Working Paper

Computational challenges for integrated micro-simulation models

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Abstract

This paper discusses the current challenges faced by large-scale agent-based approaches to transport modelling. It highlights a number of inconsistencies in modelling practice, which the field should address.

Keywords

Agent-based simulation, travel demand

Preferred citation style

1   Starting point

The translation of the ideas of the activity – based approach outlined in the late 1970s and early 1980s by Hägerstrand (1970), Chapin (1974) and the team at Oxford (Jones *et al.,* 1983) and others into operational software was slow. CARLA described in Jones *et al.* was never adopted for a practical and large scale application. The German simulation based work (see Axhausen and Herz, 1989 for a review) did not make an impact outside Germany and the software VISEM, which made an activity-chain approach available for large scale application, was tied too strongly to a particular aggregate assignment software product (Fellendorf *et al.* 1997), which had its international breakthrough only much later.

The current set of agent-based simulations of travel demand and traffic flow reflect the different pathways of their developers and their different design concerns:

- TRANSIMS (see www.anl.gov/TRACC/Computing_Resources/transims.html) shows its departure point from an complexity science viewpoint common in physic-based work on social systems. It covers both traffic flow and travel demand in an equilibrium framework.

- MATSim[1] extends the route choice paradigm to the full daily schedule (www.matsim.org). It joins TRANSIMS concern for equilibrium, scale and speed based on a simplified traffic flow model (Nagel and Schreckenberg, 1992) with the German agent-based demand modelling tradition mentioned above (Axhausen, 1990). This approach draws the schedules from the observed distributions, but conditional on the socio-demographics of the agent and adds the missing choice facets step by step.

- MOBITOPP retains the basic ideas of Zumkeller (Schnittger and Zumkeller, 2004), which had laid the basis of the German approach mentioned, but integrates a highly detailed traffic flow simulation in the Wiedemann tradition (1974). It is not concerned with equilibrium.

- The Bowman-inspired work (1995) reflects its core interest in the use and development of discrete choice models (see for example Ben-Akiva and Lerman, 1985 and Train, 2003). These models have only recently started to integrate the assignment at the agent-level, including MATSim[1].

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[1] For MATSim the best source is its website at www.matsim.org, but for an early description see Raney and Nagel, 2006 and Balmer *et al.,* 2007.

- Chandra Bhat's CEMDAP retains his structuring of the daily schedule around the daily commute, which he had already adopted in his thesis work. It is focussed on the discrete choice modelling of the demand side, and has started to integrate external traffic flow models only recently (Bhat *et al.,* 2009). The demand modelling is based on a series of sequentially applied choice models.

- FAMOS and its variants in the US and Japan arose out of the collaboration of the late Ryuichi Kitamura and his colleagues (Kitamura *et al.,* 1997 or Pendyala *et al.,* 2005). Hägerstrand's (1970) time-space prism is a central element of the approach, which in its latest implementation now fully incorporates a traffic flow model.

- Albatross incorporates a rule-based approach to demand modelling pioneered by Arentze and Timmermans (2000). It continues to rely on separate (dynamic) assignment packages for the calculation of the generalised cost of travel, recent experiments with MATSim not withstanding.

- ILUTE and TASHA follow a different rule-based approach (Miller and Roorda, 2003; Salvini and Miller, 2005). While Albatross constructs the daily schedule along its structure, TASHA constructs it by resolving conflicts, which arise when activities are added incrementally. It also continues to rely on separate (dynamic) assignment packages for the calculation of the generalised cost of travel, recent experiments with MATSim not withstanding.

- ADAPT (Auld *et al.,* forthcoming) is similar to TASHA in its constructive approach, which does not look for equilibrium.

The calculation of an equilibrium is desirable for any use of the results in policy evaluation (Sheffi, 1985) as it provides a well-defined point of comparison for assessment of the impacts of any policy change studied. The downside is the computational cost of the iterations needed to reach equilibrium, which grow non-linearly with the targeted precision (Boyce *et al.,* 2004). The non-equilibrium ABM approaches would have compute equally precise average impacts through many independent runs, which in addition would need to include a warm-up period of the simulation to avoid the unavoidable start-up deviations from the steady-state. So far none of the non-equilibrium ABM approaches has reported computational experiences with such an approach. At this point in time, equilibrium remains the preferred choice as the computational target of the simulation.

While the equilibrium is well-defined for the assignment problem (Wardop, 1952), there is no well-accepted equivalent definition for the problem of the activity based model. Still, extending Wardrop's or Nash's (1951) definition is straight forward, if difficult to measure for agent-based simulation of the daily activity scheduling. Nagel and Flötteröd (2009, p. 8) drawing on Wardrop define

> "An agent-based UE [. . .] is defined as a system state where no agent
> can unilaterally improve its plan."

and drawing on Daganzo and Sheffi's (1977) definition for the aggregate case:

> "In a SUE network, no user believes he can improve his travel time by
> unilaterally changing routes."

they define:

> "An agent-based SUE [. . .] is defined as a system state where agents
> draw from a stationary choice distribution such that the resulting dis-
> tribution of traffic conditions re-generates that choice distribution. [. .
> .] It implies that every agent considers a whole choice of (possibly
> suboptimal) plans and selects one of these plans probabilistically."

The challenge in this definition derives from the fact, that agent-based equilibria retain the granularity of the agent weight, which ensures, that some agent might still find a solution, which is still marginally better, but without changing the overall outcomes substantially, leading to oscillations. Aggregate solutions avoid this problem by calculating flows between zones to an arbitrarily chosen level of accuracy given the desired precision of the calculated equilibrium. The agent-based equivalent would be to sample not one, but five or hundred times the population under study, and giving them weights of one fifth or one hundreds in the capacity relevant calculations.

To test the achievement of this condition Meister (2011, p. 25) proposes the following:

> "…An agent-based SUE is defined as a system state where the num-
> ber of agents which perceive that they can improve their state is
> minimized, given a dynamic environment where a constant share of
> all agents [continues to] change their plans".

and adds, that this state must hold true for an arbitrary number of iterations after it has been reached first. The number or share of agents and the number of iterations are bounds set by the user and are equivalent to the precision requirements set in aggregate assignment algorithms.

Next to the obvious computational cost of this definition, but which is similar to the one the aggregate assignment models face, is the definition of "improve", i.e. the measure by which the whole activity schedule is characterised for within-person comparison. The formulation of a utility function is possible (see Bowman (1995) and related work; or the approach taken by MATSim (Charypar and Nagel, 2005) or Feil and Axhausen, 2009), but it is unclear, actually unlikely that they describe the true choice context, as they assume that the agents plan their

daily programme in one step (Doherty, 2005 or in less detail Axhausen *et al.,* 2007). For model estimation we have to abstract or average out the many elements, which shorten the true planning horizons encountered for a day:

- The desire for uncommitted time

- New chances arising from unforeseen events, meetings or calls

- Enforced change due to delays, tasks not finishable in the originally allocated time

- Unexpected constraints arsing from the integration into the schedule of a third person or organisation

Next to these issues are the difficulties to define the various other influences, such as the presence of third parties, of luggage, of the local weather etc., which are generally badly covered in travel diary surveys. The issues are also present in the generation of the choice alternatives needed for model estimation, here complete daily schedules. Acknowledging these fundamental difficulties to estimate the basic element of an agent-based model of daily activity schedules, this paper concentrates on the computational issues above and beyond reaching the extended SUE defined above. They concern the basic algorithms and their deviation from the theoretically required, the question if we have embedded all necessary actors and if we bias our results by indirectly embedding unquestioned parameters during the construction of the non-chosen alternatives, model estimation and finally the challenges of modelling the scheduling optimisation process.

2   Basic algorithms and objective functions

In the most basic terms, the algorithms used to calculate the aggregate deterministic (DUE) or stochastic (SUE) user equilibrium involve the following steps:

1) For all origin-destination (OD) pairs add a relevant route to the set of alternatives

2) Redistribute the OD-volumes among the relevant subset of routes so as to approximate the objective function

3) Check if convergence has been reached within the desired accuracy, if not go back to 1)

For the DUE this is consistent, as the relevant routes are those, which permit the travellers the shortest travel time between origin and destination (Wardrop, 1952). The solution is independent of the initial assumptions of the link travel times, as routes, which do not allow the shortest travel time, will be excluded in later iterations. It is not a behavioural model of route

choice as such, as a model of route allocation informed by a reasonable behavioural assumption.

For the logit-based SUE this approach is actually inconsistent, as it implies that the choice set is constructed incrementally, while the estimation and use of the underlying logit model assumes that the choice set is known a-priori. The SUE should therefore not be unique, but it depends on the choice sets provided to each OD pair. This problem is ignored in application, as no behaviourally credible models for the choice set generation exist, although recent progress is promising (see for example Pillat *et al.,* 2011 for a behaviourally informed choice set construction or Schüssler *et al.,* 2009 or Frejinger and Bierlaire, 2010 for computationally fast approaches).

As discussed above, DUE and SUE only look at route choice, but see Huang and Lam, 2005 or Lam and Yin, 2011 for an extension into the scheduling domain. The activity – based models (ABM) generally separate the activity demand from the route allocation step above. Assuming they have an equilibrium criterion, they proceed as follows:

1) Calculate the distribution of the schedules (number and sequence of activity, start time and duration, locations, parking location/access and egress stop, mode) given the current estimate of the generalized cost of travel

2) Aggregate the demand into demand matrices

3) Solve for route choice SUE

4) Check if convergence has been reached within the desired accuracy for the scheduling equilibrium, if not go back to 1)

Step 2) obviously destroys information through the aggregation, so it is unclear, if this process can lead to a unique equilibrium, as it will depend on the arbitrary choices of the aggregation spatially and temporally. The use of choice models in step 1) imposes potentially enormous computational costs, if the choice sets are allowed to be highly detailed: number of activities, activity types, time intervals for the start times and durations, parcel fine destinations, subtour mode choice[2]. Remember that for each schedule the choice set of routes between the destinations needs to be calculated as well. The existing implementations avoid this combinatorial explosion both in estimation and application, by dividing the choice model into subsets, which are linked with their inclusive values, and by reducing the number of alternatives through exclusion or spatially through zoning. None include route choice with its very expen-

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[2] Subtour mode choice model use the „subtour" as the smallest unit, i.e. any sequence of trips which return to the same location within the whole tour. They assume that mode choice will be fixed during the subtour, which is actually a simplification for subtours involving walking, which can always be replaced by public transport, taxi or being a car passenger.

sive choice set generation procedures (Schüssler, 2010). So, all of the formidable econometric sophistication of the usual ABMs comes at the price of not fully covering all relevant interactions.

In summary, the computational and conceptional challenge of these ABMs is the management of the choice sets. The computing costs of enumeration, random sampling or even just systematic construction grow exponentially with the number of choice dimensions and the number of alternatives within each dimension. For a model of just the usual five interacting demand dimensions: number and sequence of activities [factorial in the number of activities], duration [min], location [number of zones], sequence of modes by stage [less then factorial in the number of stages per (sub)tour], routes [non-linear with the average number of links of a route] these costs are prohibitive, which limits the true range of a choice – based ABM. See for example Cascetta *et al.,* 2006, Schüssler, 2010, Banzhaf and Smith, 2003 or Pellegrini *et al.*a2005 for the sensitivity of the parameter estimation with regards to the size and structure of the choice sets.

Of the ABMs described above, MATSim takes a explicitly optimisation oriented approach in contrast to the choice-model driven approaches, which incorporate the optimisation via the basic assumptions of the choice models (McFadden, 1981) and get the heterogeneity of the choices for free. MATSim in its search for SUE adopt an evolutionary strategy of testing new schedules until all agents have found their optimal plan within in the accuracy possible:

1) Execute the schedules[3] with the traffic flow simulation; measure the crowding at the destination facilities[4]

2) Score the experience (utility) of the schedule with the agent-specific parameters

3) Replan, i.e. randomly change or optimise the facets of the schedule for an a-priori given share of the agent-population; select a plan from among the existing plans for the remaining agents. If the maximum number of plans for an agent is reached, drop the worst one.

4) Check if convergence has been reached within the desired accuracy for the scheduling equilibrium, if not go back to 1)

At this point of its development MATSim optimises the various dimensions as a rule unidimensionally, i.e. time-of-day dependent shortest paths, optimal start times, optimal mode, optimal destination, or at best two-dimensionally, e.g. start times and modes (Meister, 2011;

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[3] The schedules are called plans in MATSim based on the name of the xml data structure used to store them.

[4] MATSim labels all types of destination *facilities* (homes, work places, shops, restaurants, sports facilities etc.) as they are treated identically.

Feil, 2010). MATSim employs a logit-based approach to select the schedule to execute in the next iteration for those agents, which do not replan. As the population of the available schedules for each agent is small due to the limited computer memory, typically three to five, and as they become rather similar as the number of iteration progresses, this process turns in a quasi-deterministic choice. Continuously dropping worst schedules ensures a steady – upward drift in the performance of the schedules.

The challenge for MATSim or any other model employing the same optimisation approach is therefore the maintenance of the variance between the agents and of the choice situations, which they face. While the home and work locations, which are fixed during the iterations, together with the socio-demographics provide a base level of variation, it is necessary to include two, better three further mechanisms to ensure the range of responses observable in real life: person-specific tastes and alternative-specific error-terms (Horni *et al.,* 2011); congestion feedback from links and destination facitilities (De Palma *et al.,* 2007; Horni *et al.,* 2009) and inclusion of co-ordination between the household members and the members of the social network, to which the agent belongs (Hackney and Marchal, 2008; Marchal and Nagel, 2006; Arentze and Timmermans, 2008; Frei and Axhausen, 2011).

3   Embedding parameters and actors

Current practise for aggregate and agent-based models is limited to a subset of all agents and responses by excluding certain dimensions and certain actors from the endogenously modelled aspects. While in many cases these choices are justified and necessary due to a limited range of policy or research questions or more often due to less easily justifiable budget, time and software limitations. Given the normality of these self imposed limitations, the lack of a culture of assessing their impacts is surprising, especially with regards to parameter estimation, actor exclusions and the completeness of the demand.

Transport demand models generally exclude segments of the demand. These segments can be defined by:

- the type of vehicle, e.g. lorry traffic
- the type of activity, e.g. delivery services (mail, express mail, store deliveries), tradesmen and professionals between their jobs (e.g. plumbers, painters, visiting nurses etc.)
- the mode, e.g. taxis, even in cities where they are crucial, such as Singapore, New York, Seoul, or pedestrians

- or the OD-type, such as through traffic.

It is clear, that the impact of these omissions varies with the relative importance of the segment in the region concerned. While their absence can be partially accounted for in the current situation through the use of roughly estimated a-priori loads on the network links, which are kept fixed during the aggregate equilibrium search, this approach is only available at substantial computing costs for the agent-based case. The assumption of such fixed a-priori loads becomes inappropriate in any after situation, as the underlying demand segments will also respond to the policy change or new infrastructure provided.

The impact of completely ignoring such segments is even more insidious for choice model estimation, which are based on model derived non-chosen alternatives: e.g. the attributes of a non-chosen route or non-chosen mode. Here the impact of the omitted segment on the estimated generalized costs of travel might be selective and therefore biasing the later parameter estimate.

There is little/no empirical or experimental work assessing the impact of omitting certain segments. Given its potential to bias the results in unknown ways, this is s major gap in the literature, especially considering that these omissions are a regular feature of practical model systems.

In a similar way but stronger way the model results are influenced through the use of unacknowledged parameters in the constructing of the non-chosen alternatives. Imagine the steps necessary for the estimation of a mode choice model: measuring travel behaviour; constructing the non-chosen alternatives for each observed/reported trip, trip chain or daily schedule; estimation. The literature is rich for step 1 and 3 (e.g. Richardson *et al.,* 1995; Louviere *et al.,* 2000; Train, 2003), but little is said about step 2. It is clear, that the composition of the non-chosen alternatives will influence the results of the estimation step. In the case of the mode choice model, the parameters of the public transport assignment model will determine the characteristics of the (best) alternatives returned as the non-chosen alternatives: say parameter of in-vehicle time, parameter of transfers, parameter of transfer weighting time, parameter of headway (schedule delay early and late), parameter of access and egress time. The set of parameters used to generate the alternatives should be finally consistent with the estimated parameters. See Vrtic (2004, 2006) for the impact of imposing this constraint on the estimation and on the elasticities and values of travel time savings derived. These assumed parameters are pervasive, as they will impact the travel times of the other modes through their impact on mode choice and therefore the volumes assumed for road assignment. See de Palma *et al.* (2007) on the comparable case of the impact of crowding in location choice models, and by

extension all destination choice models. Again, an iterative scheme incorporating the impact of the assumed and later estimated parameters is needed to assure consistent parameter estimates.

4   Schedule optimisation

The ABMs, as well as the rule-based models as well as MATSim aim to obtain optimal daily schedules to replicate the current behaviour and to predict behaviour under future conditions. Their approach is different: prediction of the distribution of the schedules arising from optimal choices due to unobservable utility components in case of the ABMs; construction of satisficing schedules for the rule based models; actually a form of optimisation under constraints, which integrates the resources (time, mental attention, money) available for the choice itself; explicit optimisation using heuristic approaches in the case of MATSim.

The challenge for each of the approaches is the number of degrees of freedom considered. Consider the following, still incomplete, list:

- Number and type of activities
- Sequence of activities
- Start and duration of activity
- Composition of the group undertaking the activity
- Expenditure division among the members of the group undertaking the activity
    - Location of the activity (at the parcel or store level of detail)
        - Location of access and egress from the mean of transport
        - Type of parking facility and its location
        - Vehicle/means of transport
        - Route/service
        - Composition of the group travelling together
        - Expenditure division among the members of the group travelling together

A discrete choice model, as already argued above, will become computationally intractable due to the shear number of non-chosen alternatives, which would need to be generated; but see Bierlaire and Flötteröd, 2010 for a potential way forward. A rule-based approach should be able to cope, but much new empirical work will be needed to establish these rules in those domains outside of the field's previous sights, e.g. expenditure division or group composition.

An optimisation approach for such a complex task requires simplification to remain tractable. It will have to structure the problems in encapsulated subproblems, where this feasible without loosing too much accuracy or better too much of the relevant search space. Feil (2010) in a first attempt proposed a two-part solution to the issue: in the first part, he developed a tabu-search based optimiser for the number and sequence of activities, which encapsulates optimal mode and departure time choices for a given number and sequence of activities. To overcome the computing time problems for even the relatively fast tabu-search algorithm, his second part proposed a recycling approach for solutions found. The idea behind this is the observation that the activity patterns of similar persons are similar. If you have optimised the pattern for an example person, then this pattern might be optimal for further similar persons. Feil suggests a method to identify suitable persons for this matching and then adjusts the patterns to suit the differences between the persons, e.g. with respect to home location or local mode availability. The gains in computing time are massive – about 90% - while the loss in the quality of the solution found is minor. These types of solutions will have to be explored further to enable the field to extend the range of its agent-based models without sacrificing practical applicability.

The list about highlighted the group with whom travel and activity is shared as two further dimensions of the schedule. Both have been giving attention in the past, but their translation into practise was strictly limited.

This limitation is most surprising in the case of (within household) ride sharing, better known as "car passenger" mode, as mode choice is central to every transport planning study. The "car passenger" is in some cases merged into a general car mode. Generally there is no check of the availability of the car with whom the passenger is travelling. It becomes a residual category of problematic nature, as there is no internal consistency between the members of the household. This is actually true for the vehicle as well as there is no check if the vehicles marked used by the mode chosen are actually physically available to the users. These issues might be minor in countries or regions where there is on average one car per driving licence owner, they are major for countries or cities where this is not the case. Unfortunately, American-informed practise has dominated the field, which has led to practises elsewhere, which reflect the high car ownership in the US but not the local conditions.

This challenge needs to be addressed as the transport models are applied in cases, where car ownership is either controlled, as in Singapore or some Chinese cities, or limited, as in most emerging market countries or high density cities in the OECD, where many resident have chosen to live without a car. Mode choice models need to be integrated at least at the household level to ensure, that the choices are consistent for joint activities between household

members. This holds also for the ABMs, but requires that their simulations become truly household-based, which is not necessarily the case. For example, MATSim until recently did not provide for households, but simulated isolated individuals.

This discussion raises the bigger issue of the missing integration of social network into travel demand models. As long as the typical transport problem was the morning peak hour with a steadily falling vehicle-occupancy rate, the neglect of the household interactions or the even less immediate wider social network interactions was acceptable. It was equally acceptable, as long as transport models were mostly used in the OECD world moving towards a one-car per driving licence situation. With the recent recognition that leisure travel is the largest and fastest growing segment of travel and with the recent emphasis on environmental consequences of car travel, this neglect is less easy to justify, as leisure travel is mostly social travel: joint travel or travel to meet others (see for Axhausen, 2008).

In recent year transport planning has filled a gap left by research in sociology and geography and studied the spatial distribution of friendship groups in detail (Mok and Wellman, 2007 analysing data which had been left unused for 30 years; Carrasco and Miller, 2006; Van den Berg *et al.,* 2009; Axhausen and Frei, 2008; Kowald and Axhausen, forthcoming). These empirical results will allow the field to synthesize social networks for the agents of its microsimulation models. Initial work was able to create networks matching two of the free dimensions of interest: spatial distance distribution, degree distribution, transitivity. Recently Arentze *et al.,* 2011 proposed an utility-based approach, which is able to match all three and which remains applicable to large agent-populations.

Still this progress is not enough, even if actually implemented in the agent-based microsimulatons without the matching behavioural models with reflect the co-ordination within the circles of friends. Here the field is wide open: from the lack of survey data, which has recorded the presence of family and friends in sufficient details, but see Axhausen, 2008 for a longer discussion of the issues involved; to the lack of suitable models, which would capture the joint choice in unbounded or at least only loosely bounded groups.

5   Integrating the demand side

In model application, the planner and the resources (time and money) available to him become a bottleneck for the full exploration of the possible solutions and equally important for

risk and scenario analysis. Each design, solution, scenario or sample of the risk analysis requires a full and internally consistent description of the network and of the services offered, here especially tolls, fares and schedules or frequencies. Their construction requires substantial amounts of time, computing resources and later attention for their analysis, none of which are likely to be available in sufficient amounts. The trade-off between careful manual construction of a small number of cases against automatic construction of many cases has so far been decided in favour of the few cases; but without fully acknowledging the losses implied: large parts of the solution space remain unexplored, which due to the strongly interacting factors in transport might yield unexpectedly good solutions; the risk analysis is limited to a small number of scenarios – say, low, high and steady-state – without any knowledge about their likelihood.

The field should explore automated tools or agents taken on their role in agent-based simulations to construct these scenarios endogenously. The availability of cheap computing power would allow then both a through exploration of the solutions space, as well as a detailed risk analysis. See Flyvbjerg *et al.* (2003) for the need for better risk analysis. The challenge is to construct the agents, which are able to fulfil the tasks of the human planner in an appropriate quality. Starting points could be Ciari (2011), who integrates retailers into a simulation of travel behaviour and shopping location choice; Ceder (2002) or Guihairea and Haob (2008) review the literature on the optimal construction of schedules and optimal frequency choice; among others Newbery (1990), Van Vuuren (2002), Jansson (1979), Nash *et al.* (2004) define solutions to optimal pricing of road and public transport. This would address only the transport side of question and would need to be complemented with an appropriate description or model of the land use side. Here the literature does offer many possible approaches, which the transport model would have to choose among (See Wegener (2004) for a current review).

The danger in the context of a risk or scenario analysis is, that these agents might be too rational, to driven by optimisation approaches. There is the danger, that the set of agents, including the many travellers, might not be able to comprise enough to find an equilibrium. It will therefore be necessary to match the optimisation approaches required for computational speed with research into the behaviour of such agents to identify their trade-offs in real situations better. The inclusion of pricing and land-use also bring the politics of planning and transport into the model with its difficult to predict dynamics. In a scenario or risk analysis sense, the agents have to be allowed to act irrationally to cover the full range of possible outcomes.

6 Outlook

The empirical and computational programme sketched above is very large and can only be accomplished with matching theoretical progress: for example proper models for the "car passenger" mode accounting for car availability within the household or of the ride sharing partner; systematic estimation of choice models including the generation of choice sets with self-consistent parameters; rules-of-thumb for the size and structures of choice sets; choice models for complete daily activity schedule; generation of social networks of different type stemming from friendship, work, civic engagement matching their spatial and structural characteristics; development of joint choice models accounting for the social network possibilities and constraints; fast traffic flow models allowing us to execute the generated schedules while maintaining the consistency of the traveller-vehicle pair and matching the capacity constraints of these vehicles and of the facilities they visit. In a second step, the agent-based models will have to integrate functionality from demographic and land use models to age and update the scenario populations and to model the response of the supply side agents on the transport and land use side (location, size and pricing of the facilities and services). This will be necessary to be credible tools for longer term planning applications; cases where one does not want to start with a population synthesis from scratch, especially if one takes the interaction between residential migration, mobility tool ownership and residential sorting serious. The integration or sharing of these modelling capabilities with the (agent-based) land use transport models will be crucial to avoid overloading the agent-based models of travel demand.

It is clear, that the agent-based models going down this development path will have to maintain their computational speed to remain relevant for practical application. In an equilibrium setting the focus will have to be on strategies to keep the number of iterations small, while accurately determining that the equilibrium has been reached. In a scenario, in which the agents and their households are aged and moved (home and work location) to reach a future planning year, new strategies will have to be developed and tested to move from one equilibrium to the next without equilibrating each and every year along the time path.

The integration of the necessary supply side agents will be a further challenge for transport modellers, which so far have treated them as exogenous. The stability of systems with substantially different classes of agents will need attention. While we can draw on the progress in game theory, the shear size of the typical transport scenario with potentially millions of agents will raise further issues.

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