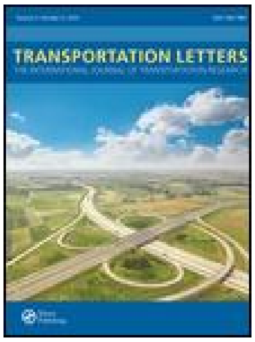

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Including joint decision mechanisms in a multiagent transport simulation

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In recent years, there has been a growing interest in the social dimension of travel, and how travel decisions are influenced not only by the global state of the transportation system, but also by joint decisions and interactions with social contacts. Empirical studies pointed out the relevance of certain types of social interactions to model travel behavior correctly: synchronization of household members has been identified as significantly influencing individual's travel decisions, and friendships were shown to influence the choice of leisure locations.

Multiagent approaches, by representing decision making at the level of the individual, seem to be one of the most promising approaches to take into account such interactions when forecasting.

The work presented here extends a state of the art multiagent simulation software, MATSim, with capabilities to capture joint decisions. It consists of a general framework to allow arbitrary joint behaviors to be represented, without constraints on the topology of the social network. An implementation of this framework for the important case of intrahousehold ride sharing is proposed, and demonstrated on a simple test scenario.

The results show that the extended process is able to find the expected state, and is mature for validation against travel diary data.

Keywords: Activity based, Joint trips, Households, Car pooling, Microsimulation, MATSim

This paper is part of a special issue on Agent-based Microsimulation Techniques

Introduction

In recent years, there has been a growing interest in the social dimension of travel, and how travel decisions are influenced not only by the global state of the transportation system, but also by joint decisions and interactions with social contacts.

The study and modeling of intrahousehold interactions and joint decision making, often using the classical random utility framework extended to group decision making, is a very active field of research. A classical way to cope with the possibly conflicting objectives of different members of the household is to specify a group level utility function. For instance, Zhang *et al.* (2005, 2007) developed a model where the time for different activity types are allocated to household members, subject to time constraints (including equality of participation duration in joint activities), using a group level utility function, formulated as a multilinear combination of the individuals' utilities; Kato and Matsumoto (2009) use a linear combination of the utility functions of the household members as a group utility. The assumption behind this kind of models is the existence of "utility transfers": individuals accept to decrease their own utility if it allows increasing the utility of others by a certain fraction of their loss. Bradley and Vovsha (2005) focus on the "daily activity pattern" generation, with household "maintenance" task (e.g. shopping) allocation and the possibility of joint activities. 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 (2005) also base their model on the daily activity pattern concept. In their model, the joint outcome (the sequence of individual and joint activities) is first determined, and individuals then choose an individual pattern compatible with the joint outcome. Those models rely on an enumeration of the possible household level patterns. Gliebe and Koppelman (2002) also derived a constrained time allocation model, which predicts the time spent by two individuals in joint activities. Rather than postulating a group level utility function, the models of those authors specify a special distribution for the error

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terms of the individuals. In this setting, the error term of the individuals are correlated so that the probability of choosing a given joint output is the same for all individuals. Ho and Mulley (2013) also estimate models in which members of the household perform choices constrained by the choice of a household level travel pattern. The estimated models show high joint household activity participation on weekends, and a high dependence of joint travel on trip purpose and household mobility resources. Those results highlight the importance of representing joint household decisions, in particular when extending beyond the "typical working day". Vovsha and Gupta (2013) formulate a time allocation model for multiple worker households, which considers a positive utility for members of the household to be home jointly, as it makes joint activities possible. The estimation results show a significant influence of this kind of synchronization mechanism. Most models listed in this paragraph are specific to given household structures; in particular, separate models need to be estimated for different household sizes.

Household level decision processes have also been modeled with approaches that significantly differ from the classical random utility framework. Golob and McNally (1997) propose a structural equation model, which predicts time allocation and trip chaining based on descriptive variables of a household. Golob (2000) also used a structural equation model to model the dependency of time allocations of the two heads (man and woman) of a household.

Another class of approaches, more oriented toward multiagent simulation than analysis, is the use of optimization algorithms to generate household plans. They handle the household scheduling problem by transforming it into a deterministic utility maximization problem. Contrary to the previously presented approaches, these alternatives did not lead to the estimation of a model against data. The first of these approaches was introduced by Recker (1995). By extending increasingly the formulation of the Pick-Up and Delivery Problem with Time Windows, a well studied combinatorial optimization problem, he formulates the problem of optimizing the activity sequence of members of a household as a mathematical programing 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 its complexity, the full problem cannot be solved exactly by standard operations research algorithms, and the activity durations are not part of the optimized dimensions. Chow and Recker (2012) designed an inverse optimization method to calibrate the parameters of this model, including the time window constraints, using measured data. Also, the formulation from Recker (1995) was later extended by Gan and Recker (2008) to introduce the effects of within day rescheduling due to unexpected events. Another 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 optimizes sequence, duration, and activity choice for a household, rewarding the fact for several members of the household to perform the same activity simultaneously, in the way also used by Vovsha and Gupta (2013). Finally, Liao *et al.* (2013) formulated the problem of creating schedules for two persons traveling together as finding the shortest path in a "supernetwork", and solved this problem using the exact shortest path algorithms. They however note that their model is specific to the two person problem, and that extension to larger numbers of agents may prove to be computationally expensive. All those approaches remained experimental, and were not integrated into multiagent simulation tools.

Another class of methods aiming at multiagent simulations is the development of rule based systems, which use heuristic rules to construct household plans. Miller *et al.* (2005) developed such a model for household mode choice. The main difference of this model from 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 who were not allocated the vehicle will fall back on their second best choice, and/or examine shared rides options. Arentze and Timmermans (2009) develop a rule based model that relies on a simulated bargaining process within the household. Though such models can easily represent complex decision processes, their calibration and validation is cumbersome.

Other authors have investigated the role of more general social networks on travel. One of the main incentives to conduct such studies comes from the continuous increase of the share of trips that are performed for leisure purpose (Schlich *et al.*, 2004; Axhausen, 2005). This fact represents a challenge for travel behavior modeling, as those trips are much more difficult to forecast than commuting trips: they are performed more sporadically, and data about those trips is much more difficult to collect. Understanding better how destination choice for leisure trip is made, is therefore, essential to improve the accuracy of those forecasts.

Various studies have been conducted with the idea that an important factor in leisure trip destination choice, or activity duration choice, is the ability to meet social contacts. Examples of empirical work include Carrasco and Habib (2009), Habib and Carrasco (2011), or Moore *et al.* (2013). All those studies show a significant influence of social contacts on the spatial and temporal distribution of activities. Based on an analysis of social network involvement and role, Deutsch and Goulias (2013) advocate considering the role individuals play in different social networks. Using latent class cluster analysis models to analyze the role of individuals in the various social networks they are involved in, they find that "the decision-making role of an individual can differ vastly across different social engagement types". Frei (2012) demonstrated in a simulation experiment how considering social interactions in leisure location choice can help increase the accuracy of predicted leisure trip distance distribution.

Another field of empirical research consists in studying the spatial characteristics of social networks. For instance, Carrasco *et al.* (2008) studied the relationship between an individual's socioeconomic characteristics and the spatial distribution of their social contacts. This kind of empirical work allows to specify and estimate models capable of generating synthetic social networks, given sociodemographic attributes and home location. An example of such a model, based on the results of a survey in Switzerland, can be found in Arentze *et al.* (2012). This kind of model is essential if one wants to include social network interactions in a microsimulation model.

This integration of social networks in multiagent simulation frameworks has already been attempted by other authors. Due to their disaggregated description of the world, such models are particularly well suited for the representation of complex social topologies. Han *et al.* (2011) present experiments that use social networks to guide activity location choice set formation in the FEATHERS multiagent simulation framework. Using a simple scenario with six agents forming a clique (a network where all agents have social ties with all other agents), they consider the influence of various processes like information exchange and adaptation to the behavior of social contacts to increase the probability of an encounter. They do not, however, represent joint decisions, such as the scheduling of a joint activity. The same kind of processes have been investigated by Hackney (2009), using more complex network topologies, within the MATSim framework, used in this paper. Ronald *et al.* (2012); Ma *et al.* (2011, 2012) present agent based systems that integrate joint decision making mechanisms, based on rule based simulations of a bargaining processes. They are not yet integrated into any operational mobility simulation platform.

Building on all those ideas, the work presented in this paper aims at including explicit coordination of individuals in a multiagent simulation software framework. This is done by generalizing the process of the MATSim simulation framework to allow taking into account joint decisions. The process is designed to be able to handle complex social network topologies, but the current implementation is restrained to a network consisting of isolated cliques. Such a network is a good abstraction for the network of intrahousehold relationships, the importance of which should be clear from the review above. This generalized process is presented here in detail, and the results of a small test scenario are analyzed.

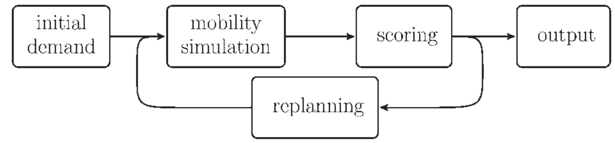
Method

The work presented herein aims at including joint decisions into the MATSim simulation framework. Before presenting the proposed simulation process, this section proposes a short introduction to the MATSim framework.

MATSim simulation framework

MATSim is an open source simulation framework that provides a platform for running multiagent large scale travel behavior simulations (MATSim, 2013). It has been used and validated in several areas, including whole Switzerland (Meister *et al.*, 2010), Berlin (Germany), and Singapore (Erath *et al.*, 2012).

The MATSim process uses a co-evolutionary approach to search for an approximation of a stochastic user equilibrium, where the expected utility of the daily plan of individuals is optimal given all other individuals' choices.

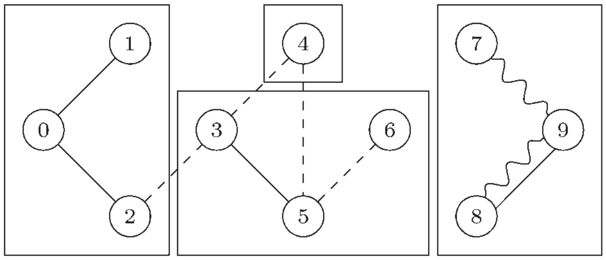


1 MATSim iterative process

The basic modeling idea is that individuals associate a utility value to their day, which increases with the time spent performing activities and decreases with the time spent traveling. Different parameters can be used for different modes or activity types, using the functional form from Charypar and Nagel (2005). Travel time is influenced by other agents via congestion. The justification for the equilibrium hypothesis is that individuals, via trial and error, learn the average time dependent travel times they can experience during a typical day, and make their plans based on this knowledge. It is called stochastic user equilibrium, because it considers the probability of an individual executing a given daily schedule, given the probability distribution of travel times, which is a function of the randomized behavior of all individuals in the population.

The MATSim process searches for an equilibrium state using a co-evolutionary algorithm, inspired from the behavioral hypothesis described above, following the ideas from Nagel and Marchal (2006). In this process, each agent performs an evolutionary algorithm to improve the utility it gets from its daily plan. The steps of this process, represented on Fig. 1, are the following:

1. *Initial demand* All agents have an initial daily plan, which will serve as a starting point for the iterative improvement process. Some characteristics of the plans are left untouched during the simulation, and should therefore come from data or external model. This is typically the case of long-term decisions, such as home and work locations, or decisions involving a larger time frame than a single day (e.g. to do the weekly shopping or not).
2. *Mobility simulation* Plans of all agents are executed concurrently, to allow estimating the influence of the plans of the agents on each other. This step typically uses a queue simulation to simulate car traffic, which gives estimates of the congested travel time. Simulation of bus delays due to congestion and bus bunching can also be included.
3. *Scoring* the information from the simulation is used to estimate the score of each individual plan. This information typically takes the form of travel times and time spent performing activities; experiments also included information such as facility crowding. This experienced utility is used to update the score associated to the plan. Averaging all experienced utilities for a given plan allows the score of the plans to converge to the expected utility of the plan, but



2 Group identification

tends to slow down convergence by limiting reactivity from iteration to iteration. Hence, scores are usually updated by allocating the last experienced utility to each plan.

4. *Replanning* Then, part of the agents select a past plan based on the experienced score, following a Logit like selection probability; the other agents copy and mutate one of their past plans. If the number of plans in an agent's memory exceeds a predefined threshold (usually 4 or 5), the worst plan is deleted, pushing the evolution toward plans with higher scores. Steps 2 to 4 are then iterated until the system reaches a stable state.

What kind of mutation is performed determines which alternative plans will be tried out by the agent. Typical replanning strategies include least cost rerouting using travel time estimates from the previous iteration, departure time mutation, and mode mutation at the subtour level. Experiments included secondary activity location choice (Horni *et al.*, 2009) and activity sequence (Feil, 2010).

Generalizing MATSim process to represent joint decisions

The MATSim process, though well suited to represent individual decision making, is not yet adapted to represent joint decision making, as an agent's decisions are only based on the average behavior of other agents.

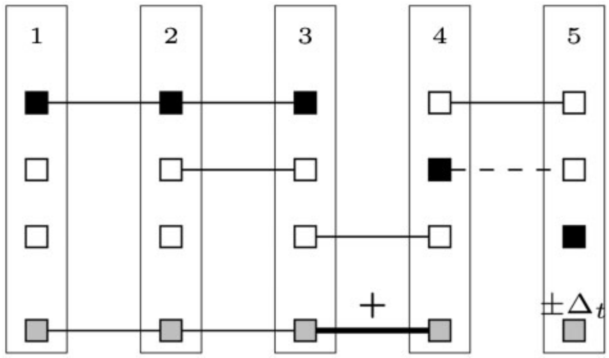
The generalization proposed here is based on the joint plan concept, and allows the representation of coordination in arbitrary social structures. As for the usual MATSim process, it uses an evolutionary algorithm to optimize full daily plans that the agents execute in a mobility simulation to obtain scores. Explicit coordination between agents is included by linking a selection of plans corresponding to joint decisions, such as joint trips or joint activities. This linkage is done using two complementary constraints on the possibility to select a specific plan for an individual, given the plans selected by relevant social contacts or household members:

1. *Joint plan:* a joint plan is a set of plans of several agents, which must always be selected together. An example is the plan of a driver and his passenger, or plans of two household members coordinating for the use of the same vehicle. It may be seen as a representation of the agreement of several agents to cooperate.
2. *Incompatible plans:* There are also cases when one does not want two or more plans to be selected at the same time: for instance, two joint plans representing coordination for the usage of the same vehicle by two non-overlapping groups of members of a household should not be selected together, though it is allowed by the previous constraint. It may be seen as the agreement of several agents not to interfere with each other.

Given those constraints on which combinations of individual plans can be chosen together, one needs a way to create new plans from old ones, and a way to select past plans based on the experienced score.

To achieve this, it is not possible anymore to consider agents in isolation, and one has to identify groups of agents to replan jointly. Figure 2 illustrates the process to identify agents which are replanned together. In this figure, circles represent agents. Solid lines represent the existence of joint plans between agents, snaked lines represent the existence of incompatible plans, and discontinuous lines represent 'social ties', that is, the possibility to create new joint or incompatible plans. For replanning, agents having joint plans or incompatible plans are put in the same group, as is the case for agents 0, 1, 2 and 3, 5 for joint plans, and of agents 7, 9 and 8 for incompatible plans. Agents being linked by social ties can, but must not necessarily, be put in the same group. In the figure, for instance, agent 5 and 6 are put in the same group, allowing them to generate a new joint plan containing individual plans for each of those agents, while agent 4 is replanned alone. The groups used in different iterations need not be the same, as long as the constraints are respected. During the process, each agent should however be replanned together with each of its social contacts, to allow the search algorithm to try interactions between any pair of social contacts. In the current implementation, the groups are fixed, each agent being always replanned with all its identified social contacts.

Once groups are identified, the process is similar to the individual case: the first mandatory step, is to select an individual plan for each agent in the group, considering the constraints. This is done by selecting the feasible combination of individual plans, which maximizes the sum of weights allocated to plans. Those weights can be the scores, possibly weighted by some agent-specific value (to obtain a selection scheme analogous to the weighted sum group utility), with or without random error term (to obtain a selection scheme analogous to a random utility choice model), or be completely random (in order to draw a feasible combination at random). This combinatorial problem can be solved efficiently using a branch and bound approach (Lawler and Wood, 1966). When weights are interpreted as utility values, this selection scheme corresponds to a 'utility transfer' assumption: agents are interested in maximizing the average utility for the replanning group, rather then their own individual utility. A nice feature of this selection scheme is that in the absence of joint plan and incompatibility constraints, it is equivalent to choosing the plan of the highest weight for each agent, which makes it a generalization of the current MATSim selection scheme. Moreover, as long as the replanning groups are identified following the rules listed above, the same plan weights will lead to the same plan



3 Group replanning

being selected for every agent, independently of the groups identified for replanning.

The second, optional step, is to create new individual plans, by copying and modifying the plans identified by the selection process. All the strategies used at the individual level can, of course, be applied on the individual plans; group level strategies, which modify the joint plan structure (for instance by creating new shared rides) or act on joint plans (for instance by synchronizing plans of cotravelers), can also be applied.

Figure 3 illustrates this replanning process. Each column represents the memory of an agent, where each square corresponds to a plan. Joint plan constraints are represented by solid lines, incompatibility constraints by discontinuous lines. The black squares represent a feasible combination, selected for mutation. The mutated copies are the gray squares: a new interaction (e.g. a shared ride) is generated between agents 3 and 4, and time allocation for agent 5 is mutated.

As in the individual case, the number of plans an agent can remember is limited. To push the evolution toward better plans, the plans pertaining to the feasible combination which minimizes the sum of the plans' scores are removed from the agents' memories, taking care not to create states where no feasible combination remains.

This updated process allows to confirm that the choice of individual plans corresponding to a joint decision is linked.

Implementation

The general simulation framework described above is designed to be applicable for general social networks. The actual implementation for such a case is however cumbersome for several reasons.

First, using social networks in a microsimulation requires being able to accurately generate a synthetic population-wide network. Though efforts are being made in this direction, no attempt to use those models to generate large scale networks is done yet (Arentze *et al.*, 2012). Second, this would require modeling different decision roles depending on the type of social contact, as identified by Deutsch and Goulias (2013). In particular, it is not clear how the plan selection process described in the MATSim simulation framework section can allow to account for the variability of decision power for the same agent with different social contacts.

Owing to those current uncertainties, the implementation used here uses a network composed of isolated cliques, where the population is divided into groups within which all individuals have (unweighted) social ties with all individuals of the group. Such networks are a good abstraction for the network of intrahousehold relationships.

At the replanning step, all individuals of the same clique are always replanned together, even in the absence of joint or incompatible plans, to allow the replanning strategies to generate new interactions between any pair of agents within the clique.

For the application to joint trips, presented in this paper, a specific group level replanning strategy had to be designed, which inserts or removes joint trips in plans. Insertion works by choosing a car trip and a public transport trip, and making the car driver drive to the public transport passenger's origin, pick the agent up and drop it off at its destination. The restriction to public transport trips for the potential passenger trips is done in order not to break trip chaining constraints, which are that vehicles must be used for full subtours anchored at the home location. As mode allocation is continuously mutated during the process, this does not restrict passenger trips to agents that would have chosen public transport without joint trip opportunities.

After removal and after each mutation of the time allocation, the end times of activities preceding joint trips in a passenger's plan are modified so as to end at the expected arrivals of the drivers at the drop-off points.

Results

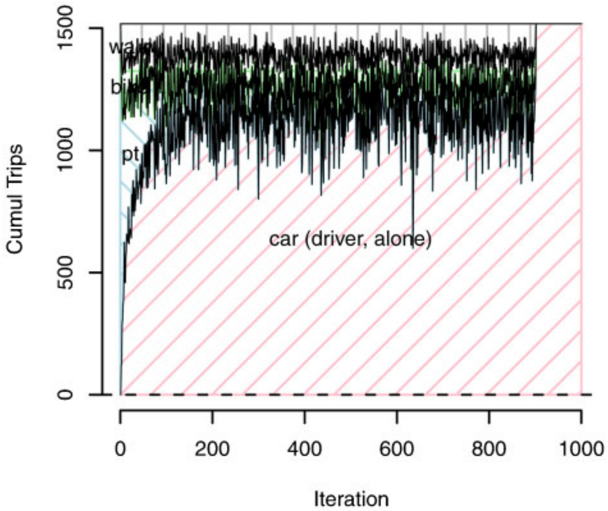
To assess the validity of the proposed process to represent joint decision making, it is applied to a simplistic 'toy' test case, for which one can predict the outcome.

This test case introduces the possibility to travel together with other household members. The network is a simple grid network of 60 by 60 bidirectional links of 1 km each, with a free flow speed of 75 km h^{-1}. Those links have infinite capacity, which means that they are not subject to congestion. The population contains 506 agents, grouped in even sized households of 2 to 20 members, with only half of them having a driver's license. All agents have home-work-leisure-home plans. All members of a household have the same home location. Work and leisure locations are randomly drawn for pairs of members, one with driving license, one without. This means that each agent without a driving license can find a driver which can drive it without making any detours. Initial departure times are random, and differ from agent to agent. In particular, this means that plans of potential cotravelers are not synchronized at the beginning, and that the process has to be able to achieve this synchronization.

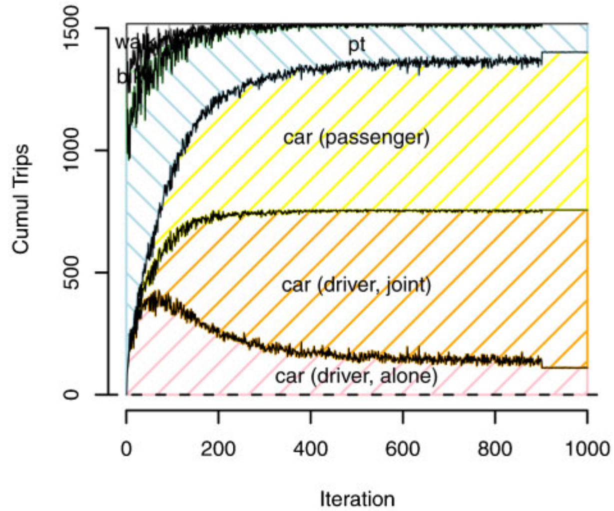
All modes have the same disutility of travel time, and parameters for the three activity types are the same for all agents. This means in particular that driving alone or with a passenger have the same utility, as long as the driver does not have to wait for the passenger.

Public transport takes twice as long as car travel.

Three scenarios are considered:



4 Mode share evolution for a run of base scenario



5 Mode share evolution for a run of the scenario with joint trips, with initial public transport demand

1. Without joint trips, and without considering driving license ownership, i.e. all agents are allowed to drive a car. This serves as a base case.
2. With joint trips and driving license ownership, starting with public transport trips for all agents.
3. With joint trips and driving license ownership, starting with bike trips for all agents.

Scenarios 2 and 3 are made to verify that the strategy of including joint trips as replacement for public transport trips does not include any bias.

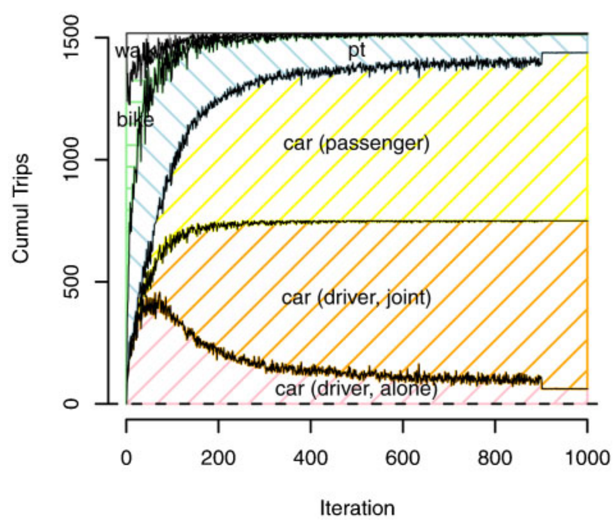
Each run is run 11 times with different random seeds.

The probability of the different replanning modules is shown in Table 1. All replanning modules except Logit like plan selection are stopped after 900 iterations, and the process is continued for 100 additional iterations. Note that as this specific scenario does not include congestion, it is not necessary to regularly compute new routes, because the shortest path depends neither on the behavior of other agents nor on time of day.

Figures 4–6 show the evolution of mode shares with iterations, for runs of the three scenarios.

For the base case, Fig. 4 shows mode share convergence in around 300 iterations. High variability is observable between consecutive iterations while innovation is enabled, as the mode mutation module reinserts trips of all modes randomly for full plans, as the plans contain only one tour. When innovation is disabled, the agents only choose car plans.

For the runs with joint trips, Figs. 5 and 6 show slower convergence, in about 700 iterations. Variability between consecutive iterations is much lower, because subtour mode choice does not touch joint trips, which are inserted and removed on a unit basis, rather than for the whole



6 Mode share evolution for a run of the scenario with joint trips, with initial bike demand

Table 1 Probability of the different replanning modules

Module	Description	Probability
Logit like selection	Selects past plans using Gumbel distributed scores	0·4
Time allocation mutation	Randomly mutates activity end times. It adds or removes a random amount to all activity end times in a plan, within a range that decreases with iterations, from [−12 h; +12] h at the beginning to [−0·5 h; +0·5 h] from iteration 750 on.	0·2
Subtour mode mutation	Changes randomly the mode of all trips of a subtour	0·2
Joint trip mutation	Inserts or removes joint trips randomly. *This module is deactivated in Scenario 1*	0·2

Table 2 Final mode shares for the three scenarios (minimum, average, and maximum over 11 runs)

	Mode shares (%)								
	No. joint trip			Joint trips from PT			Joint trips from bike		
Mode	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.
Car (alone)	100·0	100·0	100·0	4·0	5·3	7·3	4·0	5·3	6·5
Car (driver)	0·0	0·0	0·0	42·5	44·3	45·4	43·3	44·5	45·7
Car (passenger)	0·0	0·0	0·0	42·5	44·3	45·4	43·3	44·5	45·7
Car (all)	*100·0*	*100·0*	*100·0*	*92·3*	*94·0*	*94·8*	*93·0*	*94·3*	*95·5*
Public transport	0·0	0·0	0·0	5·1	5·9	7·7	4·4	5·6	6·9
Bike	0·0	0·0	0·0	0·0	0·4	0·13	0·0	0·13	0·3
Walk	0·0	0·0	0·0	0·0	0·0	0·0	0·0	0·0	0·0

subtour, and make for a large part of all trips. When switching off innovation, plans with joint trips tend to be more often selected than plans without. Evolution for the two initial demands look pretty similar: when starting with bike trips, public transport trips quickly appear and then get replaced by passenger trips.

Table 2 shows the minimum, average, and maximum final mode shares across the different runs of each scenario. When all agents are allowed to use a car, the process ends with all trips being performed with this mode. Hence, one should expect that when allowing joint trips, the share of the different car modes sum up to close to 100%. In both scenarios with joint trips, on average the total share of car modes is around 94%, which is reasonably close. Interestingly, the final share of joint trips when starting with only bike trips is higher than the one when starting with only public transport trips. It is difficult to assert what the reason is. Starting with bike trips may leave more time for the time allocation mutation to generate good time allocation to serve as a basis for joint trip insertion, while when starting with public transport trips, joint trips get inserted more quickly, and make time adaptation slower due to the synchronization mechanism.

Table 3 shows the number of joint trips and cotravelers in agents' plans, for one particular run of the process starting with public transport trips. By construction of the scenario, it is possible for each driver to drive one agent without a driver's license without any utility loss. One should therefore expect most agents to perform their three trips as joint trips, with one single co-traveler for the whole day. This is what is observed: 382 agents (75% of the population) follow this strategy, and only seven agents perform different joint trips with different cotravelers. However, a significant share of the agents (16%) perform only one joint trip during the day. More surprising, there are four times more agents which perform only one joint trip than agents which perform only two. Looking at the plans, it seems that it corresponds to drivers whose time allocation is stuck in a suboptimal state. In fact, initial activity end times being totally random, it is possible that the end time of an activity is planned for long before the end time of the previous activity. Such plans result in null duration activities during the mobility simulation phase, and get bad scores. However, as the difference between planned and actual end time is not considered in scoring, changing the activity end time in the range resulting in null activity durations does not change the score. Thus the random mutation process can have difficulties in finding end times resulting in positive durations, and remain stuck on this plateau. Due to the synchronization mechanism that estimates arrival times at the pick-up point using the end time of the previous activity, including a new joint trip in this setting means including this inconsistency in the time allocation of the passenger, most probably decreasing the utility of its plan much more than the improvement due to shorter travel time. Performing a single joint trip however improves the travel times of the passenger, without introducing any bad time allocation, and plans with one single joint trip fill the memory of those agents. This is not a critical problem, as in real scenarios one usually initializes time allocation close to the expected optimum, to minimize the number of iterations needed for convergence. This tendency to remain stuck could moreover be decreased by adding a penalty which increases with the difference between the planned and executed end time.

Table 3 Number of joint trips and co-travelers per agent

# Joint trips in plan	Number of agents			
	All	w/1 co-trav.	w/2 co-trav.	w/3 co-trav.
0	13			
1	83	83		
2	23	21	2	
3	387	382	5	0

The results of this test scenario show that the proposed process is able to find a state close to the expected equilibrium. In particular, the analysis shows that the process is able to identify the best joint traveling patterns, and can synchronize the plans of co-travelers starting from initially unsynchronized plans.

Conclusion

Social interactions in general, and intrahousehold interactions in particular, are gaining increasing attention in the travel behavior modeling literature. Those interactions are recognized as an important factor conditioning travel behavior.

The work presented in this paper aims at including such interactions in a state of the art travel microsimulation platform, MATSim.

MATSim uses an iterative algorithm to search for an approximation of a stochastic user equilibrium. In its basic formulation, this process is unable to take into account coordination. A generalization of this process was introduced, which relies on the specification of a group replanning procedure.

While this generalized process is specified so as to be applicable to general social networks, it was implemented for the simplest case of a network consisting of isolated cliques, which is an abstraction for the network of intrahousehold ties.

This implementation is tested on a simple test scenario for joint travel. The results show that the process is able to converge to a state close to the expected equilibrium.

This analysis opens a large range of possible future work. First, a validation of the joint trips generation process against travel diary data for the urban area of Zurich, Switzerland, is currently in progress. Depending on the observed accuracy, several improvements are possible. First, the current process does not include joint activities, while such activities are an important cause for joint travel. Including such activities, even in a simplistic way, may allow improvement in the results. The inclusion of joint activities includes joint activity location choice as a subproblem, which was shown to be a difficult problem even in the case of isolated agents (Horni *et al.*, 2012). Second, no experiments with alternative scoring functions have yet been undertaken. One should however consider separate parameters for joint travel, or experiment giving different weights to different roles in the household. A positive valuation of being at home together with other household members, such as the ones used by Vovsha and Gupta (2013) and Meister *et al.* (2005) could also be experimented with, and its impact on global properties of the mobility patterns investigated. One should however be careful when adding new parameters to the scoring function, as this makes the calibration process more cumbersome and error prone.

Finally, experiments with more general social networks should be undertaken. The model of Arentze *et al.* (2012) is planned to be used to generate a synthetic social network for the Swiss population. This social network could be used to test the behavior of the proposed framework in such a setting. The usage of synthetic social networks in actual forecasting runs is however still far away, and a large amount of work still has to be done to make this kind of simulation operational.

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