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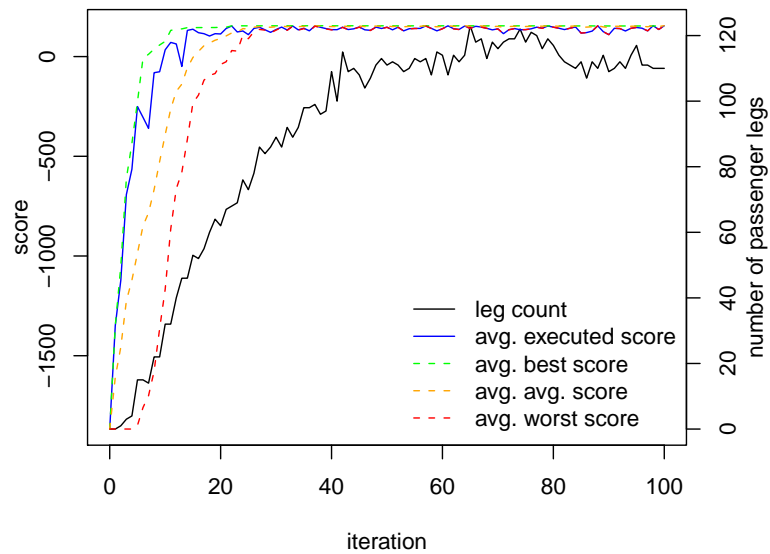
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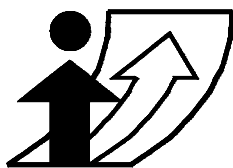
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Including joint trips in a multi-agent transport simulation

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Abstract

Among the simulation approaches, the activity-based approach is used increasingly in operational models. It allows both to focus on individual behavioural rules, and to model behaviour at a much finer level than more aggregated approaches.

A behaviour that one can and should model is the *joint travel* behaviour: the fact that several individuals may travel in the same private vehicle. An appropriate modeling of such a behaviour is important both for detailed simulations of households behaviour and for the evaluation of some policies, like incentives to perform car-pooling.

We present an approach to include such a simulation of joint travel in a multi-agent microsimulation, considering the case of MATSim as an example.

First results of this approach for the case of intra-household joint trips on a simple scenario are presented.

Keywords

activity-based, joint trips, households, car pooling, microsimulation, MATSim

Preferred citation style

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1 Introduction

Traffic simulation models are used to predict traffic flows on a network, aiming at supporting analysis and decision taking. Since the first models proposed in the middle of the twentieth century, the increase in computational power and the continuous improvement of traffic models led to always more precise and finer predictions. A successful framework for simulating traffic is multi-agent activity based transport simulation, where agents, representing individuals, travel through a simulated network from one activity to the other.

With such models, the simulation is based on individual behavioural models, and thus virtually allows to simulate any behaviour which impact on traffic is assumed, or known, to be important. The fact that several persons may coordinate themselves to travel together is such a behaviour. Its simulation can be used to predict the impact of car-pooling on traffic flows, or the impact of car-pooling incentives on the share of this mode. Another major application is to better simulate the behaviour at the household level, where the share of such trips is known to be significant.

MATSim is a multi-agent simulation software, which uses an Evolutionary Algorithm to search for a user equilibrium. This purely competitive model is not, in its current state, adapted to the simulation of cooperative behavior. To solve this issue, we propose to define the equilibrium over competitive cliques, defined as mutually exclusive groups of agents aiming at maximising a group-level utility.

This paper presents this approach in detail. First, related work is reviewed in Section 2. The approach, as well as its implementation as a MATSim module, are presented in Section 3. The results of a simulation of intra-household ride sharing for a simple test scenario are presented in Section 4.

2 Related studies

2.1 The activity-based approach

Simulation of travel behaviour is a widely used tool, which can be used for predicting the effects of some change in infrastructure, reconstruct missing data about the current state, policy evaluation or behavioural hypothesis testing.

Generally, simulation models are classified as macroscopic, mesoscopic or microscopic, depending on the level of aggregation used.

Naturally, each type of model has its strengths and weaknesses. While macroscopic models, which only work at the aggregated level, are computationally efficient and only require aggregated data as input, they have difficulties to represent time-varying aspects of traffic. On the other hand, microscopic models, by simulating agents individually, can predict traffic dynamics much more easily, but at a much higher computational cost and with finer data as input.

However, increase in computational power in the last decades has made this kind of models more and more appealing.

A successful framework while simulating individuals at a disaggregated level is to use the so-called "activity-based" approach, proposed during the early eighties (Jones *et al.* (1983), Recker *et al.* (1986)). In this approach, the fact that travel is always oriented toward a goal is taken into account explicitly: agents are assigned plans, consisting of located activities, and travel between those activities in a simulated network. A fundamental difference with trip-based approaches is the explicit modeling of travel as a need *derived* from the need or willingness to perform activities (McNally and Rindt (2008)).

The way the plans are computed depends on the model: in the following, we focus on the way the MATSim software achieves this task.

2.1.1 Equilibrium based models: the MATSim process

MATSim is an open-source software, released under the terms of the GNU Global Public License (GPL). It mainly aims at simulating time-dependant traffic flows (Balmer *et al.* (2008), Rieser *et al.* (2007)). To do so, it relies on the assumption that the state of traffic on an average day corresponds to a user equilibrium: no individual can improve the utility he gets from his day by modifying his daily plan, given the plans of the rest of the population. The only dimensions considered in the equilibrium are the ones related to short term decisions: route choice, mode choice, departure times, *etc.*.

More formally, finding the equilibrium consists in solving

$$\max_{p_i \in P_i} U(p_i | p_{-i}) \quad (1)$$

for each agent i , where p_i is the plan of agent i , P_i the set of possible plans for agent i , and p_{-i} the set of the plans of other agents.

To search for such an equilibrium, MATSim uses a co-evolutionary process, where each agent performs an evolutionary algorithm to solve the problem (1). The process is as follows: starting with initial plans, agents are moved through a simulated network, giving estimates of the cost of travel (and thus of the influence of p_{-i}). Then, plans of a given

fraction of the agents are mutated, randomly or to optimality given the previous state. Non mutated agents choose one of their previous plans based on the past scores, and the simulation is run again. This process is executed until a stopping criterion is met (currently, a fixed number of iterations fixed *a priori* is used (Meister *et al.* (2010))).

This process allows to take into account the complex relationship between traffic flows and the utility of a plan. It can be considered both as an algorithm to search for a user equilibrium or as an actual simulation of human learning (Nagel and Marchal (2006)). Depending on the approach, the way replanning will be handled will be slightly different: if one searches for a Nash equilibrium, each agent should have an optimal strategy at the end of the process; if one searches to simulate human learning, sub-optimal strategies may be allowed (and should appear), as soon as they result from a behaviourally sound search process.

Currently, replanning can include least-cost re-routing, location choice (Horni *et al.* (2009)), duration and mode optimisation (Meister *et al.* (2006)). Experiments have also included activity sequence (Feil (2010)).

2.1.2 Plan scores in MATSim

As pointed out, MATSim mainly consists in a daily plan optimisation algorithm coupled to a traffic flow simulation. Thus, a performance metric is needed.

In general, MATSim uses the so-called "Charypar-Nagel" scoring function, first introduced to generate daily plans out of the iterative MATSim process (Charypar and Nagel (2005)).

In this formulation, the utility of a plan takes the form of a sum of the activity of performing activities and of the disutility of traveling:

$$F = \sum_{i=1}^n U_{act}(\text{type}_i, \text{start}_i, \text{dur}_i) + \sum_{i=2}^n U_{trav}(\text{loc}_{i-1}, \text{loc}_i) \quad (2)$$

where the utility of an activity is:

$$U_{act,i} = U_{dur,i} + U_{wait,i} + U_{late.ar,i} + U_{early.dp,i} + U_{short.dur,i} \quad (3)$$

and:

$$U_{dur}(t_{dur}) = \beta_{dur} t^* \ln\left(\frac{t_{dur}}{t_0}\right) \quad (4a)$$

$$U_{trav}(t_{trav}) = \beta_{trav} t_{trav} \quad (4b)$$

$$U_{wait}(t_{wait}) = \beta_{wait} t_{wait} \quad (4c)$$

$$U_{late.ar}(t_{start}) = \begin{cases} \beta_{late.ar}(t_{start} - t_{latest.ar}) & \text{if } t_{start} > t_{latest.ar} \\ 0 & \text{otherwise} \end{cases} \quad (4d)$$

$$U_{early.dep}(t_{end}) = \begin{cases} \beta_{early.dep}(t_{earliest.dep} - t_{end}) & \text{if } t_{end} < t_{earliest.dep} \\ 0 & \text{otherwise} \end{cases} \quad (4e)$$

$$U_{short.dur}(t_{end}) = \begin{cases} \beta_{short.dur}(t_{short.dur} - (t_{end} - t_{start})) & \text{if } t_{end} < t_{short.dur} \\ 0 & \text{otherwise} \end{cases} \quad (4f)$$

where:

- t^* is the typical duration for the activity
- t_0 is the minimal duration for the activity
- t_{dur} is the actual utility duration
- t_{trav} is the traveling time
- t_{wait} is the waiting time
- t_{start} is the start time
- t_{end} is the end time

2.1.3 Using optimisation algorithms to replan agents

As pointed out before, the relaxation process consists in iteratively improving the plans of the agents, knowing the previous behaviour of other agents, until a steady state is reached.

The standard approach, based on Evolutionary Algorithm and Machine Learning, consists in randomly “mutating” some plans between iterations. Each agents possesses a memory, which stores a fixed number of past plans, allowing to revert changes implying a decrease in utility.

However, another approach has been implemented since then, making use of optimisation algorithms in the mutation step.

This approach was shown to allow MATSim to converge in fewer iterations to an

equilibrium state, with a score at least as high as with random mutation. Optimisation algorithms used include least-cost routing, activity duration optimisation with CMA-ES (Charypar *et al.* (2006)) or genetic algorithm (Meister *et al.* (2006)), or activity sequence and other properties with Tabu Search (Feil *et al.* (2009)).

2.2 Joint decisions modeling

The random utility theory is a well-known and extensively studied way of predicting individual's behaviour, which is widely used in transportation research (Ben-Akiva and Lerman (1985)). In this general framework, each alternative is associated a numerical utility, composed of a systematic part (its expectation) and a random error term (representing unobserved variability). The probability for an individual to choose one of the alternatives corresponds to the probability for the utility of this alternative to be higher than the utility of all other alternatives.

This framework has been applied to joint decision making, and to joint scheduling in particular: we provide here a review of those studies.

Aside from these random utility models, non-probabilistic utility maximisation techniques have been proposed for creating schedules for activity based transport simulation: we present here some of those attempts for household plans generation.

2.2.1 Random utility based models

The random utility theory has been applied early to joint decision modeling, by considering the choice problem as a group utility maximisation problem.

In the last decades, this framework began to be applied to group (mainly household) schedules generation for activity based transport simulation.

However, the choice set is of high dimension, with both discrete (activity types, joint activity participation, sequence of activities, modes *etc.*) and continuous (activity duration) dimensions. Thus, depending on the authors, different choice dimensions are considered.

Zhang, Timmermans and Borgers develop a model where time for different activity types is allocated to household members, subject to time constraints (including equality of time participation in joint activities) (Zhang *et al.* (2005)). Given individual random utilities for the different activity type, their model gives deterministic time allocation.

Bradley and Vovsha focus on the "daily activity pattern" generation, with household

"maintenance" tasks (*e.g.* shopping) allocation and possibility of joint activities (Bradley and Vovsha (2005)). To do so, they assume a layered choice structure: first, a daily activity pattern is assigned to household members; then, "episodic" joint activities can be generated; finally, maintenance activities are assigned.

Gliebe and Koppelman (Gliebe and Koppelman (2005)) also base their models on the daily activity pattern concept. In their model, the joint outcome (the succession of individual and joint activities) is first determined, and individuals then choose an individual pattern compatible with the joint outcome. The same authors also derived a constrained time allocation model, which predicts the time passed by two individuals in joint activities (Gliebe and Koppelman (2002)). Rather than postulating a group-level utility function, those models specify a special distribution for the error terms of the individuals. In this setting, the error terms of the individuals are correlated so that the probability of choosing a given joint output is the same for all individuals.

Miller, Roorda and Carrasco develop a model of household mode choice (Miller *et al.* (2005)). The main difference with an individual mode choice model is the consideration of household-level vehicle allocation. In their model, individuals first choose modes individually. If a conflict occurs, the allocation that maximizes the household level utility is chosen. The members which were not allocated the vehicle will report on their second best choice, and/or examine shared rides options.

2.2.2 Alternative approaches

Aside from the random utility theory based models, some other ways to deal with joint scheduling have been proposed.

Golob and McNally propose a structural equation model, which predicts time allocation and trip chaining based on descriptive variables of an household (Golob and McNally (1997)). Golob also used this structural equation model approach to model the dependency of time allocations of the two heads (man and woman) of an household (Golob (2000)).

Another class of approaches is the use of optimisation algorithms to generate households plans. They handle the household scheduling problem by transforming it into a deterministic utility maximisation problem. Contrary to the previously presented approaches, those alternatives did not lead to estimate a model against data.

The first of those approaches was proposed by Recker in the mid nineties (Recker (1995)). By extending increasingly the formulation of the Pick-Up and Delivery Problem With Time Windows, which is a well studied combinatorial optimisation problem, he formulates the problem of optimising the activity sequence of members of an household as a mathematical programming problem, taking into account vehicle constraints, individual

and household level activity, possibility of choosing whether to perform or not an activity, with the possibility of shared rides. However, due to the complexity of the problem, the full problem cannot be solved exactly by standard operations research algorithms, and the activity durations are not part of the optimised dimensions. However, Chow and Recker (2012) designed an inverse optimisation method to calibrate the parameters of this model, including the time window constraints, using measured data. Also, the formulation from Recker (1995) was latter extended by Gan and Recker (2008) to introduce the effects of within-day rescheduling due to unexpected events.

A more recent attempt to generate plans for households uses a genetic algorithm, building on a previous genetic algorithm for individual plan generation (Charypar and Nagel (2005), Meister *et al.* (2005)). This algorithm optimises sequence, duration and activity choice for an household, rewarding the fact for several members of the household to perform the same activity simultaneously (*i.e.* "joint activities").

3 Inclusion of joint trips in a multi-agent simulation

3.1 Joint trips and user equilibrium

As stated in Section 2.1, the equilibrium approach to activity based travel modeling consists in maximizing, for each agent, the utility of his daily plan, given the daily plans of other agents. We expressed this in equation (1): $\max_{p_i \in P_i} U(p_i | p_{-i})$. The influence of the plans of other agents p_{-i} is due to congestion.

In the case of the MATSim process, this influence is not computed explicitly, but estimated using $U_I(p_i)$, the utility of the plan in the last iteration I when it was executed. This is reasonable, as:

- the plans of agents are only slightly modified between iterations, implying only small changes in traffic conditions. This makes the estimates reasonably accurate.
- actual individuals are unlikely to base their decisions on the plan of other individuals. They rather base their decisions on the state of traffic they experienced in the past. In this way, the process can be seen as a simulation of actual human learning.

This situation is somewhat changed when including the possibility for several agents to travel in the same private vehicle, as:

- the utilities that the co-travelers get from their daily plans is highly dependant on the plans of the few co-travelers. For example, the score of a passenger's plan is highly dependant on whether the driver actually chooses to pick him up or not.

- actual individuals *are* likely to correlate the choice of their daily plans on the plan of their co-travelers, for example via negotiations on the departure times.

Thus, a way to explicitly represent the co-dependance of the utilities of co-travelers plans must be found.

A simple way to do so is to perfectly correlate the plan choices, by always selecting the same plans together. As seen in Section 2.2, a classic way for such group-level choice is to consider a group-level utility, made by aggregating individual utilities. Members of the group are assumed to be willing to maximise the utility of the group rather than their own.

A way to see this is to postulate “utility transfers” between group members: if a driver decreases his utility to increase the utility of a passenger, some of the utility of the passenger is supposed to be “transferred” to him. Those transfers may come from willingness to help relatives (*e.g.* in an household) or from monetary compensation (*e.g.* in formal car-pools).

Even though we follow this tradition, the specification (and the existence) of this group utility is problematic. Particularly, it seems likely that no such function can be defined for totally unrelated people: identifying collaborating agents can be a challenging task.

For the current work, we do not focus on the problem of identifying which agents should travel together, but on the following: *given* a group of agents which may travel together, how to optimise their plans?

Considering those remarks, when simulating joint trips, the equilibrium is defined over groups of agents. For this, we include the concept of *clique* in the multi-agent framework:

Definition 1 (Clique) *The set of agents is partitioned in cliques. Each agent pertains to one and only one clique. Joint plans are defined at the clique level.*

A clique may represent an household, a group of colleagues, or whatever group of interest.

Definition 2 (Joint plan) *A joint plan is a set of individual plans, one for each agent of a clique. All individual plans of a joint plan are always chosen together. A unique score is affected to a joint plan.*

Please note that due to the transfer assumption, some care must be taken in the clique definition. In particular, cliques should be small enough so that travel times on the links

cannot be changed dramatically by replanning just one clique. In the limit case with one “clique” containing all agents, the “equilibrium” would be the so-called “social optimum”, which is usually different of the user equilibrium, as is well known (Roughgarden and Tardos (2002)).

3.2 MATSim implementation

As stated in Section 2.1.1, MATSim uses an iterative relaxation process to search for a user equilibrium. In this framework, agents’ plans are iteratively simulated, scored and modified until no improvement can be made.

In MATSim, a daily plan is represented as a sequence of activities and “legs” (movement with one transport mode). In this context, a “joint trip” is a set of individual trips, themselves consisting in a sequence of legs, pick-up and drop-off activities.

To simulate joint trips, special care is needed at the replanning step, so that synchronized plans are generated. Thus, special replanning modules were implemented, which take into account the specificity of joint trips. At each iteration, one module is chosen randomly for each clique.

Joint trip insertion This module creates joint trips by grouping individual trips together. It works by selecting randomly a car trip and a public transport trip for two different agents, replacing the car trip by a driver trip and the public transport trip by a passenger trip. The driver picks the passenger up at his origin and drops him off at his destination.

To guide the search toward plausible joint trips, the probability to join two trips decreases with the detour imposed to the driver and the difference in departure times.

Departure times and modes at the subtour level, with consideration of the need to synchronize, are then optimized using the algorithm described thereafter.

Note that nothing is done to prevent creating impossible joint chains. However, such chains would result in passenger and driver mutually waiting each other in the mobility simulation step, leading to very bad scores and to the quick discarding of such plans.

Time and mode optimisation This module optimizes activity durations and mode at the subtour level, using time dependent travel time estimates based on the observed travel times in the previous run of the traffic flow simulation. This “best response” approach

builds on previous successful experiments with the optimisation of various dimensions of an individual plan (Meister *et al.* (2006), Feil *et al.* (2009)).

Activity durations and modes are optimized using a Tabu Search algorithm, inspired by a previous approach for individual plans (Feil (2010)). Tabu Search is a metaheuristic method, initially aimed at solving combinatorial optimisation problems (Glover (1989)). It directs local search heuristics by the use of a *tabu list*, containing information on the previous moves. The rationale of this method is to avoid getting trapped in local optima, by preventing to re-explore already known parts of the search space. The interested reader may consult Glover and Taillard (1993) for a good introduction.

The details the algorithm are the following:

- **activity durations:**
 - **neighborhood:** each solution of the neighborhood corresponds to the current solution, where the duration of one single activity is increased or decreased by a given amount. A set of amounts is defined as a parameter of the algorithm.
 - **tabu list:** when such a move is selected, all moves going in the opposite direction (*e.g.* the moves decreasing the duration of an activity which duration was increased) are tabu for a fixed number of iterations.
- **modes:**
 - **neighborhood:** each solution of the neighborhood corresponds to the current solution, where the modes of a subtour and its parents tours are changed to one mode.
 - **tabu list:** when such a move is selected, mode moves resulting in the same mode chain are marked as tabu for a fixed number of iterations.
- **constraints:** moves resulting in illegal plans (negative durations or infeasible mode chains) are marked as tabu.

The different pick-ups related to a same joint trip must be synchronised. This synchronisation is enforced by penalising unsynchronised plans, in the last iterations of the algorithm, with a penalty increasing linearly with the difference in planned departure times.

“Legacy” modules Standard MATSim replanning modules can also be applied on a random member of a clique. These modules are:

- random mutation of the departure time of a trip
- random choice of the mode for a subtour, taking into account mode chaining constraints (assuming all vehicles — car, bike — are located at the home location at the beginning of the day). Mode of subtours with joint trips is not changed by this module.

Using such mutation approaches for the dimensions optimized by the best response module described above allows to obtain more variability in the plans of the agents, and avoid some artifacts due to over-optimization. The best response module feeds the process with good solutions to mutate, allowing to reduce the number of iterations and avoid getting trapped in local optima. This is particularly relevant with joint trips, for which synchronization of individual plans is needed. Using a random mutation approach, the process would be likely to get trapped at the first synchronized plan found, and thus discard relevant joint trips.

Finally, for most cliques, a past plan is selected based on the experienced score, using a logit-like probability.

4 First results

As an example of the output of the process, we present here the results for a run on a toy scenario, meant to test the approach. Only the car mode (including joint traveling) suffers from congestion. Waiting between co-travelers is simulated.

4.1 Scenario

The test network is a simple grid network of 10×10 intersections. Home and work activities are situated on the outer links, leisure and shop activities on inner links.

Cliques were generated by randomly grouping agents with the same home location. Figure 1 presents the resulting cliques sizes. Part of the agents have no car available. All plans are of the form *home – work – secondary activity – home*. Figure 2 presents examples of plans on the network.

The utility function uses default values. In particular, all modes have the same disutility of travel time. A cost of distance is added to car and public transport, to represent monetary costs. Shared ride passengers do not suffer from this cost of distance (thus, the monetary cost for the groups depends on the number of vehicles used, not the number of travelers).

4.2 Settings

Table 1 details the probability of the different replanning strategies. 100 iterations are run, and joint trip insertion is not performed in the last iterations, to avoid a too high

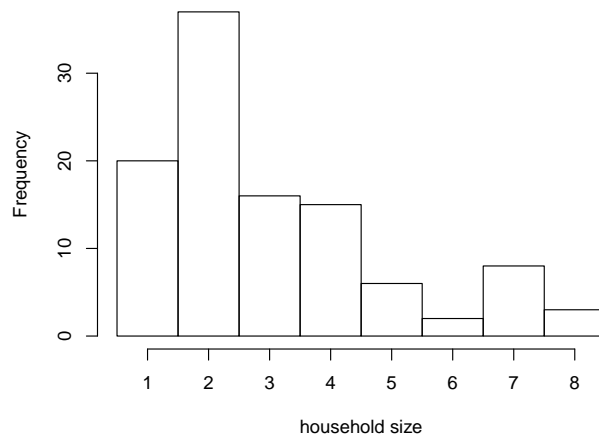


Figure 1: Cliques sizes

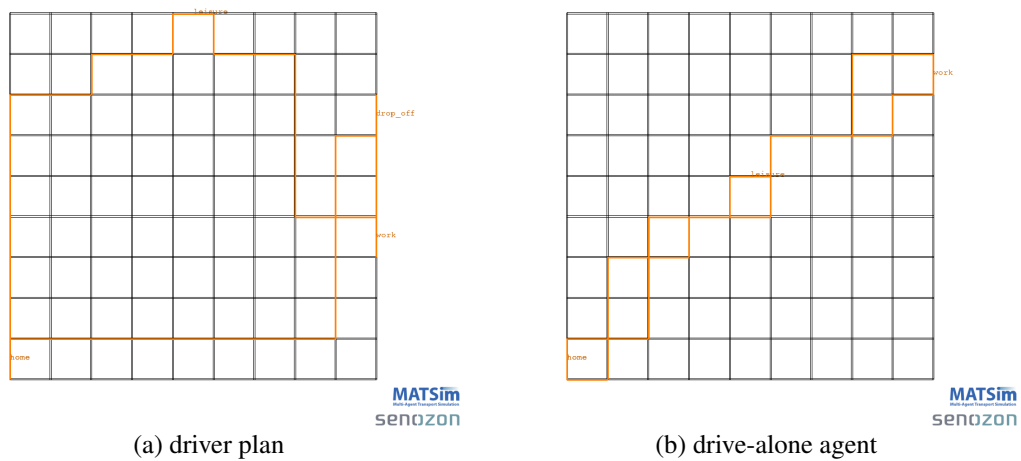


Figure 2: Examples of agents plans

proportion of freshly created, possibly non pertinent joint trips.

The agents' memory size is 4 plans long: if this limit is reached, the plan with the worst score is definitively removed.

Table 1: Probability of the replanning strategies

module	probability	from iteration	to iteration
time and mode optimisation	0.02	0	80
joint trip insertion	0.23	0	80
selection of a past plan	0.55	0	100
re routing	0.02	0	100
departure time mutation	0.09	0	100
subtour mode mutation	0.09	0	100

4.3 Results

Table 2 presents the mode shares in the last iteration, and Figure 3 shows the evolution of the number of passenger trips throughout the iterations, together with the evolution of the scores of the agents' plans. "Worst", "best" and "average" scores refer to the scores of the plans in each agent's memory. "Executed" refers to the plan actually simulated in the traffic flow simulation. Note that in Table 2, trips, not legs, are counted: the access and egress legs of a joint trip are not counted in the shares of other modes. The share of passenger mode grows with the iterations, and stabilises around 11% of the trips. This share remains stable after the creation of new joint trips is stopped, indicating that pertinent joint trips were actually identified. The number of joint trips takes longer to stabilize than the average score, though. The main reason for this is the usage of a mutation approach for joint trip generation, whereas best-response approaches are used for other dimensions (departure times, mode, routes).

Table 2: Mode shares in the final state

mode	count	share
car (drive alone)	613	63.1%
car (driver)	110	11.3%
car (passenger)	110	11.3%
public transport	130	13.4%
bike	6	0.6%
walk	3	0.3%

Figure 4 shows an histogram and a box plot of the amplitude of the drivers' detours, based on crow-fly distances. The detour is defined as the additional distance the driver has to drive to pick up and drop off his passenger, expressed as a proportion of the direct distance. In the joint trips selected during the last iteration, those detours are small, and more than half of them are actually null.

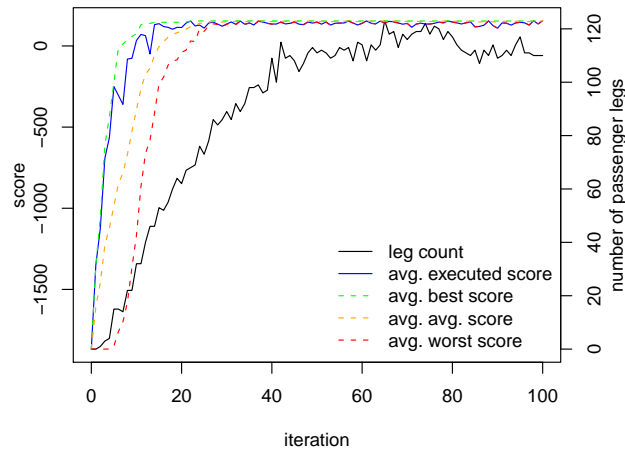


Figure 3: Evolution of the scores and of the number of car passenger legs

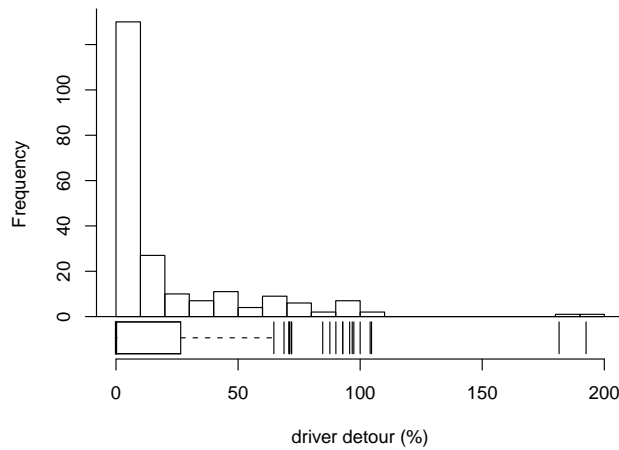


Figure 4: Detours

Figure 5 shows the number of passenger trips per passenger (the red dots represent the mean value), depending on the clique size. A risk of the approach is that the random selection of joint trips gets lost when the clique size becomes too large, leading to a decreasing number of passenger trips per agent when clique size increases. Such an effect cannot be clearly observed. However, due to the low number of cliques of high cardinality (and the low number of cliques in general), it is difficult to conclude definitely on the performance of the algorithm with large cliques. One can however see in Figure 5(b) that a high portion of the passengers have several passenger trips. This

is expected: due to the fact that in subtours with passenger trip, no car is available for the other trips, most agents should have return trips as passenger as well. The approach seems able to identify this kind of fully joint tours.

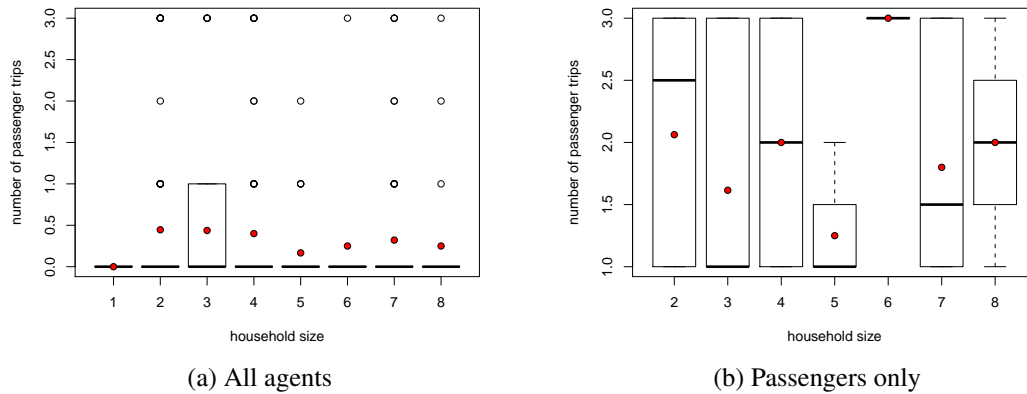


Figure 5: number of passenger trips per plan

Figure 6 shows the distribution of car availability in the population of agents and among the agents having at least one passenger trip. The proportion of agents having no car available is much higher among the passengers than in the whole population. However, most of the agents with a passenger trip do have a car available. Remembering the fact that most drivers have a null detour and that a large portion of passengers have several passenger trips, this indicates trips for which several members of the household have the same origin and destination. Joint trips have in this case an advantage over driving alone, due to the sharing of costs.

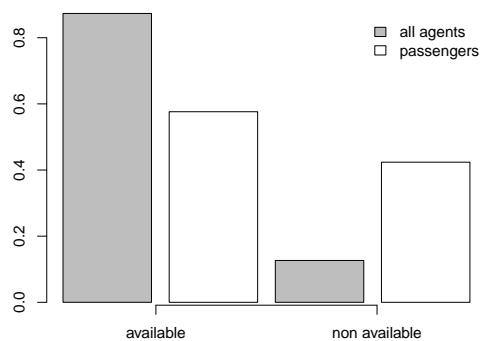


Figure 6: Car availability in the population and among passengers

The different results presented in this section indicate a good behaviour of the approach. However, due to the artificial nature and the small size of the scenario, no strong conclusions can be drawn. A real world scenario for the Zürich area is being prepared, in order to validate the model against data on intra-household ride sharing available for Switzerland.

5 Conclusion and further steps

In this paper, we presented an approach to simulate joint trips in a multi-agent transport simulation, as well as an implementation of this approach within the MATSim software. This approach is a first step in considering collaboration in a user-equilibrium framework.

The output of a test run on a simple artificial scenario indicate a good behavior of the approach. However, further validation runs must be undertaken. For this, a scenario for the Zürich area, Switzerland, is being prepared. The output of runs for this scenario will allow to compare the output of the model with surveyed data, in order to assess rigorously its performance. The planned source for the validation data is the swiss national travel survey, a travel diary survey performed by the Swiss Federal Statistical Office every five years (Swiss Federal Statistical Office (2006)).

However, even though the implementation can be considered as mature enough to be validated against data on intra-household ride sharing, lots of improvements still have to be done.

First, ride sharing is not the only joint decision that households undertake. Allocation of maintenance activities, joint activity scheduling, allocation of scarce resources (in particular vehicles) are consistently recognized as important features of household scheduling models (Zhang *et al.* (2005), Bradley and Vovsha (2005), Gliebe and Koppelman (2005, 2002), Miller *et al.* (2005)). Work to include this kind of dimensions in MATSim is in progress (Fourie (2012)). A nice feature of including such decisions in the MATSim approach would be to let joint patterns *emerge* from simple behavioral rules, rather than having to identify such patterns *a priori*, as is required for discrete choice modeling approaches.

Second, the current approach is to consider joint trips in pre-identified groups, to which we referred as cliques. A central, and strong, assumption in our approach is that “utility transfers” exist between clique members, making the existence of a clique-level utility function possible. This assumption was included in the model in order to take into account the high dependency of the scores of a plan on the actual co-travelers plans. However, it is planned to relax this assumption, passing again to individual utility maximisation, but using special plan selection modules, where the choices of plans

by co-travelers are correlated. Utility transfers could still be represented explicitly, whenever the assumption is applicable.

Finally, on the long term, co-traveler identification in social networks of arbitrary topology should be researched.

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