is still often very large (Wang and Miller 2014).

The issue of the interconnections between gap (start time), duration, location, and travel mode choices is discussed further in the next section.

With respect to the second issue of location attributes, modern GIS-based datasets (POI, etc.) are significantly improving the ability to characterize location attributes (at least for the base case; what they will be in the future is another matter), but even these have limitations in terms of detail and accuracy.

New/emerging, passive datasets (smartphone apps, third-party sources, smartcard data, etc.) generally seem to be compounding this problem since we often don't know/observe the purpose of the trip/activity. We, instead, impute it from the "land use" at the destination. This may introduce some circularity in the modelling logic (we choose this destination for a given purpose because of its attributes, but we impute the destination purpose based on these same attributes). This may cause us to redefine how we define activity type/purpose, and, hence, how we model activity generation and scheduling.

Activity episode location choice is also an important use case for returning to the Sect. 4.2 discussion of the role of information on decision-making. Time-space prisms are intended to identify the set of locations that are feasible to visit during a given time gap in a person's activity schedule. But what we also ideally need to know is what locations are known to/considered by the decision-maker—the so-called consideration or awareness set. Attempts have been made to model the probability that a person will have a particular choice set using a variety of methods, including latent class models, these are generally difficult to construct and typically become computationally intractable for operationally sized problems. Ideally, one would like to have a dynamic, simulation-based learning process in which individuals build up their awareness sets as they experience their environment over time. As discussed in Sect. 4.2, however, there may always be practical limits to what can be implemented in this regard.

4.5 Multi-dimensionality and Sequencing of Activity/Travel Decisions

Activity Scheduling Within the Overall Demand Modelling System

Over and above the challenges in modelling activity/travel behaviour posed by unobserved information flows, agent, and environment/context heterogeneity, and other issues discussed in the previous sections, the sheer multi-dimensionality of this behaviour poses major theoretical and practical problems in building behaviourally sound, operationally practical models. The traditional four-step model system represented a practical approach to this problem by decomposing it into a sequence of individual decisions (generation, distribution, etc.) which incrementally construct the entire set of trips and their attributes for an urban region. Although organized somewhat differently, activity-based models for practical reasons similarly decompose the overall decision process into a set of components or stages. Unlike the four-step paradigm, however, no strong consensus yet exists across the various models developed to date as to how best to do this.

It is standard practice to separate longer-term decisions from shorter-term ones. The so-called mobility tools—auto ownership and ownership of driver's licences and transit passes—are all longer-term decisions that do not vary from day to day and so are modelled separately and are treated as exogenous inputs into the activity/travel model *per se*. It is arguable that insufficient attention has generally been paid to mobility tool modelling, at least in the North American context, given the importance that these "resources" play in enabling travel. Indeed, in many models these are not modelled in detail at all, but simply taken as non-policy-dependent exogenous inputs, perhaps generated as part of the population synthesis process. These are, however, potentially important policy levers for influencing travel behaviour. Encouraging households to own one (or maybe even no) rather than two or more cars clearly is an important way of reducing auto usage and increasing transit and active transportation usage. Similarly, increasing transit pass ownership leads to increased transit usage. Further, as we enter an era of electric and/or autonomous vehicles, decisions concerning the number and type(s) of vehicle(s) to own—or whether to own any vehicles at all—are becoming even more important to understand and to include as an endogenous component of the overall travel demand modelling system.

Work and school participation and locations are also clearly longer-term decisions that should also be determined prior to modelling daily activity/travel. Some models, however, do include work and school location choice within the travel model. In terms of work locations, this may be a practical solution in the case where a more formal labour market or place of residence—place of work model is not available, but it must be recognized that is a mis-specification of the overall decision process since work locations are not determined on a day-to-day basis.[5] Students' school locations are generally poorly modelled in most models. While school location choice is a difficult process to model for both theoretical and data availability reasons, it is still surprising how little attention has been paid to this problem, given the importance of school-related travel (especially during peak travel periods), both in terms of the students' travel itself and the significant impacts that travel by younger children has on their parents' activity/travel schedules.

At the "other end" of the decision chain, route choices through the road and transit networks[6] (trip assignment) are generally modelled separately from the other components of trip-making, taking the origin-destination trips by mode and time and day generated by the rest of the demand model as inputs. This is a very reasonable and practical approach, for at least three reasons:

1. Route choice is a very complex and computationally intensive problem requiring specialized software to address. Enormous effort worldwide has been put into focussing on this problem and developing these models as stand-alone products.
2. Actual travel through the transportation network occurs within a time scale that generally is measured in minutes and seconds. Activity/travel-scheduling/planning is concerned with activity participation over the course of a day (or perhaps a week).[7] Thus, just as longer-term mobility decisions are separated from shorter-term travel planning decisions, so too does it make sense to separate daily planning decision-making from the modelling of even shorter-term trip execution.

[5]Exceptions, of course exist. Service workers (plumbers, etc.) and salespersons may have no fixed place of work, travelling each day to wherever their clients on a given day are located; construction workers move from site to site on a frequent basis, etc. But these special cases should be dealt with as such (and certainly are not in current operational models). For most workers, their primary work location is still determined by a longer-term work participation process.

[6]And, in principle, the bicycle and pedestrian networks as well, although bicycle and pedestrian route choices are rarely, if ever, explicitly modelled in operational models to date.

[7]Of course, this planning may go down to the level of the minute (or a few minutes), but the overall scale of the problem is at the level of the day.

3. Road and transit networks are physical systems that exist independently of the people using them (although their performance depends on this usage). In object-oriented terms, they are objects with their own attributes and behaviours (performance functions) that respond to travellers' usage of their services. Trip-makers clearly are different objects (agents) who make decisions within their individual minds about why, where, and when to travel given, among other factors, their perceptions of transportation network service levels. Network assignment models can be thought of as a "market" within which trip-makers' demand for transportation services is matched with the services that the transportation system is able to supply, with the "price" of these services (travel times, etc.) being determined through this demand–supply interaction (as in many other markets). Put another way, the trip assignment model simulates the <u>execution</u> of trip-makers' travel plans within the physical transportation system, whereas the "rest" of the demand model system represents the formation of these plans (activity/travel scheduling) in the trip-makers' minds. Although connected through the "feedback" of travellers' experiences when using the transportation system, there are quite distinct and separate processes.

Having said this, it must be recognized that there is a trend towards trying to integrate travel planning with route choice, so that trip plans (e.g. destinations and possibly even whether a trip will be made at all) are dynamically altered as the simulated day proceeds. That is, activity/travel decisions are continuously updated as the individual moves through the day and travels through the transportation system. Such dynamic rescheduling obviously can happen (I may cancel or reschedule an appointment because I am stuck in traffic) and may be important for modelling the effects of real-time information systems or responses to emergency situations (e.g. a road closure due to an accident). It is an open question, however, whether such models are appropriate/needed for all demand modelling applications, especially long-range forecasting, which remains the primary objective of most activity/travel models. Issues with very tight, within-day, dynamic integration between activity/travel planning and execution of these plans with simulation of the realized network flows include:

- Such tightly integrated models are computationally very burdensome.
- It is also questionable whether this level of within-day dynamics is necessary (or even appropriate) for long-range forecasting applications. Given the level of uncertainties concerning future year scenarios (population and employment levels and distributions, traffic signals, etc.), is this very fine level of modelling detail meaningful?
- While rescheduling obviously exists, it may not be critical to the determination of overall future travel patterns. Arguably, most people most of the time execute their daily travel plans more or less as planned. The extra complexity and computational cost of very detailed rescheduling may not be worth the effort.
- Since one almost always observes the final outcome of travel decisions (including route choice, if it is observed), it is very difficult in general to observe cases of rescheduling that might be used to estimate/calibrate such models.

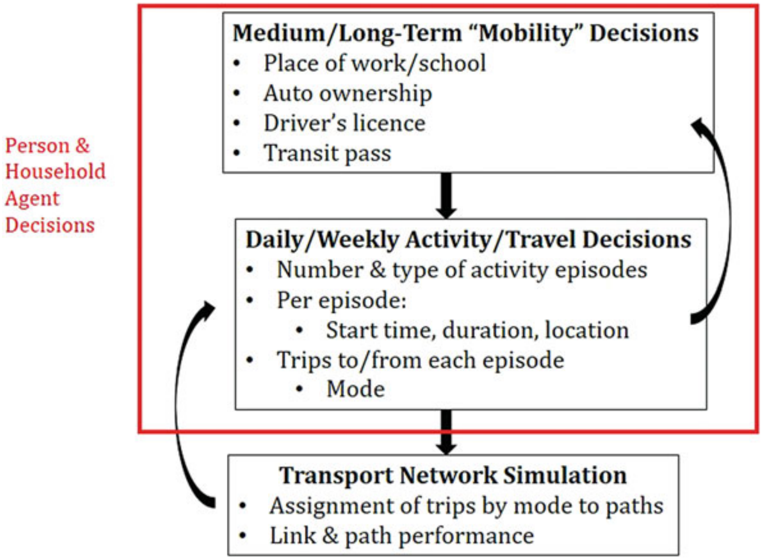

Fig. 5 High-Level Architecture of Activity/Travel Model Systems

- Unless traffic accidents, etc. are being explicitly modelled (which to date they never are in long-range forecasting models), there will be little in the model in the way of events to trigger rescheduling. In particular, it is generally impossible to differentiate such rescheduling from the overall equilibration of demand and supply through iterative feedback between the demand and network models that always occurs in such models.

Given these observations, it is argued that, for most applications, a fairly "classical" segmentation of processes (with appropriate feedbacks) such as sketched in Fig. 5, remains appropriate as a high-level architecture for developing activity/travel demand models (and, indeed, represents that vast majority of current model structures).

Activity-Scheduling Decision Structures

What remains to be determined is how to structure the actual generation and scheduling of daily/weekly activity episodes and their associated travel. This is also a multi-dimensional problem of determining:

- How many episodes[8] of what type in which to engage

[8]In this discussion, it is assumed that we are only concerned with out-of-home episodes. In-home episodes are briefly discussed in Sect. 4.8.

- For each episode determining its start time,[9] duration,[10] and location[11]
- For each trip determining its mode

It is fair to say that no consensus currently exists concerning how to structure these decisions, with different models varying considerably (indeed, fundamentally) in their approach to this problem. The closest that exists to a standard are the (primarily US-based) tour-based models briefly described in Sect. 2.2, which generally share a roughly similar structure. Activity-scheduling models, on the other hand, display considerable diversity in terms of the extent of joint versus sequential choices across the various dimensions of the problem, the ordering of decisions when being sequentially made, and the actual modelling methods (random utility, rule-based, etc.) to be used. It is beyond the scope of this chapter to enter into a detailed review and discussion of these various designs and their strengths and weaknesses, but a few observations/"propositions", based largely on the author's experiences with such models are presented for consideration below.

First, it is important to note that the basic scientific challenge in developing such models is the intrinsic latency (unobservability) of this decision process. We can only hypothesize what we hope is a "reasonable" model, at best based on well-argued axioms that are then empirically validated as best as possible. Psychological theories of decision-making, such as Maslow's Hierarchy of Needs (Maslow 1970), behavioural economics (Kahneman 2011), and standard microeconomic theory (random utility theory, etc.), all provide useful insights, but only take us so far. At the end of the day, a model must be hypothesized and tested against observed behaviour in order to assess its reasonableness and usefulness.

Second, continuing the theme of decomposition as a practical means for modelling complex decision bundles, it is suggested that the activity/travel-scheduling/planning process can be divided into three main components:

- Activity episode generation
- Episode scheduling (includes the generation of travel episodes—trips—to travel to and from the episode)
- Trip mode choice

Episode Generation: The "idea" of the desire to participate in an activity must "come from somewhere". Generation is the model component that instantiates specific episodes for possible scheduling and eventual execution. As part of the generation process, at least some attributes of each episode need to be determined—

[9]And/or "gap" in the current provisions schedule, as briefly discussed in Sect. 4.4.

[10]An episode's end time equals its start time plus duration, so only two of these three attributes are independently determined. While an ending time may sometimes be the primary consideration for scheduling a given episode (I need to be home by 5 pm), it is generally assumed that start time and duration are generally the more "primary" attributes.

[11]As per above, it is assumed herein that work and school locations are known. Locations for non-work/school locations, however, are assumed to be chosen as part of the activity episode generation/scheduling process.

at a minimum the activity episode type (shopping, social, etc.). It is suggested that for work and school episodes start time and duration should also be determined as part of the generation process, while for non-work/school (NWS) episodes at least duration should also be (at least provisionally) determined during generation. It is arguable that it is difficult to think of participating in an activity episode without at the same time having some idea of how long it is likely to take. Work and school start times arguably should also be included within the generation process, given that these are largely determined by the "logic" of the job or the education programme, rather than by scheduling considerations (this is discussed further below). NWS episode start times may vary in terms of their flexibility, but arguably from practical modelling considerations, may generally be handled within the scheduling process, since these start times are often influenced by scheduling considerations.

Episode Scheduling: Once a person has thought of possibly engaging in an activity episode, the feasibility of scheduling this episode—and where in the person's schedule this episode will be placed, needs to be determined. It is arguable that separating episode generation from scheduling is computationally attractive and behaviourally plausible in that it permits the episode generator to be only concerned with the logic of the given episode (I'd like to go golfing this weekend) without being concerned with trade-offs with other possible episodes (the lawn needs mowing this weekend). These trade-offs (and choices among them) reside within the scheduler, which "sees" all the proposed episodes and assesses which can be scheduled when and which might need to be rejected, or at least have their attributes (e.g. duration) modified to feasibly fit into the overall schedule that is being planned. The scheduler can be thought of as the person's time budget manager that allocates the resource of time to competing activities. Determination of NWS episode start times (and/or allocation to "gaps" in the schedule), as well as generation of the trips needed to travel to/from each scheduled episode also logically and conveniently should reside within the scheduler, since it is generally not possible to assess the feasibility of participating in a given episode without determining when it is to occur and how one is going to travel to/from it.

Trip Mode Choice: A trip is a special type of activity episode that is generated every time we decide to participate in an out-of-home activity. Like any episode, trips have start time and duration (travel time). They also have mode (auto drive, transit, walk, etc.), which determines the trip's travel time.[12] Trip mode choice, therefore, is an intrinsic component of the activity/travel-scheduling process. Trip mode choice models are themselves typically sophisticated choice models and so treating these as a separate (but interacting) component within the scheduling process is a practical approach. Ideally, this model is framed as a tour-based model to capture the tour-level interactions discussed in Sect. 2.2. This, however, introduces complications

[12]In such models, trip start time is usually determined by either subtracting the expected travel time from the desired start time of the activity episode being travelled to, or adding the travel time to the activity episode end time if one is leaving this episode to travel to another location.

into the overall scheduling process that need to be addressed in any practical implementation.

Implicit in the discussion above is the assumption that work and school activity generation and scheduling are treated somewhat differently than other activities. While debate about this approach exists, and some models treat work and school as "just another activity" (Doherty et al. 2001; Habib 2018), strong arguments exist that they are, in fact, "primary" activities, that generally take precedence over other activities in the activity generation/scheduling process (Dianat et al. 2018a, b). This largely derives from the "contracts"/"commitments" that they involve with other agents (the worker's employer; the legal requirement for students under the age of 16 to attend school; the need for university students to attend classes so that they can pass their courses; etc.) and that the location, timing, and duration of these episodes is typically determined by the arrangements of these contracts (I must work an 8-h shift from 8 am to 4 pm at the factory; my Chem Lab starts at 9 am in the Chemistry Building on campus; etc.) rather than by personal preferences or activity-scheduling considerations. Indeed, work and school episodes are generally assumed to be scheduled first in the scheduling process and thereby provide "anchor points" or a "skeleton schedule" around which other, lower-priority (and/or higher-flexibility) activity episodes can then be scheduled.

The final observation to be made here is that NWS location choice is a particularly problematic issue to deal with in model design, for at least two reasons. First, as noted in the previous section, it is easily argued that location choice is often intertwined with duration, start time (gap), and/or mode choice. Jointly modelling all these attributes simultaneously is very challenging, however, especially if duration is treated as a continuous variable. Thus, some structuring of these decisions is generally a practical necessity.

Second, for some activities, location may well be predetermined by longer-term processes, similar to work or school (I don't randomly pick a doctor for my annual check-up; my grandmother whom I want to visit this Sunday lives at a known location; my son's hockey game is at a pre-scheduled arena; etc.), while others are much more dynamically determined on an episode-by-episode basis (Where should we eat tonight? Stopping at a hardware store that is "on the way" home from work, etc.). But longer-term location choices are generally not observable within typical practical data collection methods, and, even if they were, predicting them in future years would be challenging. As a result, it is usually necessary to include them with episode-specific location choices in a single model.

How best to improve our models of activity location mode choice is perhaps the single biggest challenge in terms of improving the practical utility of these models for operational planning purposes. Bringing better data to bear on the problem that has often not been available in the past will certainly help. In particular, the widespread availability of high-quality GIS-based datasets greatly improves the set of explanatory variables potentially available for describing the attractiveness of different locations for different purposes. But finding a computationally attractive, behaviourally robust modelling structure for dealing with location, gap, and mode choice is also essential if significantly improved, practical location choice models are to be developed.

4.6 Inter-Agent Interactions

Over and above social network information flows, inter-agent interactions and constraints are clearly extremely important in determining activity/travel behaviour. To begin, it is fundamentally essential to observe that all individual person travel occurs within a household context, with associated constraints, collaboration, joint activities, etc. While including household-level variables (auto availability measures, etc.) in person-level models is commonplace, explicitly modelling activity/travel within an explicit household-level model is still not common. An exception to this rule is the TASHA ABM, which is fully household based and which is the operational travel demand forecasting system used by the City of Toronto since 2016 (Miller et al. 2015). TASHA endogenously models within-household car allocation, ride-sharing, and joint activity participation in a parsimonious and computationally efficient manner (Miller et al. 2005).

A particularly important, but usually neglected household-level interaction is that of "serve-dependent" activities in which one or more (adult) person within the household is responsible for taking care of one or more dependents (young children, the very elderly, physically/mentally disabled persons) who require assistance in travelling (taking one's child to school or daycare) or in-home assistance/supervision (e.g. young children are legally not allowed to be at home without adult supervision). These interactions can have very significant effects on the supervising adults' activity/travel schedules, but are rarely considered in individual-based models.

A concern with increasing use of smartphone app activity/travel tracking, cellular data records, transit smartcard records, and other large-scale passive data streams is that these all track individual trip-making, usually anonymously (so that attributes of the trip-maker are not known) and, without any linkage to the trip-maker's household. This may pose a significant challenge to household-based modelling, despite the case presented above for the need for such models. An important research challenge is to investigate ways in which household-level effects can be retained within models based on such individual-based datasets.

Inter-person interactions with non-household members are, of course, also important in determining activity/travel behaviour. Visiting friends and relatives, social outings, carpooling, etc. are all of importance. "Carpooling" (ride-sharing between non-household members) is a particularly challenging problem, which arguably is not handled well by <u>any</u> current travel demand model, trip-based or activity-based. Historically, lack of appropriate data and major computational issues have severely limited what could be done. As new mobility services continue to emerge, the modelling of ride/car/bike-sharing in a wide variety of service designs is going to be a major challenge. If access to data from such services becomes available this may facilitate the development of improved models. Given that these data, however, are invariably privately held, their availability for academic or public use is not clear at this time.

4.7 Activity Episode Utility and the Treatment of Time

Adopting a utility-based approach to activity scheduling is very attractive for a variety of theoretical and practical reasons. Indeed, it is not clear how trade-offs among activity episodes "competing" for scarce time slots in a person's schedule can be systematically assessed outside of some form of utility calculation. Utility-based models are still relatively new, but are evolving fairly rapidly. A significant literature on "time-use" also exists which is predominantly utility based. Utility-based models (or at least parameterized functions with policy- and schedule-sensitive explanatory variables) are also essential if elastic activity/travel generation models are to be developed.

Time is a resource to be spent, like money. To the extent that we try to construct episode utilities, these are usually expressed as a function of episode duration (time spent). This is probably appropriate for some activities, but not others. For example, the utility that I get from a visit to the doctor has almost nothing to do with the duration of the visit, nor is this duration in any way under my control, i.e. it is not the outcome of my choice involving trading the marginal utility of time spent at the doctor's versus competing possibilities. Much remains to be understood concerning how utility is derived from episode participation and the relationship of this utility to the time spent. Why is a minute spent shopping valued differently than a minute spent visiting friends? How does it change with duration, context, person, time of day, etc.?

4.8 In-Home Activities

Although literature exists concerning in-home activities and the interplay between in-home and out-of-home activities, the preponderance of activity/travel models understandably have focussed on out-of-home activity and associated trip-making. The basic assumption of this approach, obviously, is that little substitutability exists between in-home and out-of-home activities, or, at least, that this substitutability is essentially stable over time and so can be treated as a constant, implicit contextual factor rather than an explicit, endogenous component of the decision-making being modelled.

The considerable growth in online shopping, home entertainment options, shopping and meal delivery services, etc. all call this assumption into question. In addition, two in-home activities that are of particular importance to constraining out-of-home activities are:

1. As noted in Sect. 4.6, in-home supervision of dependents (young children, etc.) represents a major constraint on the out-of-home activities of supervising adults. This constraint is almost never recognized in current models.

2. Night-sleep is a mandatory activity[13] that consumes a significant portion of most people's days. It also heavily conditions (interacts with) both morning activity start times and evening/night activity end times. One can generally get away with not explicitly modelling night-sleep in a 1-day model, but it becomes essential to model it explicitly in multi-day/week-long models. Night-sleep arguably should join work and school activities as elements of a person's skeleton schedule (Dianat et al. 2018a, b).

Traditional time-use surveys as well as potentially new data sources, such as credit card transaction data, would appear to provide a sound starting point for modelling in-home activities in conjunction with out-of-home activities, as this becomes necessary to do. Further, in anticipation of eventually needing to model both in- and out-of-home activities, any activity-scheduling model conceptual design should be general/flexible enough to be extended to in-home activities. Opportunities and methods for obtaining both in-home and out-of-home activities in new data collection efforts should also be actively pursued.

4.9 Beyond Daily Urban Travel

Multi-Day (Week-Long) Activity/Travel Models

As noted in Sect. 4.2, multi-day (e.g. week-long) models of travel behaviour may provide significant improvements on our ability to understand activity/travel behaviour. Dianat et al. (2018a, b), for example, demonstrate that activity/travel patterns differ significantly from 1 day within the week to another. They also demonstrate the practicality of constructing a week-long model, providing that suitable data are available for model estimation.

Steadily improving methods for collecting large-sample activity/travel data for a week or more (e.g. smartphone apps, cellular data records), combined with ever-increasing computing power (notably cloud computing) make the possibility of week-long activity/travel models a much more practical possibility than has previously been the case. The major practical limitation at this point in time is the question of how to model road and transit assignments within a week-long model, given the still-too-long run times for these models for large urban areas. Even this concern, however, is not an insurmountable problem, again given cloud computing options, as well as the possibility of a "next generation" of highly parallelized, quick-running assignment models being developed in the coming years.

The other question concerning week-long models is how they would be used in operational practice by planning agencies. At a minimum, the results for the 5 weekdays could be aggregated to provide a true "average" weekday forecast that is free of

[13]The occasional "all-nighter" getting a term paper done, "partying 'till the cows come home", etc. notwithstanding.

the “temporal aggregation bias” of current “typical weekday” models that are based on pooled data from different weekdays naively combined in the development of a single weekday model.

A week-long model would also provide (for the first time in virtually all agencies worldwide) information on weekend travel, which should be of policy interest for a variety of reasons. A week-long model also would provide much better estimates of greenhouse gas and air pollution emissions than is possible from even a 24-h single-day model. It would also provide a much better basis for expanding model results to the annual totals which are often required for economic evaluation and other policy analysis purposes.

Intercity/Long-Distance Travel

Models of intercity and/or long-distance travel have always lagged behind the urban travel demand modelling state of the art and practice for a variety of reasons (Miller 2004). Increasing attention is now being paid to modelling longer-distance, non-intra-urban travel (Aultman-Hall et al. 2015; LaMondia et al. 2016). These efforts are hindered by a general lack of data to support advanced modelling, as well as lack of consensus on even very basic concepts such as the definition of a “long-distance” trip.

The extent to which ABM is a promising approach for developing the next generation of long-distance travel models is an open question, but one well worth investigating. The fact that long-distance travel is relatively “sparse” compared to urban trip-making actually is a strong argument for a microsimulation approach in which such trips are randomly generated as discrete events. Long-distance travel is also extremely heterogeneous in nature (think of all the different reasons that people generate business trips or possible destinations for “visit friends and relatives” and vacation trips), again arguing for a microsimulation approach.

5 Summary Comments

This chapter has discussed a broad range of issues and options for developing next-generation activity/travel models. Although it has not spoken very directly to the emerging major challenges associated with autonomous vehicles and Mobility-as-a-Service (MaaS) concepts, these very much provide an explicit subtext for this discussion. The assumption motivating this discussion is that we need to significantly improve our general travel demand modelling capability so as to be better able to model the impacts of these new, disruptive technologies and services. Current models make many assumptions that may have been acceptable given past circumstances, but these assumptions are being aggressively challenged by the “brave new world” that is rapidly approaching.

At the same time, new data collection methods and technologies are opening doors for new "views" of activity/travel behaviour, including much larger samples of behaviour, over extended periods of time, than have been available in the past. This is creating the possibility of building new models in new ways that perhaps will transcend some of the data limitations that we have experienced in the past.

Without trying to summarize the long list of items discussed in the chapter, a few key observations that emerge from this discussion include the following:

- A strong case exists for moving from models of one "typical" day's activities and travel to models of 1 week's activities. Such models arguably would be both more behaviourally representative and useful for policy analysis. They are also much more feasible to construct given current and emerging data, modern computing capabilities and improving theory concerning how to model activity and travel over a 1-week planning period.
- Heterogeneity in both agents and choice contexts is a continuing challenge that will always be a major issue in model design and application.
- Similarly, difficulties in observing and modelling information acquisition and usage by trip-makers is another major modelling challenge. It is easy to talk about building more dynamic models of agent learning and adaptation, but implementation of significantly improved models will continue to be difficult.
- While the new, "big" data streams are generally very promising for the development of next-generation models, one potential problem is that these are inevitably individual based and do not directly collect household-level behaviours and interactions. Being able to explicitly model household-level resources, constraints, and interactions, however, arguably is very important in order to understand individual-level travel. How we can "retain the household" in future models based on new data sources is a significant challenge going forward.

Finally, much of this chapter has, one way or another, wrestled with how one might best design the decision structure for modelling activity/travel decisions. This issue of "model architecture" is critical to the overall behavioural fidelity, computational efficiency, data requirements, and practical ability to implement the models in operational settings. No standard architecture currently exists, especially for activity-scheduling models. This chapter provides some "hints" as to where model design might usefully head, but much work remains to examine and test alternative designs, hopefully in a way that does lead to the emergence of new models that are both behaviourally sound and operationally useful.

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