Solution concepts for the simulation of household-level joint decision making in multi-agent travel simulation tools

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Abstract

In the recent years, there have been a growing interest in understanding and forecasting *joint* travel-related decisions, that is, decisions taken by several individuals together, including binding agreements. Such forecasting would first allow to predict the impact of policies aiming at influencing this kind of behavior (for instance policies aimed at increasing car occupancy), but also improve the forecasts in general, by taking into account the effect of spatial dispersion of social contacts when choosing a joint leisure location, for instance.

A large number of attempts at simulating the state of transport systems have had a game theoretic view: individuals are seen as agents getting a utility from their travel decisions, this utility depending on the decisions of others (mainly via congestion). Game theory is aimed at defining and studying *solution concepts* for such situations, that is, ways to predict probable outcomes of such games. Most of the research in travel behavior forecasting relied on the *equilibrium* family of solution concepts. In this setting, individuals are seen as selfish agents competing for limited joint (capacity) resources.

Another field where game-theoretic concepts have had important impact is in the field of *co-evolutionary* computation. An important stream of literature in this field in particular insists on the importance of the *game-theoretic solution concept* explicitly or implicitly underlying the search process, which will favor one solution or the other.

Equilibrium is not the only solution concept from game theory, and its applicability in the case of decisions taken amongst emotionally related individuals, such as household members, is dubious. In particular, the possibility of realizing *binding agreements* is excluded from such formulation.

This paper uses a *co-evolutionary* algorithm, built using the MATSim software framework, to investigate the usage of two different solution concepts for the problem of predicting intra-household joint travel: (a) a "Group Utility" concept, classical in the research on household decision-making, and (b) an "Absence of Blocking Coalition" concept, which allows to represent selfish but coordinating players with arbitrary social network topologies.

The implementations of those solution concepts in MATSim are used on a scenario for the Zurich area, to reveal their strengths and weaknesses.

1 Transport Systems, Joint Decisions, Game Theory and Co-Evolutionary Computation: a Short Overview

This paper focuses on the comparison of two game-theoretic *solution concepts* for the household joint planning problem, by their implementation in a co-evolutionary algorithm.

This first section aims at answering preliminary questions: why are joint planning decisions important for transportation science (Section 1.1)? What do we understand by game theoretic solution concept, and how can co-evolutionary computation help us (Section 1.2)? Finally, how can we represent *joint decisions* in a game theoretic framework (Section 1.3)?

Section 2 then describes the implementation of a simulation system for two different solution concepts, and Section 3 describes the simulation results and compares the two solution concepts for realism.

1.1 Joint Decisions in Transport Systems

A current trend in transportation research considers the importance of *explicit coordination* between individuals on travel behavior. This wide interest comprises several sub-topics: studies usually focus either on intra-household coordination, or on coordination with extra-household social contacts. Within those two approaches, one can then further separate empirical, statistical work, aiming at better understanding coordination behavior, and simulation approaches, which aim at bringing this understanding to the forecasting front.

Studies analysing intra-household coordination often use the classical random utility framework extended to group decision making. 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) 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), 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 to increase 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" tasks (*e.g.* shopping) allocation and possibility of joint activities. To do so, they assume a layered

choice structure, choosing first a daily activity pattern for each member, and then assigning joint and maintenance activities. Gliebe and Koppelman (2005) also base their model on the daily activity pattern concept, choosing first a "joint outcome" (the sequence of individual and joint activities), and then an individual pattern for each household member. 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 passed 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 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 going 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 which 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.

Building on those mostly utility-based empirical models, several studies considered the use of optimization algorithms to generate households plans for simulation. They handle the household scheduling problem by transforming it into a deterministic utility maximization problem. The first of those 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 programming problem. 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 optimized dimensions. Chow and Recker (2012) designed an inverse optimization method to calibrate the parameters of this model 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) formulate the problem of creating schedules for two persons traveling together as finding the shortest path in a "supernetwork", and solve this problem using 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.

Some studies also tried to use the freedom given by simulation to depart from the pure utility maximization approach. Thus came the development of rule based systems, which use behaviorally plausible heuristic rules to construct household plans. Miller et al. (2005) develop such a model for household mode choice. 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 fall back on their second best choice, and/or examine shared rides options. Arentze and Timmermans (2009) develop a rule base model which relies on a simulated bargaining process within the household. Though such models can easily represent complex decision processes, their calibration and validation is cumbersome.

Apart from those studies on households, a stream of research focuses on understanding what influence, if any, the characteristics of social networks have on travel behavior.

One of the main incentives to conduct such studies comes from the continuous increase of the share of trips which 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.

A first important factor when considering travel are the spatial characteristics of social networks. Carrasco et al. (2008) studied the relationship between individual's socioeconomic characteristics and the spatial distribution of their social contacts. This kind of empirical work allows to specify and estimate models able to generate 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 microsimulation model.

In parallel, 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 analyse 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"*. This is both good and bad news for microsimulation: good news, because microsimulation approaches may be the only way to represent such diversity for forecasting; bad news, because of the amount of complexity that it adds to the simulation frameworks and the calibration procedure, with all the negative effects that this can have on usability of the method and robustness of the results. Often, in this field, *less is more*.

However, the importance of social networks in travel behavior calls for at least a partial consideration in simulation approaches. Frei (2012) for instance demonstrated in a simulation experiment how considering social interactions in leisure location choice can help increase the accuracy of predicted leisure trip distance distribution. Han et al. (2011) present experiments of using social networks to guide activity location choice set formation in the FEATHERS multiagent simulation framework. Using a simple scenario with 6 agents forming a *clique*, 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) and Ma et al. (2011, 2012) present agent based systems which do 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.

1.2 Game Theory, Co-evolutionary Computation and the Simulation of Transport Systems

Game theory, as a theoretical framework to represent competition, has been used in many forms in transportation research. One of the earlier examples, and probably one of the most influential,

is the *Wardrop equilibrium* condition in traffic assignment (Wardrop, 1952), which is simply a Nash equilibrium of a specific congestion game. This equilibrium notion has then widely spread in transportation research in general, and traffic assignment in particular, and doing an exhaustive review is not the purpose of this paper.

Another field where game-theoretic concepts have had important impact is the field of *co-evolutionary* computation (see Popovici et al. (2012) for a thorough introduction). Such algorithms are an extension of *evolutionary* algorithms. Contrary to a classical evolutionary algorithm, where a reproduction and selection process is performed, giving better survival probability to solutions maximizing a known, *explicit* fitness function, co-evolutionary algorithms are based on a *implicit* fitness function: the fitness of a component depends on interaction with other components, which are themselves part of the evolution process. Such components can for instance be solutions and tests, or sub-solutions combined into a complete solution. As emphasized by Ficici (2004), such algorithms are essentially *game theoretic* in nature, and the *solution concept* used to select individuals surviving the selection process has a major influence on the output of the algorithm. While seeming obvious once written, this fact took some time to be that clearly stated, and Ficici (2004) claims that most (if not all) pathologies exhibited by co-evolutionary algorithms come from *"a general lack of rigor in our* solution concepts*"*. The practical implementation of a solution concept in a coevolutionary algorithm is however no evident matter. As noted by Ficici et al. (2005), when they perform a theoretical analysis of different selection methods in a coevolutionary context, *"Coevolutionary dynamics are* notoriously complex. *To focus on our attention on selection dynamics, we will use a simple evolutionary game-theoretic framework to eliminate* confounding factors *such as those related to genetic variation, noisy evaluation, and finite population size"*. Those "confounding factors" can however not be eliminated from an actual implementation of a coevolutionary algorithm, and rigorously proving that a given algorithm actually implements a specific solution concept is very tedious, if not impossible.

Even given those difficulties, this game-theoretic nature makes this kind of algorithm particularly well-suited for solving problems defined over what Popovici et al. (2012) call an *interactive domain*. A particular kind of problem over an interactive domain, which contains all the problems this paper focuses on, is the *compositional co-search problem* kind. In short, a *compositional co-search problem* is the combination of:

- *domain roles* $1 \leq i \leq N$, played by *entities* $x \in X_i$, with X_i being named an *entity set*
- a *potential solution set* C, often a subset of $X_1 \times \ldots \times X_N$, or a set of distributions over the elements of $X_1 \times \ldots \times X_N$ (the *compositional* aspect)
- a *solution concept*, which defines $\mathcal{S} \subset C$, the set of actual solutions, (the *search* aspect, as opposed to the kind of problem where there is a global function to optimize)

The problem of multi-agent activity-based demand forecasting pertains to this class of problems: each agent i has a set of physically feasible plans X_i, a system-wide solution is the allocation of a daily plan to each agent in the system, and the quality of a daily plan depends on system performance such as congestion or facility crowding, which depend on the daily plans of the other agents. Solution concepts for this problem are based on a behavioral hypothesis, and specify which transport system states are *stable*. More detailed descriptions of such solution concepts can be found in Section 2.

It is then no wonder that such algorithms were used when implementing travel demand forecasting tools. An important example is MATSim, which is used in this paper, and is described in more details in Section 2.1.

1.3 Joint Decision and Game Theory

Although the outcome of any game is a decision "joint" in some way (the decision of a player depends on the decisions of the other players), this work uses a more restrictive definition of what is a joint decision. A joint decision, as we understand it here, is a set of interlinked decisions by several players, requiring the usage of *explicit coordination*, or *binding agreements*. Including such possibility in a game theoretic framework requires a shift in solution concept.

This can be illustrated by a classical game, called the *House Allocation Problem* (Schummer and Vohra, 2007). This game consists of n players and n houses. Moreover, each player has its individual ordering of the houses, from the most preferred to the least preferred, and players prefer being allocated alone to any house rather than in the same house as somebody else. The strategy of a player is the house it chooses to live in.

An interesting feature of this game is that any one-to-one allocation of players to houses is a Nash Equilibrium: no player can improve its payoff by *unilateraly* changing its strategy, as it would require choosing an occupied house. This result however contradicts basic intuition about the stability of such an allocation. In this particular case, a more realistic solution concept is the *Absence of Blocking Coalition*: given a one-to-one allocation of houses to players, a blocking coalition is a set of players which could all be better off by re-allocating their houses among themselves.

It is to be noted that both solution concepts correspond to rational agents, *i.e.* agents having a preference ordering over outcomes. What differentiate both solution concepts is the degree of communication which is hypothesized: in a Nash Equilibrium, for a given player, the strategies of the others are taken as given; in an Absence of Blocking Coalition, players have the possibility

to "negotiate" a change of strategy with other players, which will be accepted only if all agents in the negotiation are better off after the re-allocation. In this work, we consider that a Nash Equilibrium corresponds to *individual* decisions only, whereas the blocking coalition concept allows what we phrase *joint* decisions.

Experimental data, however, tends to indicate that individuals are not as rational as the classical game theoretic models assume: in laboratory game-playing, players' behaviors exhibit systematic discrepancies with the game theoretic predictions. In particular, along with the profit-seeking behavior, it seems most individuals are *inequity averse*, in two ways (Fehr and Schmidt, 1999):

1. individuals having the impression to be unfairly treated will attempt to punish the players considered as selfish, even if it implies decreasing their objective (often monetary) payoff;
2. individuals having the impression to get an unfairly better payoff than the others will tend to decrease their objective payoff, if it allows to make the discrepancies between payoffs smaller — though this effect is much smaller than the previous one.

Other research, in particular on the special class of games called *social dilemmas* — the games were there exist strategy profiles where all players are better off than at equilibrium — also revealed that some *competitive* players actually try to maximize the difference between self and partner, rather than maximizing their own payoff (Kollock, 1998).

Other authors, in particular Rabin (1993) or Falk et al. (2003), model those observations using a "kindness" concept: what matters would be not the material *difference* of payoffs, as in (Fehr and Schmidt, 1999), but the *intention* which led to the outcome: individuals tend to be mean to whom they consider being mean to them, and kind to whom they consider being kind to them.

Another way to model seemingly irrational cooperation is with the introduction of *iterations* (**?**). In this setting, players are assumed to repeat the same game over and over. Each iteration has decreasing payoff, and the strategy chosen in a given iteration depends on the past plays of the other player. An interesting feature is the fact that in the *iterated prisoners dilemma*, the "tit for tat" strategy (collaborate until the opponent defects, and then defect forever) is a best response to itself, leading to an equilibrium where the two player eternally cooperate. Intuitively, this kind of model is able to represent some kind of "trust": players will collaborate to ensure future action of the other player. Leaving with the bounty will increase the payoff for a particular iteration, but the resulting decrease in payoff for the rest of the game is greater than the immediate increase.

This kind of result, though not resulting from what we called a *joint* decision, is to be kept in mind when modeling joint behavior, as individuals involved in a group decision making process may attempt to achieve a fair agreement — in particular when the members of the group are

members of the same household or close friends.

2 Joint Decision Problem: Formulation, Solution Concepts and Algorithms

The previous section showed the importance of what we called joint decisions in mobility behavior. It also exemplified how one can use game theoretic concepts to model the transportation system, and how "joint decisions" can be accounted for in a game theoretic framework.

Building on those insights, this section presents an operational co-evolutionary algorithm designed to model joint mobility decisions and search an approximate solution to the resulting game. Two solution concepts are presented: one specific to the simulation of intra-household coordination, the other applicable to social networks of arbitrary topologies. The corresponding evolutionary operators allowing to solve one or the other solution concept are presented.

2.1 MATSim: a Co-Evolutionary Algorithm for the Simulation of a Transportation System

This work builds on MATSim, an actively developped open-source software using a co-evolutionary algorithm to simulate individual's daily mobility behavior.

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

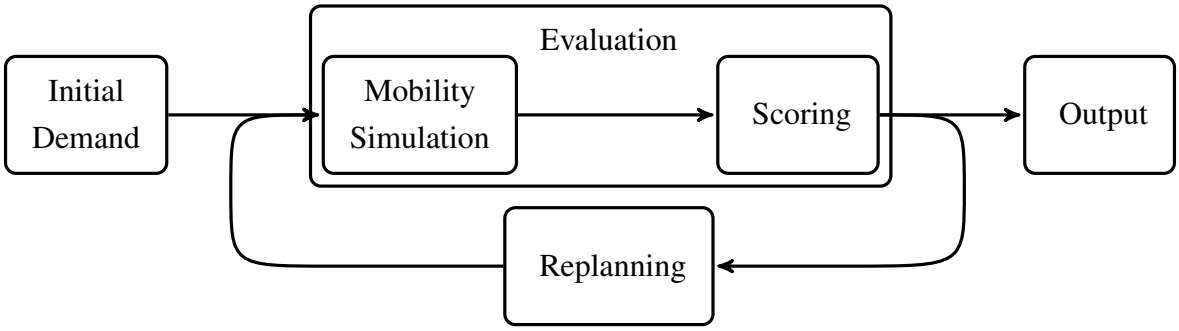
The MATSim process uses a co-evolutionary approach to search for an approximation of a stochastic user equilibrium, where the expected utility of the daily plan of individuals is optimal given all other individuals' choices.

The basic modeling idea is that individuals associate a utility value to their day, which increases with the time spend 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 search problem resulting from those hypotheses can be formalized as a *compositional co-search problem*, as introduced in Section 1.2:

- for each agent i, the *entity set* X_i represents the set of physically feasible daily plans. In practice, what is explored is actually a subset of this *universal choice set*, defined as the set of plans which can be created by iteratively applying evolutionary operators on an initial plan.
- the *potential solution set* $C \subseteq X_1 \times \ldots \times X_N$ is simply $X_1 \times \ldots \times X_N$, the set of all possible combinations of individual daily plans.
- the *solution concept*, which defines the set of solutions $\mathcal{S} \subset C$, is akin to the Nash Equilibrium concept, with important differences. Nash Equilibria would be the states where no agent can improve the utility it derives from its day, given the exact choice of the other agents — which requires perfect and complete knowledge. This is a strong requirement, both behaviorally and computationally: rather than a Nash equilibrium, the solution concept embedded in MATSim considers imperfect knowledge and random behavior. This solution concept has been described as an *Agent-Based Stochastic User Equilibrium* by Nagel and Flötteröd (2009), formalized as *"a system state where agents draw from a stationary choice distribution such that the resulting distribution of traffic conditions re-generates the choice distribution"*. That is, the solutions are the states which are part of the stationary state of a dynamical system, where agents have probabilistic responses to the state of the system, itself resulting from their decisions. Alternatively, one could define the solution as the *stationary distributions themselves*.

Figure 1: The MATSim iterative process



The co-evolutionary algorithm used by MATSim to solve this problem is an emulation of a learning process, suggested by the essentially dynamic solution concept (Nagel and Marchal, 2006). Using the formalization of the problem above and iterative learning analogy, the specification of the algorithm is quite natural: each agent will perform an evolutionary algorithm to optimize its own daily plan, the fitness of which will be evaluated by executing all daily plans on the network to evaluate the resulting state of the transportation system. 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.* 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. Together with the next step, this step constitutes the *evaluation* stage of the co-evolutionary algorithm.
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 (Horni et al., 2009). The functional form is the one used by Charypar and Nagel (2005). It uses a linear disutility of travel time, and a logarithmic utility of time passed performing activities. Different parameters can be defined for each mode/activity type.

   This gives the score from a single *interaction*. The *fitness* of the daily plan (*entity* of the algorithm) can then be *updated*, as $(1 - \alpha)\, f_{old} + \alpha\, f_{new}$, with $\alpha \in [0.5, 1]$ being the *learning rate*. The lowest the learning rate, the more the fitness of a plan will be close to an *average* fitness over the evaluated interactions. While this is consistent with the hypothesis that individuals react to the *expected* state of the transport system, most applications use a learning rate of 1, which results in more reactive agents, and thus faster convergence.
4. **Replanning** This step actually groups two of the important components of co-evolutionary algorithms: (a) selection of the interactions for evaluation, and (b) application of the evolutionary operators (selection and mutation).

   To do so, part of the agents select a past plan based on the experienced score, following a Logit selection probability. This will have two consequences: (a) the state of the transport system, used for evaluation, will only evolve slowly from iteration to iteration, giving the time to the agents to adapt, and (b) those plans will be re-evaluated, given the new plans of the other agents. 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 towards 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, considering mode chaining constraints. A tour is a sequence of consecutive trips starting and ending at the same location, named anchor point. A subtour is a tour, possibly without other tours it contains. Vehicular modes can only be performed for whole subtours, which must be anchored at home or in subtours of the same mode. Experiments included secondary activity location choice (Horni et al., 2009) and activity sequence (Feil, 2010)

Those steps are iterated until a stationary state is reached, and the state of the system in this stationary state is taken as a result.

2.2 Daily Plans and Joint Decisions: Formulation and Algorithm

The MATSim process, by design, embeds a solution concept close to a Nash Equilibrium, with the important difference that behavior of other agents is random, and the choice probabilities of agents are independent, knowing the experienced states of the transport system. This independence is particularly problematic when trying to include what we called joint decisions, as it forbids the representation of binding agreements.

Hence, a generalized algorithm, which first state was presented in Dubernet and Axhausen (2013), was developed. It aims at including a way to represent binding agreements and their influence on individual scores. The solution concepts which can be represented using this framework will be described in the next sections.

The generalization here relies on the introduction of *joint plans* constraints. The individual plans of two agents are linked in a joint plan if the score of one of the plans is assumed to depend heavily on whether the second individual plan is executed or not: an obvious example is a daily plan including the "car passenger" mode, which makes sense only if the agent identified as a driver indeed plans to perform the ride. Such links are used as constraints for the process, linked plan always being executed together. This ensures that the score derived from a plan corresponding to a joint decision takes into account the decision of all parties. This new element has no effect on the entity set nor on the potential solution set: all combinations of individual plans are still potential solutions; allowing to test a given individual plan in the context of several *joint plans* however allows to introduce new *solution concepts*, which take into account the influence of binding agreements on the utility of this individual plan.

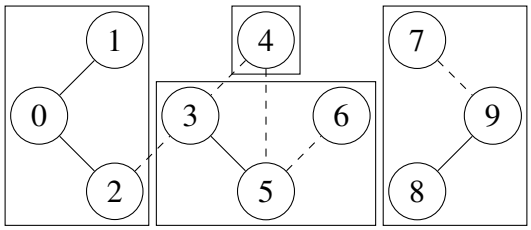
Those constraint come into play in the replanning step. Joint plan constraints are enforced when agents simply select a plan from their memory for execution, but may be broken when selecting plans as a base for mutation: those breakages act in a similar fashion as cross-overs in genetic

algorithms, and allow a quicker propagation of "good" individual plans within the joint plans. They are created after each mutation, using a set of rules, such as linking plans of co-travelers.

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. Fig. 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, and discontinuous lines represent "social ties", that is, the possibility to create new joint or incompatible plans. For replanning, agents having joint plansare put in the same group, as is the case for agents 0, 1 and 2 , agents 3 and 5, and agents 8 and 9. 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, or 7 and 9, are put in the same group, allowing to generate a new joint plan containing individual plans for each of those agents, while agent 4 is replanned alone. This allows to break big connected components, such as the one of agents 1 to 6, to be broken down in smaller groups, each group being treated by different operators. 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. For the household case, presented in this paper, agents are always replanned with the totality of their household's members.

Figure 2: Group identification



Once groups are identified, the process is similar to the individual case: for some agents, plans are selected without modification, considering the joint plan constraints. For the others, plans are selected for mutation, allowing to break "weak" plan links, such as links due to the performance of a joint activity.

If agents have too many plans (the definition of too many varying depending on the solution concept), a plan, and the plans of the corresponding joint plan, are removed. The selection strategy for removal is of prime importance for several reasons: (a) it must not create states where no feasible combination exist, and (b) it is this selection strategy which drives the learning

process towards one stable state or the other, much more than the selection strategy for the executed plan. The selections strategies are thus the most important elements for specifying the solution concept that the algorithm implements: the next two sections illustrate two possibilities, on specific to intra-household coordination (Section 2.3), the second also applicable to arbitrary social networks (Section 2.4).

2.3 First Solution Concept: Household-Level Utility Maximization

The first solution concept for household-level decision making that will be used here postulates that individuals do not try to maximize their individual utility, but the utility of the household. This formulation is classical in the literature, as seen in Section 1.1. The group-level utility is constructed by combining individual-level utilities, most usually using a (weighted) sum, though other formulations are possible.

In the weighted sum formulation, a player will be willing to decrease its individual utility if it allows to increase the utility of the other players in the group by at least the same amount. This is similar to what is often termed a game with *transferable utility*, with the difference that transferable utility is usually understood as a cost, which sharing across players is part of the strategies of the players (see *e.g.* Jain and Mahdian (2007)).

One must note that this solution concept is specific to the case when individuals are part of well-identified *cliques*, such as households, but is not applicable for arbitrary social network topologies: it basically transforms the game in a competition between groups rather than players. It is akin to the user equilibrium solution concept, with players being the pre-defined groups.

The specific components implemented in the algorithm to search for this solution concept are:

- **Selection operator**: when selecting a plan from the agents' memory, the feasible combination which maximizes the sum of *randomized* scores is chosen. Scores are randomized by adding a Gumbel-distributed error term, to emulate a Logit model, such as the one classically used for selection in the classical MATSim process — making the generalized process equivalent to the classical process when no joint plans are evaluated. A branch-and-bound approach is used, which allows to keep the computational burden acceptable (Lawler and Wood, 1966).
- **Removal operator**: when the number of plans remembered by an agent exceeds a pre-defined threshold, the plan pertaining to the plans combination which minimizes the sum of scores is removed, taking care not to create a state where no feasible combination exists. If the plan pertains to a joint plan, plans of other participants are also removed from their

respective agent's memory. This also reproduces the classical MATSim behavior when no joint plan is evaluated.

2.4 Second Solution Concept: Absence of Blocking Coalitions

The solution concept defined in Section 2.3, though common in the literature, is not really satisfying: (a) not only is it only applicable for a very specific social network topology (isolated cliques), but (b) it also makes strong assumptions on the altruism of the individuals, and (c) requires the individual utilities to be comparable.

Hence, we search here for a solution concept which (i) is valid with any social network topology, and (ii) allows for egoistic behavior, while still allowing for binding agreements.

This can be done by applying the concept of *Absence of Blocking Coalition* within our framework: agents can agree with another agent on which daily plan each of them will perform, but the agreement will be accepted only if none of the agents can get a better utility by not performing the agreement.

The specific components implemented in the algorithm to search for this solution concept are:

- **Selection operator**: when selecting a plan from the agents' memory, the system selects a feasible combination such that no blocking coalition exists, given Gumbel-randomized scores. A group of agents constitute a blocking coalition for a given allocation A if they are the participant of a joint plan which improves the score of all of them, compared to the ones they perform in allocation A. This kind of allocation is found using an algorithm inspired by the classical "top trading cycle" algorithm for the house allocation problem (Schummer and Vohra, 2007). Note that there may be a variety of such allocations; in which case, one of them is arbitrarily chosen. Space here does not allow us to present this algorithm in detail.
- **Removal operator**: The algorithm above makes more sense if agents have the choice between a large number of *joint plans*, creating a wide variety of possibly blocking coalitions. Thus, the criterion for removal has been changed here, by putting a maximum number of plans *per joint plan composition*. In order to avoid memory consumption to go out of control, a high limit also had to be defined for the number of plans in an agent memory.
  When the limit for a given joint plan composition is reached, one should keep the plans which have the highest probability to create blocking coalitions, that is, to be preferred to the other plans in the agents memory. To this end, a lexicographic ordering is used:

the process removes the plan which maximizes the number of plans which are the worst of the agents' memories. If several joint plans have the same number of worst plan, the process chooses among them the joint plan which maximizes the number of second worst plans, and so on until the "worst" plan is unique.
When the overall maximum number of plans in the memory of an agent is reached, the worst individual plan for this agent is removed, taking care to always let at least one plan not part of a joint plan, as there may otherwise not be any state without blocking coalition. Agents are parsed in random order, to avoid the emergence of "dictators" over iterations, whose worst plan would always be removed, even if it is the only "bad" pan of a joint plan.

3 Results

This section will present the results of four simulations for the case of intra-household ride sharing, on a scenario for the Zürich area.

The scenario is composed of the following elements:

1. **Population:** The initial demand comes from the full-Switzerland scenario described by Meister et al. (2010). It was generated by allocating activity chains from the national travel survey from the years 2000 and 2005 to records from the national census 2000, which is a 100% sample of the Swiss population, containing in particular information as home location at the hectare level and work location at the municipality level, as well as household membership information. The agents are grouped according to the household information from the census, and only the households having at least one member performing a trip passing less than 30km from the Bellevue Place, in the center of Zurich, are kept. A sample of 10% of those households is used for the simulation. This results in a scenario containing 206,943 agents, grouped in 88,439 households, and performing a total of 788,931 trips. This rather old scenario is used because from 2010 on, the Swiss census is not a full sample anymore, and hence does not allow to reconstruct households as easily. Though this approach is not applicable to most recent data, it is sufficient for the purpose of this paper. The generation of a synthetic population from the most recent data is in progress.
2. **Network:** a planning network is used, using data from the Federal Office for Spatial Development. It models the Swiss network at medium-level resolution, as well as the major arterials in the neighboring countries. It allows faster runs than a navigation network.

3. **Public Transport:** the public transport schedule from the Cantonal Transport Model is used to get realistic travel time estimates.
4. **Facilities:** the "facilities" contain the information about opening times for different activity types, and roughly correspond to buildings. Data comes from the federal enterprise census 2001.

Due to the evolving code base, the parameters of the scoring function which were calibrated for previous studies did not give satisfying results anymore. Therefore, the parameters were adjusted so as to obtain reasonable results. Due to the duration of a single simulation, calibrating a scenario is a time-consuming process. The aim of the study described herein being to test the behavior of the model rather than producing accurate forecasts, it was not attempted to get a perfect fit, but rather to obtain values of the good order of magnitude. The scoring function was extended in the following way:

- only the driver of a car gets a marginal utility of traveled distance (representing fuel cost)
- for shared rides, both driver and passenger get a *positive* marginal utility of travel time, to represent that passing time in a vehicle with a relative is more enjoyable than waiting. Note that this positive value is set such that it is lower than the *opportunity costs*, that is, the cost incurred by the fact that traveling longer forces to perform shorter activities; this way, shorter trips are still preferred over longer trips.
- the time passed in a leisure facility jointly with a household member gets an additional logarithmic utility. This introduces a willingness to travel further to meet contacts (here only household members). The parameter might get more importance when simulating more generic social networks.

Four runs are performed, to test the influence of the new utility terms and of the solution concepts on the results:

1. **Absence of Blocking Coalition, utility of being together in leisure activities *(ABC.t)*** uses the selectors for the Absence of Blocking Coalition concept (see Section 2.4), plus a high logarithmic utility of time passed with household members in leisure activities: at the "typical duration" of a leisure activity (see Charypar and Nagel (2005) for the exact meaning of this term) the marginal utility of time passed with a given household member is 100 times higher than the marginal utility of time passed in the leisure location.
2. **Group Utility, utility of being together in leisure activities *(GU.t)*** uses the selectors for the Group Utility concept (see Section 2.3), plus a high logarithmic utility of time passed with household members in leisure activities.
3. **Absence of Blocking Coalition, utility of sharing a ride *(ABC.s)*** uses the selectors for the Absence of Blocking Coalition concept (see Section 2.4), plus a positive linear utility

of time passed in the same vehicle as a social contact. The utility of time passed in activities with household members has the same form and parameters as the utility of time passed in a leisure activity.

4. **Group Utility, utility of sharing a ride *(GU.s)*** uses the selectors for the Group Utility concept (see Section 2.3), plus a positive linear utility of time passed in the same vehicle as a social contact.

The results are compared with the results from the national travel diary survey 2005, which was used as one of the sources for the scenario generation (Swiss Federal Statistical Office (BFS), 2005). The mutation operators, which, together with the initial plans allocated to the agents, define the set of possible plans for each agent, are described in Table 1. At each iteration, for each group, a replanning module is selected with a probability proportional to the module's weight. Sequence mutation and leisure location choice are included to allow for the emergence of *joint leisure activities*, which are an important source of joint travel. The various approaches already implemented for location choice in MATSim (Horni, 2013) are not usable here, as we need a reasonably high probability to generate activities at the same location for different household members. 1600 iterations are run, with all mutation operators deactivated after iteration 1500 (the process only selects past plans based on score from this iteration on).

Each time the execution of mutation operators generates new plans for a group, the newly generated plans are grouped into joint plans using the following heuristic rules:

- plans of co-travelers are linked. Those links cannot be broken at replanning (plans of co-travelers are always mutated together), as there is a strong dependency of the scores of the plans of the co-travelers.
- plans having expected overlapping leisure activity at the same location are linked. Those links can be broken when selecting plans for mutation, but not when selecting plans for mutation, allowing to explore more party compositions for joint activities.

Fig. 3 shows the evolution of scores for the four runs, Fig. 4 shows the evolution of mode shares. It seems convergence is still not reached after 1500 iterations, as a slight slope is visible in all graphs. Quite unsurprisingly, the group utility concept allows to reach slightly higher average scores, as agents attempt to maximize the *average* score of the household.

Fig. 5 shows the mode shares, per trip length category, at the end of the four runs and in the national travel survey. All runs tend to underestimate a lot the share of joint travel — note however that the shares from the National Travel Survey include both intra- and extra-household ride sharing. The Absence of Blocking Coalition concept leads to much lower shares of joint modes than the Group Utility concept, due to the egoism of drivers: in Absence of

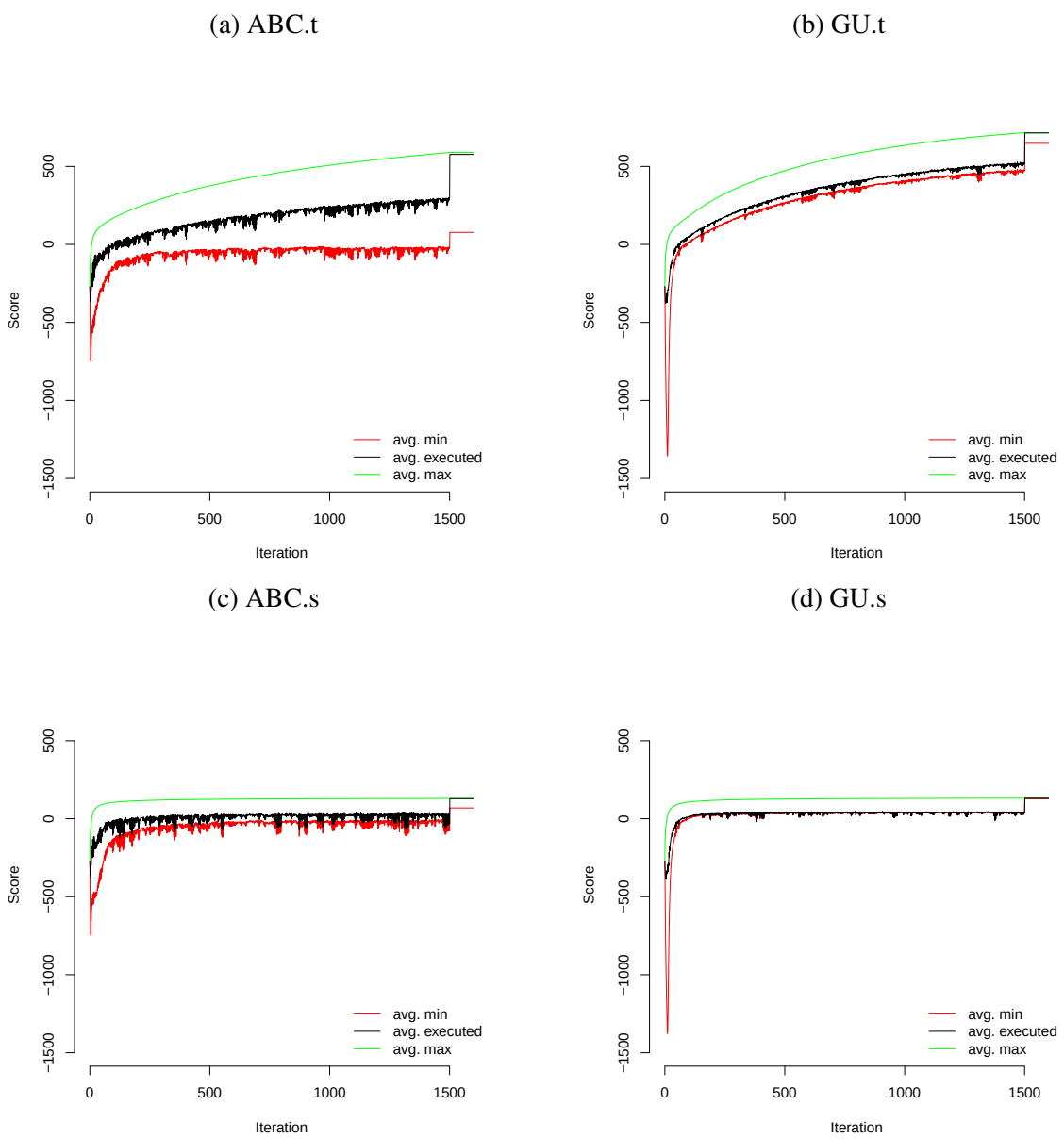
Table 1: Replanning Modules

Module	Description	Weight
Past Plan Selection	see Section 2.3 and Section 2.4	2
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 which decreases with iterations, from $]-2.5h; +2.5h[$ at the beginning to $]-0.5h; +0.5h[$ from iteration 750 on.	1
Subtour Mode Mutation	Changes randomly the mode of all trips of a subtour. It considers car availability (*i.e.* the combination of driver's license and car ownership) and trip chaining constraints: subtours with chain-based modes (car and bike) must be anchored at home or in a subtour of the same mode. Subtours containing one or more joint trips are not modified.	1
Re-routing	Computes new routes for all trips in the plan, using a least-cost path algorithm based on the travel times observed in the previous iteration.	1
Activity Sequence Mutation	randomly switches two activities	1
Joint Trip Mutation	Inserts or remove joint trips randomly	1
Joint Location Choice	Randomly mutates leisure locations for several agents at the same time, by selecting a location which minimizes the maximum distance traveled by one of the participants.	1

Blocking Coalition, a driver will perform a joint ride only if its side effects (presence of an household member in the vehicle or at the leisure location) have a positive effect on its utility; in Group Utility, drivers will also perform a ride if it helps increasing the utility of the cotraveler. Interestingly, the share of joint travel with high utility of joint activity time is higher than the share of joint travel with a utility of shared in-vehicle time. This shows how the process, by considering the utility of the whole day, is able to represent the interaction between different choice dimensions. Unfortunately, this also points the difficulty of the calibration process, as parameters for activities have influences not only on characteristics of the activities, but also on mode shares and other statistics.

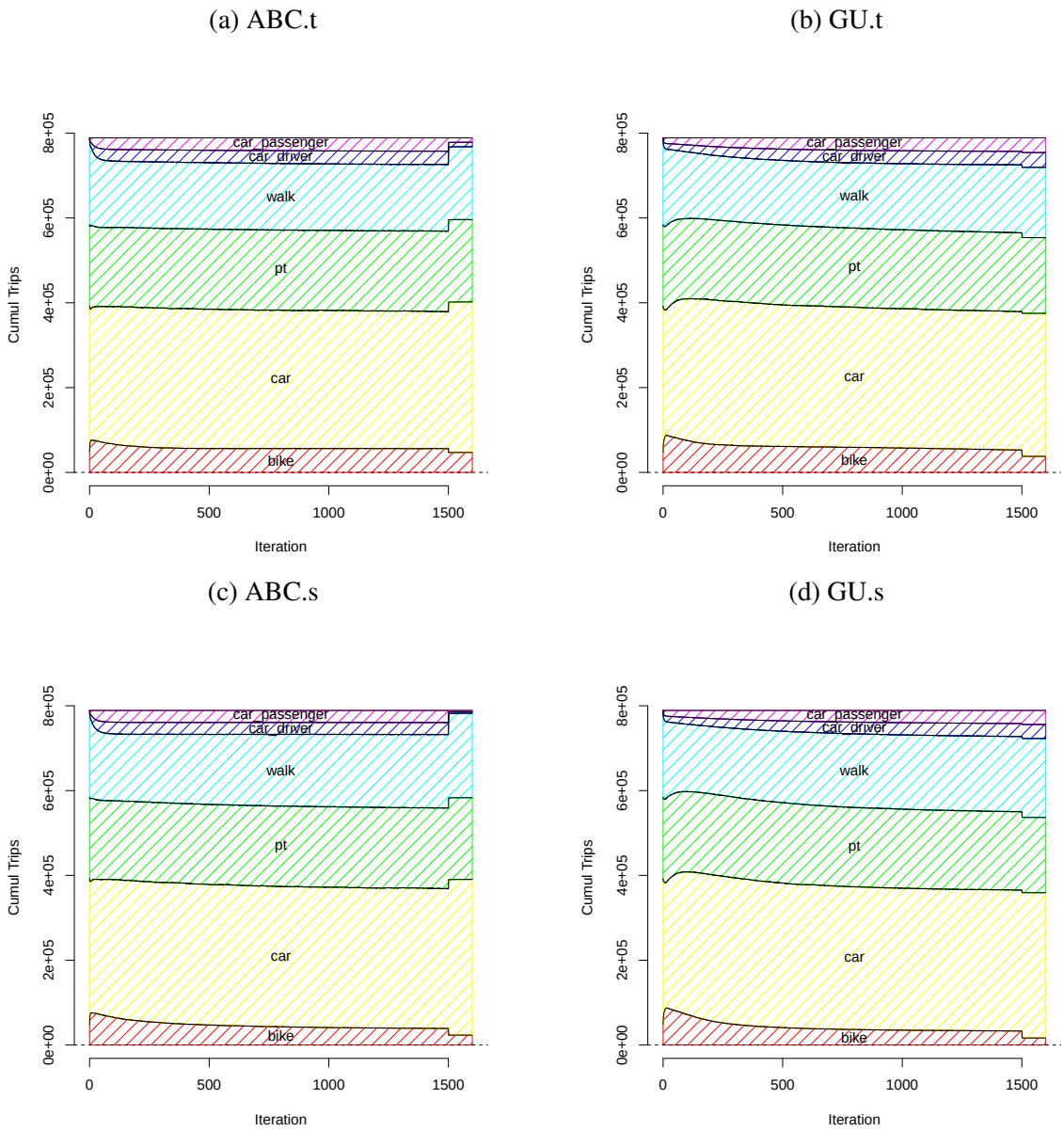
Fig. 6 shows the trip distance distribution, per mode, at the end of the four runs and in the

Figure 3: Evolution of Scores



national travel survey. Except for bike trip lengths, which tend to be overestimated, the fit for non-joint modes is rather satisfying. What is interesting here is to look at what happens with joint modes. Let's first have a look as the case with a high utility of joint activity time, and no utility of joint traveling. "Car driver" trip length tends to be overestimated, a little for the Absence of Blocking Coalition concept (mainly due to too few short trips), a lot for the Group Utility concept (too few short trips *and* too much long trips). The longest driver trips for the Group Utility concept comes from an over-estimation of *driver detours*, which remain performed by the agent if they result in enough increase in the utility of the co-traveler. Also, the fact that there are too few short trips for the Absence of Blocking Coalition concept points to the fact

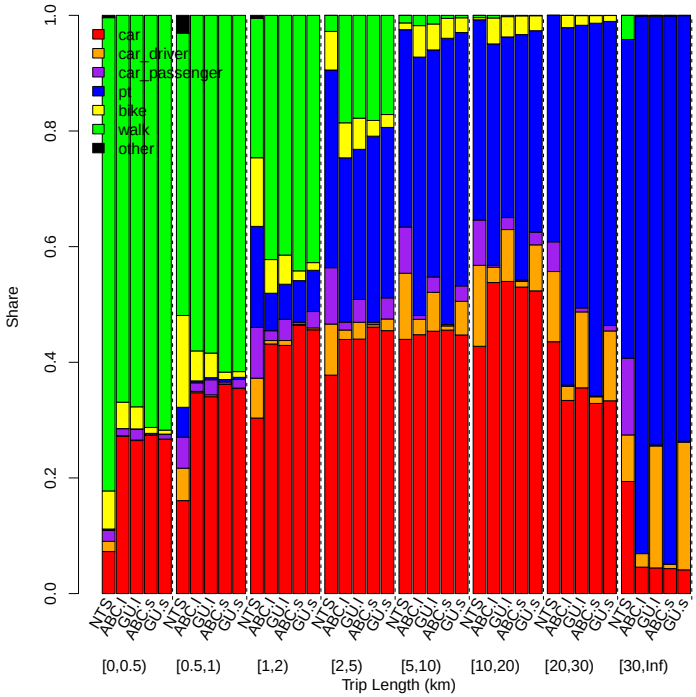
Figure 4: Evolution of Mode Shares



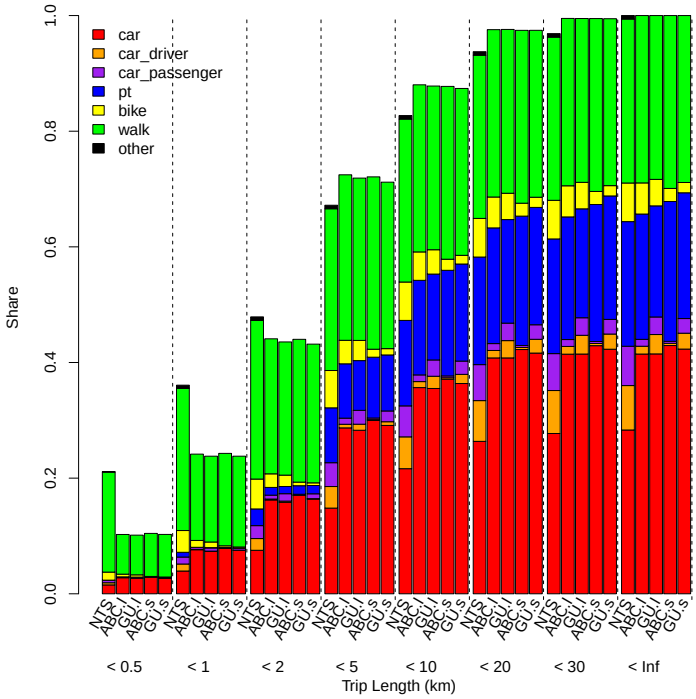
that there are probably not enough household members having the same OD pairs in their plan, which is not compensated by the location choice strategy used here: the detours drivers have to do in the simulation are longer than the detours individuals perform in reality. On the opposite, "car passenger" trips tend to be too short for both solution concepts. The reason may be twofold: first, given two arbitrary OD pairs, the longer the passenger trip, the higher the expected driver detour, and hence the higher the probability of the joint ride being rejected by the driver. Second, being passenger for one trip forbids to use a vehicular mode for the rest of the tour: the other trips of the tour then have to be performed by walk, public transport, or again car passenger. Performing a long trip as a passenger may thus force to perform long trips by public transport or

Figure 5: Mode Shares per Distance Class

(a) Non Cumulative



(b) Cumulative



walk, inciting the agent to rather take the car from the beginning. The picture with a utility of joint in-vehicle time is pretty much the same, with the important difference that driver detours are overestimated even for the Absence of Blocking Coalition concept, even if the effects of this term on the utility of the day are much smaller: the utility of joint in-vehicle time, while making joint travel more likely, also compensates for the opportunity costs, while the utility of joint activities, in addition of inciting to travel together, increases the opportunity costs of travel.

Figure 6: Trip Distance Distribution per Mode

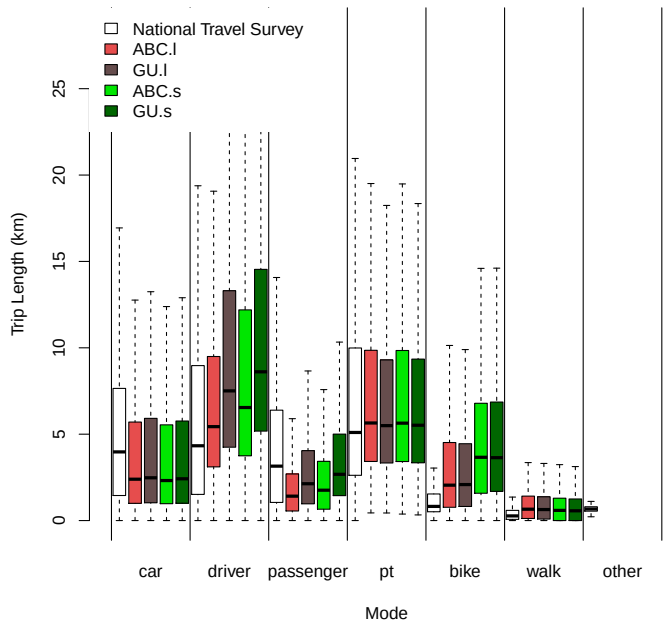


Fig. 7 shows the shares of the passenger mode per trip purpose, for the four runs and the National Travel Survey. The data from the National Travel Survey shows a clear pattern: trips for leisure purpose have a higher probability to be performed as shared rides. When considering a high utility of joint activities, the Absence of Blocking Coalition run seems to show slightly such a pattern for trips *to* leisure only. The Group Utility runs show a completely different picture, with a dominance of passenger trips for trips to and from education — for both utility formulations. Interestingly, shares for this purpose are quite close to the shares observed in the National Travel Survey. Those differences come from the difference between the two runs: in Absence of Blocking Coalition, a joint trip is performed only if it is the best for all co-travelers, while in Group Utility, it is performed if it increases the average utility of the co-travelers. Thus, the (slightly) higher share for leisure purpose in run ABC.t comes from the willingness of agents to perform joint activities, together with the flexibility in activity location. The significant dominance of education purpose in Group Utility shows that this concept seems to be able to

represent *children escorting*, by combining the strong altruism assumption with the impossibility for children to drive a car.

Those results show that both solution concepts seem to have their pros and cons:

- The Group Utility concept seems to be able to represent intra-household commitments, such as escorting the children to school, by capturing a certain kind of altruism. This utility-based "altruism" however tends to create agents driving unrealistically large distance just to drive somebody else on a short distance.
- The Absence of Blocking Coalition concept, with its pure egoism, results in much more realistic driver detours. It is however unable, in this form, to represent willingness to serve, and produces very low joint travel shares. Adding a utility of joint in-vehicle time to correct for this underestimation makes driver perform unrealistic detours, while still dramatically underestimating the number of shared rides.

One might thus want to extend the Absence of Blocking Coalition concept, which seems to lead to the most realistic trip distribution, with "altruistic" components, to allow to reproduce the relatively realistic behavior of the Group Utility concept for children escorting.

However, the only way to get significant, though low, shares of joint travel, was to unrealistically reward joint leisure activities, until the scores obtained form this component completely dominate the other components. This brings several remarks to mind:

- First, household-specific processes may have to be represented explicitly: limited vehicle resources, or "maintenance" tasks having to be performed by any, but at least one, member of the household during the day, *etc.*
- Other processes, not specific to households, may remain to include. Section 1.3 listed some studies in the fields of experimental game theory, which show significant (and consistent) deviations of observed behavior from the rational outcomes. Researchers were able to model those deviations using different forms of inequity aversion, kindness, or just by considering iterated games. Those insights from game theory are however difficult to consider here, for at least two reasons. First, "inequity" is difficult to quantify: utility is private to the agent and difficult to compare between agents, and it is not obvious what should one consider for inequity — utility, travel time, activity time, waiting time? Second, the short horizon of the simulation makes it difficult to represent the trust-building process modeled in iterated games, which might indeed be an important process in real life — one might agree to drive somebody just to keep good relationships, and ensure that the other person continues to act kindly.
- The initial plans and mutation operators (which together define the actual *entity sets* of

the co-evolutionary algorithm) need to be carefully selected. In particular, initial plans which lead to good results when letting joint decisions aside may prove incorrect when including such decisions. In particular, the classical MATSim utility function is not well suited for activity insertion or removal (see *e.g.* Feil (2010)), but individuals do modify their activities depending on their binding agreements: household heads may agree on who escorts the children to school and who does the grocery shopping (which allocation depends on a lot of factors, see *e.g.* Schwanen et al. (2007)); friends do agree on a date for their dinner at the restaurant, rather than first planning each one a different date and then checking who wants to go on the same date (which is roughly what happens in the algorithm presented here) — in other words, the choice of which activities to perform during a given day is *correlated* between social contacts, which is broken by the independent sampling of activity chains used for scenario generation.

- Here only household joint travel was considered, letting more generic social contacts out. This is not only problematic for representing joint trips: Section 1.1 lists some studies showing a significant impact of the spatial distribution of leisure social contacts on the characteristics of leisure travel. The application of the Absence of Blocking Coalition concept is however possible in this context, and experiments are currently in progress, using a Switzerland-wide social network generated from the model by Arentze et al. (2012).

4 Discussion

Since their formulation in the middle of the 20th century, game theoretic concepts have been refined and used in a variety of contexts involving competing agents, from economics to computer networks, passing by transportation systems. In transportation systems in particular, they have been a successful framework to describe and model the retroaction of congestion on travelers' behavior.

Game theory defines *solution concepts*, which define the set of outcomes being "solution" of the game. Those concepts are usually based on a stability criterion: which outcomes are stable, given rational players? Though the most widely spread *solution concept* is the Nash equilibrium, other formulations are possible, and may be necessary. In particular, to represent what we called *joint decisions*, one needs to go away from this concept and find other formulations, which allow to model *binding agreements*.

This paper demonstrates the inclusion of two such solution concepts in a travel forecasting tool, one specific to the case of isolated cliques, the other one applicable to generic social network

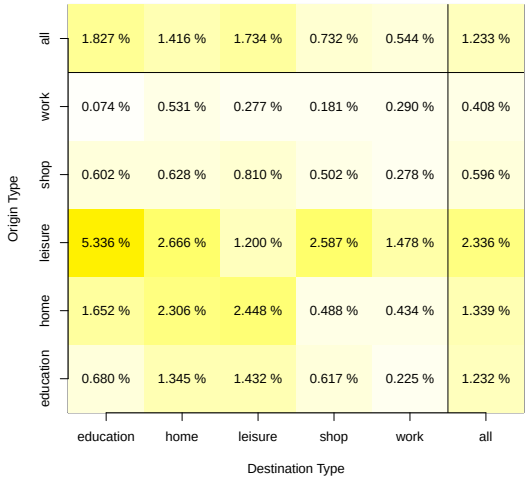
topologies, and analyzes the kind of results that were obtained.

The outcome of both solution concepts are quite different, and it seems a hybrid solution concept would be optimal. A particularly difficult problem seems to be to achieve realistic shares for shared (car) rides, while maintaining realistic travel distance distribution.

Though the analysis here was focused on households, one of the two solution concepts is applicable for any social network topology. The application of this concept for friendship network is being experimented with, to verify the hypothesis that considering social activities can help in the prediction of leisure trip distributions.

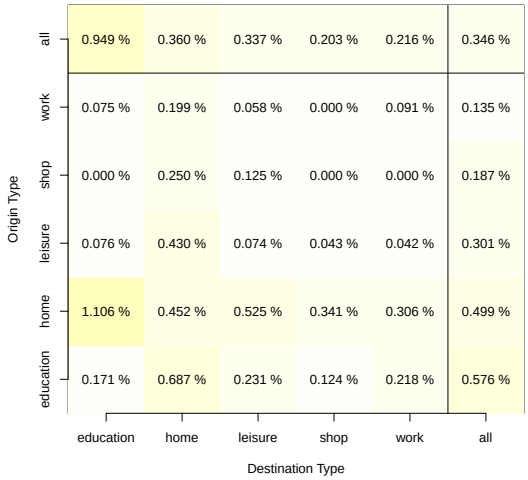
Figure 7: Passenger Mode Share per Purpose

(a) ABC.t

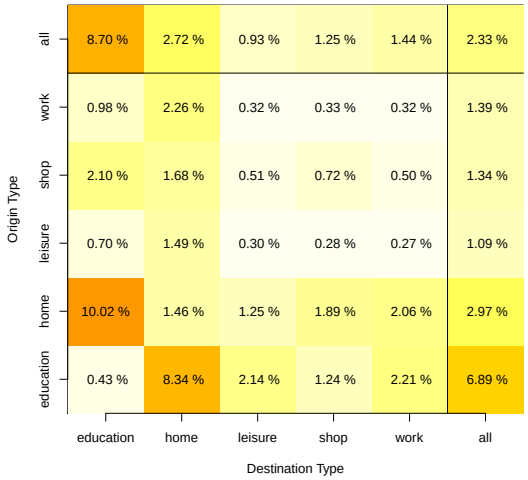


(b) GU.t

(c) ABC.s



(d) GU.s



(e) National Travel Survey

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