Cooperative location choice for leisure activities

Johannes Illenberger
Transport Systems Planning and Transport Telematics, TU Berlin, D-10587 Berlin
phone: +49 30 314 78793
fax: +49 30 314 26269
illenberger@vsp.tu-berlin.de

words: 6256, in captions: 231, figures: 4 (4x250) = 7478

VSP working paper 12-13, see www.vsp.tu-berlin.de/publications

Abstract

The joint participation in activities represents a major determinant of leisure travel. Following this observation, researchers have started to build models that involve the social network in the activity planning process. Existing studies, however, are still in a state of rather explorative research. This article intends to shed some light on the practical use of social networks in a leisure travel demand model. Two models are proposed, one with cooperating individuals, where the cooperation is determined by a social network generated from empirical observations, and one with independent individuals. Comparing both models in a scenario using real-world land-use and population data shows that the impacts of the social network become irrelevant at a macroscopic scale. Yet, at the microscopic scale, the social network contributes to the explanation of the dynamics of cooperation and joint activity participation.

1 Introduction

In european countries, leisure represents the dominating purpose for human mobility. For instance, in Germany the share of leisure related trips is about 32 %, in the UK about 31 %, and in Switzerland even up to 41 %. The amount of research, however, appears to be at odds with the dominance of leisure travel. A query to Google's search engine for scientific articles (scholar.google.com) results in 446 entries with the words "work" or "commuter" and "travel" in their title. The result of a query for articles with the words "leisure" and "travel" in their title counts 260 entries.[1] Nevertheless, research on leisure related mobility is increasing and has gained important insights that explain the heterogeneity of that travel segment. Existing studies agree that a crucial aspect of leisure activities is the question "with whom" activities are conducted (Berg et al., 2010, 2012; Carrasco, 2006; Srinivasan and Bhat, 2008). For instance, going to a restaurant is not only for the purpose to have something to eat, it is also for the purpose to socialise with other people.

The usual travel survey does not include information about with whom activities are conducted. However, realising that the actor's social environment represents an important component in the decision making process, researchers have started to survey the actor's mobility patterns and social network simultaneously (Berg et al., 2008; Carrasco, 2006; Kowald and Axhausen, 2012; Silvis et al., 2006). These studies combine tools of transport engineering and social network analysis. Results have made their way into simulation models, usually of microscopic architecture, investigating the influence of the social network on the decision behaviour (Arentze and Timmermans, 2008; Hackney and Marchal, 2011; Marchal and Nagel, 2005; Ronald et al., 2012). While these models provide useful insights from a theoretical perspective, they are often restricted to "sandbox" scenarios and are rather of explorative nature missing any validation with empirical data. Moreover, it is still unclear how much explanatory power a social network features and at what level of detail the impacts of a social network become relevant.

This article intends to shed some light on the practical use of social networks in a model for leisure travel. Two models are proposed: A reference model where the activity planning is conducted independently for each individual, and a cooperative model where individuals jointly plan and conduct leisure activities. With whom individuals plan and conduct activities is determined by an underlying social network, which is generated based on empirical observations. Using a simulation scenario with real-world land-use and population data, the question is addressed which properties of a social network become at which level of detail of the analysis relevant to the model.

The reminder of this article is organised as follows: Section 2 provides a concise review of existing studies on leisure travel and simulation models incorporation social networks. The simulation framework, the simulation scenario, and both models, the reference model and the cooperative model, are presented in Sec. 3. Several simulation experiments are conducted and analysed from a macroscopic and a microscopic perspective in Sec. 4. Section 5 closes the article with a conclusion.

2 Related Work

Based on an increasing availability of empirical data sets, researchers have gained important insights into leisure travel behaviour. On the basis of the 2000 San Francisco Bay Area Travel Survey, Bhat and Gossen (2004) investigate the patterns of weekend in-home and out-of-home leisure activities depending on household and individual socio-demographics, as well as land-use variables. The timing and frequency of leisure activities is analysed by Kemperman et al. (2006) using data from the Netherlands. Surveying more than 800 respondents in Switzerland, Ohnmacht et al. (2009) classify leisure mobility into different mobility styles to explain the heterogeneity in travel behaviour. While the above studies investigate in the variance of travel patterns among individuals, longitudinal data sets, such as the German 6-week travel diary "Mobidrive", allow to investigate the variations of individuals' travel patterns

[1] The queries are "`allintitle: travel work OR commuter -non`" and "`allintitle: leisure travel -non`".

over time (Schlich et al., 2004; Tarigan and Kitamura, 2009). Generally, the above studies agree that a lot of heterogeneity in leisure travel behaviour is explained by the heterogeneity of the households' and the individuals' socio-demographic attributes. Travel involved in leisure activities is at average longer, in terms of time and distance, and activities are usually driven by the need for social interaction with friends or relatives. Research has realised that the latter aspect, the question "with whom", offers a lot of explanatory potential.

Activities conducted jointly with household members and non-household members are analysed by Srinivasan and Bhat (2008). However, since the usual travel survey does not include detailed information about non-household members, researchers have started to survey the individuals' travel behaviour and social network simultaneously. Berg et al. (2010, 2012) addresses the question of how the "with whom" influences the activity scheduling. Data from a social interaction diary collected in the Netherlands reveals that activity duration increases if activities are conducted jointly. Activities become more likely to be prearranged if the number of participants increases or the distances between participants increases. That is, activities with high scheduling complexity are preplanned. Similar observations are made by Habib and Carrasco (2011): Social activities tend to be longer if more people are involved, and people with more social contacts tend to have longer social activities.

There are a couple of simulation models that incorporate these empirical observations. Middelkoop et al. (2004) propose a model for annual activity-travel patterns of leisure and vacation travel that is built upon a set of discrete choice models and rule-based models. The model of Bradley and Vovsha (2005) for daily activity patterns involves an added utility for joint participation in activities. This adds much of realism to the model as it prevents the construction of unrealistic entire-household patterns, such as a preschool child staying at home while all adults go to work. Social influences on the decision of residential locations are addressed by Páez et al. (2008). In their model, individuals are linked by a social network over which the decision makers can exchange information and learn from the decisions of others. The simulation results show the influence of the social network topology on the decisions: While the clustering coefficient is almost irrelevant, variations of the degree distribution has implications on the outcomes at the macroscopic level.

The interaction between social networks and travel behaviour is reciprocal (Larson et al., 2006): Social networks and travel patterns coevolve in that, on the one hand, the social network induces travel, and on the other hand, travel opportunities enables the spread of the social network. The idea of coevolution is incorporated in the simulation framework of Arentze and Timmermans (2008), where social connections are created and dissolved according to the individuals' attributes and their travel patterns. Persons can interact if they meet at the same place at the same time and exchange information through the social network. While the complexity of Arentze's and Timmermans' model limits its applicability to small scenarios, Marchal and Nagel (2005) and Hackney and Marchal (2011) seize the same idea, yet in a large-scale context and with an underlying traffic flow model. Traditional models for location choice require the enumeration over all alternatives. The work of Marchal and Nagel (2005) emphasises that the inclusion of social networks as an information exchange channel offers the construction of plausible choice sets in reasonable computation times. In the simulation model of Hackney and Marchal (2011) social connections are created or reinforced if people meet at the same place in an overlapping time window, and fade out over time if they are not reinforced. An added utility for joint activities compensates for longer trips and shorted activity durations, and moreover, it draws agents together in the same spatiotemporal patterns. In contrast to the latter two simulation models, the model of Ronald et al. (2012) explicitly models cooperative planning of activities, yet lacking an underlying traffic simulation. In Ronald's model, individuals negotiate about social activities from which they gather information about new activity locations and acquaintances. It is shown that person with a lot of social contacts participate in more activities, and that persons who are similar in their socio-demographics tend to socialise more often.

The discussed models provide useful insights into the reciprocal interaction between travel behaviour and social networks. However, the rather explorative character of all models has not resulted in applicable travel demand models, yet. With the exception of Marchal and Nagel (2005) and Hackney and Marchal (2011), none of them uses real-world land-use data, nor do they use social networks based on real-world observations. The model proposed in this article intends to do a step into the direction of building a travel demand model applicable for real-world scenarios. The article presents a simulation model of cooperating agents that are linked through a social network, which based on real-world observations, and test our model on real-world land-use data.

3 Simulation Models

3.1 Simulation Framework

The simulation framework uses the concepts and code parts of the MATSim project (Multi Agent Transport Simulation, www.matsim.org, accessed July 2012). It implements the agent-based approach where each actor in the social network as well as in the transport system is modelled as an individual software entity denoted as agent. Each agent posses a *day-plan* describing the activities it intends to perform during a 24 hours period. A day-plan consists of a sequence of activities connected by travel legs. An activity specifies the type, location and end time. A travel leg specifies the path through the road network from the previous to the next activity.

The simulation framework distinguishes between a mental and physical layer, which are iteratively executed in alternating order. The mental layer takes over the scheduling of activities in the day-plan. Agents can either cooperatively or independently re-schedule their day-plans. Day-plans are simultaneously executed as best as possible conditional on physical constraints in the physical layer. Based on the feedback of the physical layer, day-plans are evaluated and either accepted or rejected. This procedure can be considered as a Markov process with the agents' day-plans as state vector. For the identification of agents in the social network, the nomenclature of the sociologists is used: An agent of interest is called *ego*, its neighbours in the social network are called *alters*. The terms vertex, ego, agent, and individual are synonymously used throughout this article.

3.2 Scenario Description

Switzerland is used as the simulation scenario. From census data (Swiss Federal Statistical Office, 2005) a synthetic population is generated (Balmer, 2007). That is, a random realisation of census data such that a census on the synthetic population would approximately result in the statistics of the original census. The synthetic population counts more than 140 k persons, which corresponds to a 2 % sample of the entire Swiss population.

A usual Sunday is considered as the simulation period. This simplifies the scenario with respect to two aspects: (i) About 75 % of trips are related to leisure activities (Federal Office for Spatial Development and Swiss Federal Statistical Office, 2007) so that just about 25 % of trips remain unexplained by this model. (ii) The average Sunday activity episode consists of 1.6 out-of-home activities. Considering only *home–leisure–home* activity episodes in the simulation model represents thus a reasonable approximation.

Each agent posses a desired leisure activity type: *visit* means visiting other people at their residential location, *culture* comprises going to a movie theatre, concert, museum, doing active or passive sports, outdoor recreational activities or similar, and *gastro* denotes going to a restaurant or bar. The activity type *visit* implies that this activity is jointly done with at least one other person. In contrast, activities of type *culture* and *gastro* can be also conducted alone. The desired activity type for each agent is a priori determined by a weighted random draw with weights according to the trip purpose share of the Swiss national travel survey (Federal Office for Spatial Development and Swiss Federal Statistical Office, 2007). Furthermore, each agent posses a desired start time and desired duration for each possible leisure activity type. They are both a priori generated random realisations from the Swiss national travel survey. Specific to each leisure activity type are also the individual location choice sets. In case of *visit*, it is given by the residential locations of the ego and its alters (or a sub-sample of alters, depending on the model, see below). The fact that the choice set contains also the ego's residential location implies that staying at home in order to receive a visit is also a valid option. In case of *culture* and *gastro*, choice sets are manually generated by randomly drawing facilities from land-use data according to the probability distribution

$$P_i(l_a) = \kappa_a \cdot d(i, l_a)^\gamma \ , \tag{1}$$

where $d(i, l_a)$ denotes the beeline distance between i's residential location and facility l_a with an activity opportunity for type a. Parameter γ is arbitrarily set to -1.4.[2] The constant of proportionality κ_a controls the expected number of locations in the choice set and is adjusted so that each individual knows at average about five locations. The spatial distribution of facilities where activities of type *culture* or *gastro* can be performed are taken from the census of enterprises (Swiss Federal Statistical Office, 2007). This data contains 28095 facilities for activities of type *gastro* and 7243 facilities for activities of type *culture*.

3.3 Reference Model

3.3.1 Model Description

In the reference model, the agents' decision process is independent from other agents. Yet, agents are linked through a social network, which, however, affects only the location choice of *visit* activities. Each agent is initialised with a day-plan including three activities. The first and last activities are of type *home* and located at the agent's residential location. Both activities are fixed in type, location, and position within the plan and do not change over the course of the simulation. The second activity is initialised with the priori given desired activity type, the a priori given desired start time and desired duration, and at a random location, which, however, can change during the simulation. The simulation logic proceeds as follows: Select an agent uniformly at random. Randomly select a location out of the choice set of activity locations specific to the desired activity type. The agent's day-plan is then modified according to the above location decision and executed in the physical environment. From the feedback of the physical environment, which are in this case activity start and end times, the utility of the new plan is calculated. The new plan is likely to be accepted if the utility is greater than the utility of the old plan.

Let $\mathcal{V}$ be the set of vertices in the social network. $\mathbf{P}$ denotes a vector of plans with one entry p_i for each individual in $\mathcal{V}$. $\mathbf{P}_k$ denotes the plans vector at iteration k. The formal specification of the simulation logic is:

1. Randomly select an agent i.
2. Randomly select a new activity location l from the a priori given location choice set, which is specific to each activity type a and to the agent i.
3. Create a new state vector $\mathbf{P}_{k+1}$ with the plan of agent i modified according to the choice l, the a priori given desired arrival time $t_a^{(\mathrm{arr})}$, and desired duration $t_a^{(\mathrm{dur})}$ while leaving all remaining plans unchanged. The end time of the preceding *home* activity is adjusted so that the agent is expected to arrive in time at the leisure activity location.
4. Execute $\mathbf{P}_{k+1}$ in the physical environment.
5. Calculate the utility sum $\bar{V}_{k+1} = \sum_{i \in \mathcal{V}} V(p_{i,k+1})$.
6. Accept $\mathbf{P}_{k+1}$ with transition probability $\pi = \exp\left(\bar{V}_{k+1}\right) / \left(\exp\left(\bar{V}_{k+1}\right) + \exp\left(\bar{V}_k\right)\right)$ or return to state $\mathbf{P}_k$ otherwise.
7. Repeat step 1–6 until the system reaches a steady state distribution.

Note that in the reference model, for each agent $j \neq i$ the utility does not change: $V(p_{j,k}) = V(p_{j,k+1})$. Thus, the expression for π collapses to $\pi = 1/(1+\exp(V(p_{i,k}) - V(p_{i,k+1})))$ so that it depends only on the changes of i's utility.

[2] Parameter γ is set arbitrarily, yet somewhat consistent with the exponent of the power-law with which individuals accepts other persons as social contacts (Sec. 3.5).

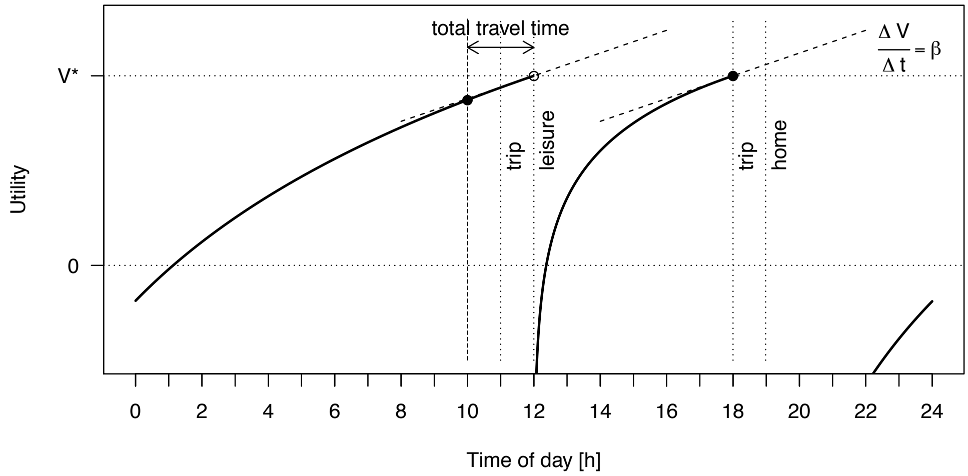


Figure 1: Illustration of the utility function. The day-plan contains two activities: A leisure activity with start time 12:00 and a duration of 6 h and a home activity with desired start time 18:00 and a desired duration of 18 h. The trip between both activities takes 1 h. The travel time is taken from the home activity, and thus the realised realised durations reduces to 16 h. The total utility is obtained by summing up the partial utilities indicated by the black dots (•).

3.3.2 Utility Function

The utility of a plan depends only on the activity start times and end times. The function $V(p_i)$ evaluates activities with positive utility and represents a stripped-down version of the utility function proposed by Charypar and Nagel (2005):

$$V(p_i) = \sum_n V_n^{(\text{act})} \;, \tag{2}$$

where n denotes the indices of the activities. The utility of performing an activity is modelled logarithmically in activity duration $t^{(\text{act})}$:

$$V^{(\text{act})} = \beta \cdot t_a^{(\text{dur})} \cdot \ln\left(\frac{t^{(\text{act})}}{t_a^{(\text{dur})}} \cdot \exp\left(\frac{V^{(\text{act})*}}{\beta \cdot t_a^{(\text{dur})}}\right)\right) \;, \tag{3}$$

where β denotes the marginal utility (the function's slope) at the desired duration $t_a^{(\text{dur})}$, and $V^{(\text{act})*}$ denotes the resulting utility if $t^{(\text{act})} = t_a^{(\text{dur})}$. For leisure activities, the desired duration $t_a^{(\text{dur})}$ is a priori given. The desired duration of the home activity is then given by $t_{(\text{home})}^{(\text{dur})} = 24\text{ h} - t_a^{(\text{dur})}$. Although, a day-plan consists of two home-activities, the first and the last activity, during the evaluation both activities are treated as one activity such as if the succeeding day would be executed with the same day-plan. That is, the merged home activity starts at the beginning of the second home activity and ends at the end of the first home activity. This accounts for the fact that the simulation starts at midnight and thus the home activity is unintentionally split into two activities. Travel time is implicitly evaluated with negative utility. The longer a travel leg takes, the shorter the realised home activity duration. If the realised duration is less then the desired duration, the utility for that activity decreases (Fig. 1).

3.3.3 Physical Environment

The physical environment determines the activity start and end time given the constraints of the road network. To make this simulation approach computational feasible, the standard queueing model in MATSim is replaced by a pseudo simulation. Travel times are calculated on the basis of an uncongested road network and are multiplied by a factor of three. This means that there is no explicit traffic flow model. The pseudo simulation neglects any capacity constraints and does not know about congestion effects. The factor of three is intended to account for different means of transportation and is validated by comparing travel distances and travel times from the Swiss national travel survey. The road network counts 60 k links, representing motorways and trunk roads in rural regions and additionally main roads in conurban areas.

3.4 Cooperative Model

3.4.1 Model Description

The dynamics of the cooperative model are driven by the agents' desire to perform joint activities with other agents of their social network. An agent randomly selects a subset of its alters to cooperate with for the activity planning. One can consider this as an invitation to all alters to conduct a joint activity, whereas alters randomly accept or reject the invitation. The ego and the randomly drawn alters are denoted as an activity group. The activity type of the inviting ego determines the choice set of possible activity locations. If the activity is of type *visit*, the joint location choice set includes the residential locations of each activity group member. Again, each agent has its own a priori generated location choice set for activities of type *culture* and *gastro*. The joint location choice set for *culture* and *gastro*, respectively, is then built by merging each activity group member's individual choice set into one set. From the joint location choice set a random activity location is selected. This can be considered as a sharing of knowledge about activity locations between agents, yet agents do not remember locations of other agents in succeeding iterations. The selection process for the activity duration and arrival time works in the same manner. All members of the activity group adapt their plan according to the location, start time, and duration of the joint activity. The adapted plans are simulated in the physical environment. This determines the realised activity start and end times, as well as the realised joint activities. If activities are conducted jointly with alters they gain an extra utility for socialising in the evaluation process. Formally, the cooperative simulation procedure works as follows:

1. Randomly select an ego i from the set of vertices $\mathcal{V}$.
2. Create an activity group by (i) drawing a random number p between 0 an 1, (ii) adding each alter of i with probability p to the activity group, and (iii) adding the ego itself to the activity group.
3. Set the activity type a of the joint activity to the one a priori assigned to ego i.
4. Randomly select a location l from the location choice set that is constructed by joining each activity group member's individual location choice set.
5. Randomly select an arrival time $t^{(\mathrm{arr})}$ from the arrival time choice set, which contains each activity group member's desired (and a priori given) arrival time.
6. Randomly select an activity duration $t^{(\mathrm{dur})}$ from the activity duration choice set, which contains each activity group member's desired (and a priori given) activity duration.
7. Create a new state vector $\mathbf{P}_{k+1}$ with the plans of the members of the activity group modified according to the choices a, l, $t^{(\mathrm{arr})}$ and $t^{(\mathrm{dur})}$, while leaving the remaining plans unchanged.
8. Execute $\mathbf{P}_{k+1}$ in the physical environment.
9. Calculate the utility sum $\bar{V}_{k+1} = \sum_{i \in \mathcal{V}} V\left(p_{i,k+1}\right)$.
10. Accept $\mathbf{P}_{k+1}$ with transition probability $\pi = \exp\left(\bar{V}_{k+1}\right) / \left(\exp\left(\bar{V}_{k+1}\right) + \exp\left(\bar{V}_{k}\right)\right)$ or return to state $\mathbf{P}_k$ otherwise. .
11. Repeat step 1–10 until the system reaches a steady state distribution.

This simulation logic has two implications: First, either the entire activity group accepts their new plans, or the entire activity group rejects their new plans. It is not possible that just some members accept the new plans, while the others remain with their old plans. An interpretation of this would be that if one member would personally gain less utility with the new plan while the remaining members gain more utility (so that the systems' total utility increases), it still would accept the new joint activity in order to do the remaining members a favour. Second, the change of the system's total utility is not only dependent on the utility change of the activity group but also on the utility change of the activity group members' alters. This mean that if one agent leaves an activity group in order to join a new activity group, the transition probability accounts also for a possible loss of utility of the old activity group.

3.4.2 Utility Function

The utility function of the reference model is extended with a utility component to reward socialising. Agents that are linked through the social network and conduct a joint activity gain an extra positive utility. The extended utility function reads:

$$V(p_i) = \sum_n \left(V_n^{(\mathrm{act})} + V_{i,n}^{(\mathrm{join})} \right) , \tag{4}$$

where $V^{(\mathrm{join})}$ denotes the utility for socialising (see also Bradley and Vovsha, 2005; Hackney and Marchal, 2011). It is a function of the fraction of participating alters:

$$V_i^{(\mathrm{join})} = V^{(\mathrm{join})*} \left(1 - \left(\frac{f_i - f_a^*}{f_a^*} \right)^2 \right) , \tag{5}$$

where f_i denotes the fraction of the ego's alters that join the activity, and $V^{(\mathrm{join})*}$ denotes the maximum utility that can be obtained if the activity is performed with the desired fraction f_a^* of alters. Fraction f_a^* can be specific to activity type a. This function implies that conducting an activity with too many alters is likewise bad as conducting an activity with too few alters, where conducting an activity with no alters yields always no socialising utility. Further, the definition is independent from the time agents join, and it also specifies that staying at a location with a foreign person does not contribute any socialising utility. The desired fraction f_a^* is rounded to realisable values for practical evaluation. That is, if an agent possesses five alters and intends to meet with half of its alters ($f_a^* = 0.5$), then f_a^* is rounded to 0.6 so that the maximum utility $V^{(\mathrm{join})*}$ can be achieved.

While in the reference model the only degree of freedom is the choice of locations, the cooperative model implicitly introduces the activity type, activity start time, and activity duration as additional choice dimensions. Regarding time choice, the function describing the utility for conducting an activity $V^{(\mathrm{act})}$ has two decisive features (see also Charypar and Nagel, 2005). First, the maximum utility is gained if activities are performed at their desired duration. For instance, extending the leisure activity for one hour while shortening the home activity for one hour yields less utility. The logarithmical form of the function causes that the additional utility for the extended leisure activity is less than then the loss of utility for the shortened home activity. Second, if both activities cannot be performed at their desired duration because the trip between both activities requires time, the travel time is taken from the activities proportional to their desired duration. The derivative of $V^{(\mathrm{act})}$ with respect to $t^{(\mathrm{act})}$ decreases slower for activities with a long desired duration compared to activities with a short desired duration. That is, shortening a longer activity yields less utility loss than shortening an already shorter activity.

3.4.3 Physical Environment

The physical environment of the cooperative model additionally needs to determine if activities are conducted jointly. Activities are conducted in facilities linked to the transportation network. The simulation registers if an agent enters and leaves a facility. From this information it is determined if an ego and alter rest at the same facility for an overlapping time window.

Apart from the fact that the pseudo simulation does not have a computational expensive traffic flow model, the only interaction of agents remains in the joint performing of activities. The physical environment only needs to simulate those agents that are affected by the decisions of the activity group. In particular, these are the members of the activity group, the members' alters because their utility may change, and the alters of the alters, that is, agents that are two edges distant from the egos. The latter group of agents is required in order to properly determine the joint activities of the activity group members' alters.

3.5 Social Network

Agents are linked through a social network. The type of the social relations between agents can be considered as friendship or kinship, that is, contacts individuals physically meet for leisure activities. The social network is assumed to be given and does not change over the course of the simulation. The structure of the social network and the process of network generation is described in detail in Illenberger et al., accepted. The following paragraphs provide a concise overview of those aspects that are relevant for this model.

The social network is based on empirical data obtained from a survey that collects data on a social network of leisure contacts in Switzerland (Kowald and Axhausen, 2012). The sampling design involves a so-called *snowball sampling* technique. In a snowball sample, respondents are asked to report their social contacts, which are then invited to participate in the survey as well. The new respondents are asked to report their social contacts, which in turn also are invited. This iterative process is continued until a predefined number of iterations is conducted or the desired number of samples is collected. The name of the approach stems from the image of a snowball accumulating more and more material when it is rolled through the snow.

The network model generates social networks that reflect the empirical network with respect to the following properties:

- The degree distribution (distribution of number of contacts per person) follows a log-normal distribution. The mean degree is $\langle k \rangle = 14.9$, and the maximum degree is $\max[k] = 43$. Each individual posses at least one social contact.
- The probability that an individual accepts an other person as social contacts scales in distance d with the power law $p(d) \sim d^{-1.4}$.
- Individuals tend to connect to other individuals of same age and same gender. The Pearson correlation coefficients yield $r_{(\text{age})} = 0.54$ and $r_{(\text{gender})} = 0.34$, respectively.

The spatial structure of the generated social network is decisive for the travel demand model. On the one hand, it defines the spatial distribution of activity locations with purpose *visit*, and on the other hand, it determines the spatial distribution of the members of an activity group.

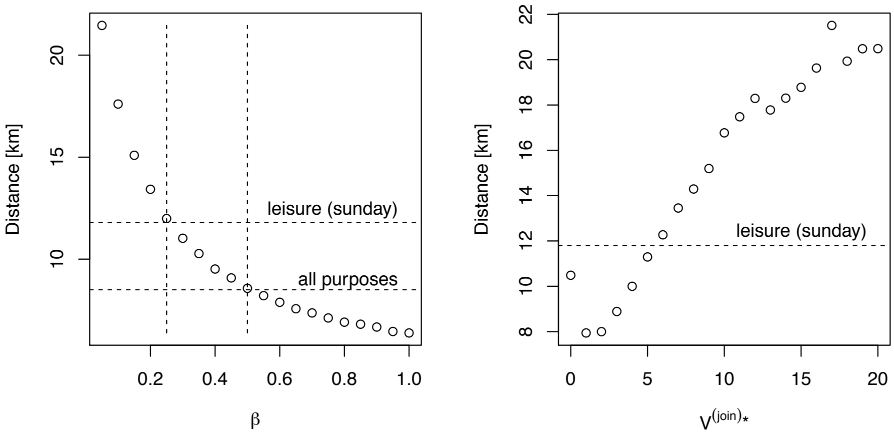
The network generation process involves two phases: In the first phase, a network is generated with the desired degree distribution but that is random with respect all other properties. Each vertex is assigned a degree randomly drawn from the desired degree distribution. Then, random vertex-pairs are drawn and connected if the degree of both vertices is less than their target degree. This process is repeated until all vertices reached their target degree. Self-loops and double-edges are not allowed.

In the second phase, edges are re-order based on spatial and social interaction forces. The re-ordering process, however, does not change the vertices' degrees. This is achieved by flipping edges (ij) and (uv) to (iu) and (jv). The spatial interaction force incorporates the probability that individuals accept other individuals as social contacts with $\sim d^{-1.4}$, and the social interaction force incorporates the homophily effects with respect to age and gender. The re-ordering process is repeated until the system reaches a steady state distribution.

4 Simulation Experiments

4.1 Macroscopic Perspective

In the reference model, the location of the leisure activity represents the only degree of freedom. The distance to the selected location is controlled by the marginal utility β, which represents the only adjustable parameter. Figure 2(a) shows the average



(a) (b)

Figure 2: (a) Average distance to selected leisure activity location depending on β in the reference model. (b) Average distance to selected leisure activity location depending on $V^{(\text{join})*}$ in the cooperative model.

distance while varying the marginal utility. Increasing the marginal utility reduces the average distance to the realised activity location because then travel time causes more utility loss. One can say that agents react more sensible towards travel time. The approximate average distance of 11.8 km for Sunday leisure trips observed in the Swiss travel survey is obtained by setting $\beta \approx 0.25$.

With the utility for joint activities $V^{(\text{join})}$, the cooperative model adds a second adjustable parameter. Increasing $V^{(\text{join})*}$, to be interpreted as making joint activities more attractive, increases the average distance (Fig. 2(b)). This means that the cooperative model features a mechanism to adjust the distance for leisure trips independent from the marginal utility. For instance, consider setting β to 0.5, which would be the corresponding value for all trip purposes in the reference model, then, setting $V^{(\text{join})*} \approx 5$ results in the correct average distance for leisure trips in the cooperative model.

The similarity between the reference model and the cooperative model is explained by considering the choice probabilities. In the logit choice model, the utility of an alternative is model as a composition of the systematic utility and a Gumbel distributed error term accounting for the unobserved heterogeneity (Train, 2003). In the reference model, this leads to

$$U(p_{i,l}) = V(p_{i,l}) + \epsilon \tag{6}$$

where $U(p_{i,l})$ denotes the utility of i's plan that includes a leisure activity at location l, and ϵ denotes the Gumbel distributed error term. Factoring out β of $\sum_n V_n^{(\text{act})}$ (Eq. 2), Eq. 6 can be rewritten as

$$U(p_{i,l}) = \beta \cdot \tilde{V}(p_{i,l}) + \epsilon \; . \tag{7}$$

In the logit choice model, this translates to the choice probability

$$\pi(p_{i,l}) = \frac{\exp\left(\dfrac{\beta}{\sigma}\tilde{V}(p_{i,l})\right)}{\sum\limits_k \exp\left(\dfrac{\beta}{\sigma}\tilde{V}(p_{i,k})\right)} \; , \tag{8}$$

where $\sum_k$ goes over all alternatives and the marginal utility β is rescaled by the *scale parameter* σ, which corresponds to the variance of the Gumbel distributed error term. This means that a greater variance of the error term (more heterogeneity) yields a smaller coefficient of $\tilde{V}(p_{i,l})$ in the logit model, and thus the choice becomes more random.

Both models, the reference model and the cooperative model, implicitly add an error term with scale paramter $\sigma = 1$ in step 6 (Sec. 3.3.1) and step 10 (Sec. 3.4.1)

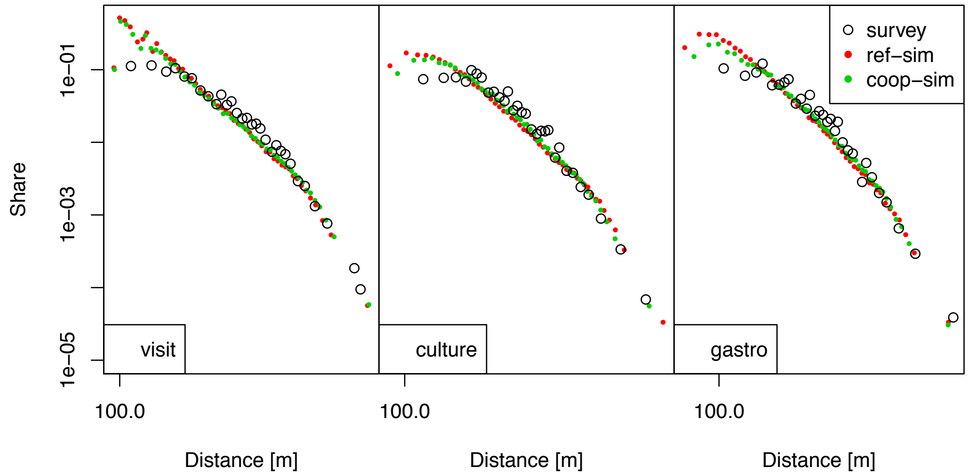


Figure 3: Trip distance distributions classified according to leisure activity type.

of the simulation logic, respectively. For illustration, consider the error term as a utility offset that is assigned to each activity location. Increasing the variance of the distribution, that is, increasing the absolute value of the offsets, results in more random choices and consequently more distant locations. Equally, one can decreases the marginal utility β.

In the cooperative model, an additional utility offset is assigned to each location where a joint activity is conducted. This offset is determined by the utility for socialising $V^{(\text{join})}$. It is rather binary distributed than Gumbel distributed, and its spatial distribution is determined by the social network rather than being fully random. Albeit the distribution of $V^{(\text{join})}$ violates the requirements of the logit model (not iid Gumbel distributed), it yields the same effect: Increasing the variance of the distribution of $V^{(\text{join})}$, which is achieved by increasing $V^{(\text{join})*}$, makes the choice of locations more random and distances increase (for a similar approach see also Horni et al., 2012).

Figure 3 shows the distance distribution for each considered leisure activity type. The distributions of the reference model and the cooperative model are almost congruent. In comparison to the empirical trip distribution, both simulation models predict too many trips in the very short distance domain (< 1 km) and slightly too few trips in the mid-range domain (1–10 km). On the one hand, this can be a result of the missing traffic flow model so that very short distances are simulated with a too short travel times. On the other hand, the survey data may lack very short trips due to underreporting (see also Bricka and Bhat, 2006) so that the empirical distribution shows fewer trips then actually conducted.

4.2 Microscopic Perspective

With respect to trip distance distributions, both models exhibit almost congruent results. Turning to a microscopic analysis, however, reveals the shortcomings of the reference model. Quite obvious, the reference model does not know about joint activities, and thus *visit* activities, which are per definition joint activities, are conducted alone. One can imagine this as an agent travelling to a friend's home without that friend being at home.

The concept of activity groups allows the cooperative model to reproduce (at least in a qualitative regard) the empirical observation that an increasing number of participants reduces the average distance to the joint activity (Fig. 4(a)). This effect is explained with costs induced by a greater willingness to compromise agents are required to exhibit in activities with many participants. Each agent has a desired activity duration. A divergence of the realised duration from the desired duration yields in less utility. If activity groups consist of two participants, than those groups in which the desired duration of both participants is most congruent, that is, those groups that yield a greater utility, are preferred. If the number of participants increases, there is more heterogeneity within the group with respect to the desired duration so that it

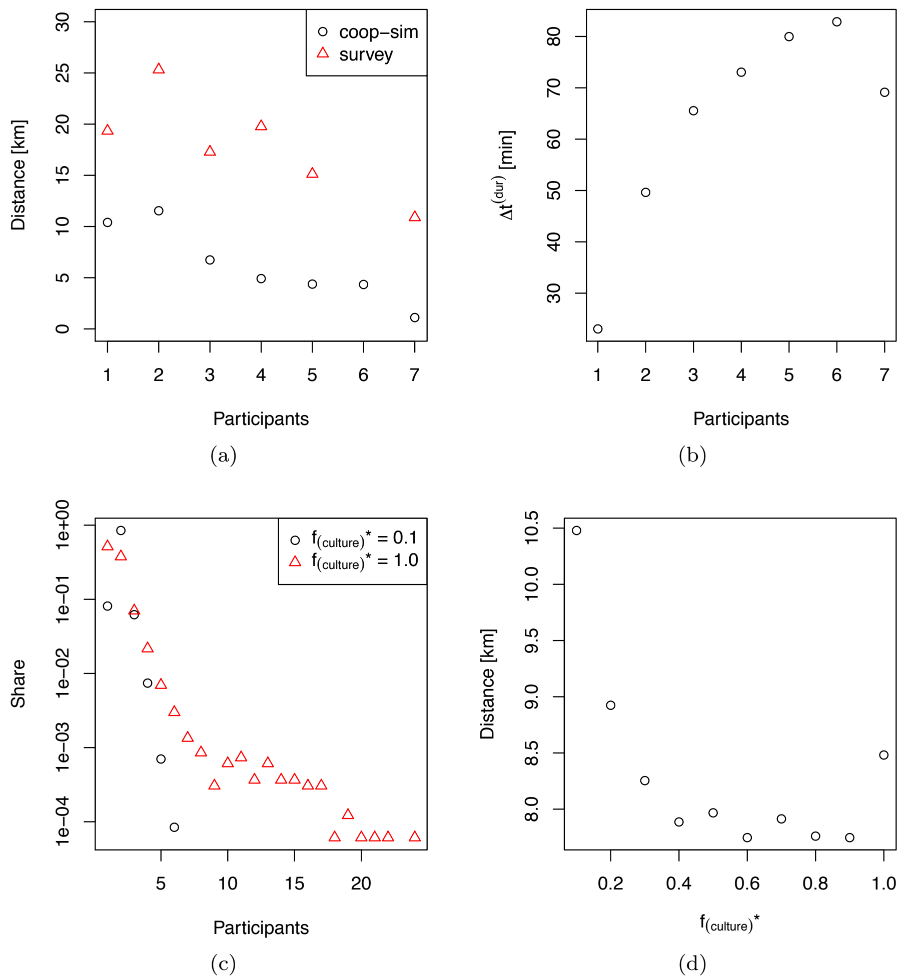


Figure 4: Microscopic dynamics of the cooperative model: (a) Trip distance depending on the number of participants: Comparison between census data and results of the cooperative model. (b) Average difference between realised and desired activity duration depending on the number of participants. (c) Distribution of activity group sizes depending on the fraction of participating alters $f^*_{(\mathrm{culture})}$. (d) Average trip distance to *culture* activities depending on the fraction of participating alters $f^*_{(\mathrm{culture})}$.

is more probable that a participant does not meet its desired duration (Fig. 4(b)). This means that agents need to compromise regarding the activity duration, which is quantified by a utility loss. This utility loss, however, is compensated by choosing more nearby activity locations so that the travel time decreases, which in turn positively affects the utility.

Following the above causality, the distribution of activity group sizes affects the average trip distances. The distribution is controlled by the desired fraction f_a^* of alters an agent intends to join with. The parameter f_a^* can be set individually to each leisure activity type. Increasing the desired fraction causes the distribution of activity group sizes to evolve into two extrema: There are a few groups with many participants and many groups with just one participant, that is, the agent conducts the activity alone (Fig. 4(c)). Increasing f_a^* makes activities with more participants more attractive. However, if the utility loss induced by the divergence of the realised duration from the desired duration becomes to high, for single participants it is more beneficial to drop out of the activity group and conduct an activity alone. As a consequence, increasing f_a^* yields, on the one hand, greater activity groups having shorter trips, and on the other hand, more single activities that gain no joint utility and thus also exhibit shorter trips compared to joint activities with two participants (Fig. 4(d)).

Apart from the spatial structure, the network's social structure affects the resulting travel patterns. In the social network, persons tend to be connected to other persons of same gender and similar age. Both kinds of homophily are recovered in the structure of activity groups: Participants of an activity group tend to be of same gender and similar age. The Pearson correlation coefficient of the participants' age is $\tilde{r}_{(\text{age})} = 0.52$ and of the participants' gender is $\tilde{r}_{(\text{gender})} = 0.31$. Both values are quite close to the correlation coefficients found for the contacts in the social network: $r_{(\text{age})} = 0.55$ and $r_{(\text{gender})} = 0.34$. However, at the aggregated level, these effects are irrelevant because age and gender are equally distributed in space. This means that the homophily effects observed in the activity groups have no impact on the spatial distribution of trips.

5 Conclusion

The study presented in this paper makes a step out of the "sandbox" of purely explorative models incorporating social networks and travel behaviour. Using real-world population and land-use data and a social network generated from real-world observations, this work sheds some light on the alleged explanatory power of social networks in travel demand modelling. The key finding is that with respect to those aspects analysed, the question of "with whom" can be reduced to the question of "where". That is, it is not the organisational structure of the social network that is decisive for the resulting travel patterns, it is just its spatial structure. This knowledge is gained by comparing a reference model, where the planning process of agents is independent of other agents, and a cooperative model, where the planning process is conducted jointly. In both models the spatial distribution of social contacts determines the location choice set for activities of type *visit*.

From a macroscopic perspective, both models can be calibrated so that they yield the same results. In case of the reference model, the marginal activity utility controls the distance to the chosen activity location. This appears to be a valid calibration approach considering that empirical studies observe that the perceived travel costs depend on trip purpose (Vrtic et al., 2008). The utility for socialising in the cooperative model, however, represents a further parameter that allows to calibrate travel distances without varying the marginal activity utility. That is, according to the cooperative model, longer travel distance are not explained by smaller perceived travel costs for leisure travel but by an additional utility for joint leisure activities.

Turning to a microscopic perspective, the cooperative model explains empirical observations that the reference model is incapable to reproduce. Naturally, the observation that the average travel distance of members of an activity group decreases with an increasing number of participants cannot be reproduced by the reference model since it does not model activity groups. Moreover, homophily patterns in the social network are recovered in the resulting travel patterns through the formation of activity groups. This effect, however, vanishes at the macroscopic scale because the population is, with respect to both attributes, age and gender, equally distributed over space. Considering other attributes such as income or ethnic groups, a spatial segregation is more plausible. The effects of a social network accounting for homophily with respect to these attributes would then also be visible at the aggregate level. The question that remains is how strong the spatial segregation needs to be so that it becomes relevant.

In summary, at the current state of research, there may be no practical use of social networks for an operative travel demand model since a simple model such as the reference model yields the same results. However, basically, this represents just a statistic fit, which renders the forecasting power of the model questionable. The cooperative simulation is based on a sound behavioural model that provides an illustrative and intuitive explanation why greater travel costs for leisure trips are observed. Moreover, it represents a basic concept on which further models accounting for the interplay of social networks and travel behaviour can build on: For instance, evacuation simulations accounting for joint evacuation strategies of social contacts (Kowald et al., 2012).

Acknowledgement

This work is fundeded in part by the VolkswagenStifting within the project "Travel impacts of social networks and networking tools". I thank Kai Nagel and Gunnar Flötteröd for helpful comments and suggestions.

References

Arentze, T. and H. Timmermans (2008). "Social networks, social interactions, and activity-travel behavior: a framework for microsimulation". In: *Environment and Planning B* 35.6, pp. 1012–1027.

Balmer, M. (2007). "Travel demand modeling for multi-agent transport simulations: Algorithms and systems". PhD thesis. Switzerland: Swiss Federal Institute of Technology (ETH) Zürich.

Berg, P. van den, T. Arentze, and H. Timmermans (2008). "Social networks, ICT use and activity travel patterns: Data collection and first analyses". In: *Proceedings of the International Conference on Design & Decision Support Systems in Architecture and Urban Planning*. Eindhoven.

Berg, P. van den, T. Arentze, and H. Timmermans (2010). "Factors Influencing the Planning of Social Activities". In: *Transportation Research Record* 2157, pp. 63–70.

— (2012). "A latent class accelerated hazard model of social activity duration". In: *Transportation Research Part A* 46, pp. 12–21.

Bhat, C. R. and R. Gossen (2004). "A mixed multinomial logit model analysis of weekend recreational episode type choice". In: *Transportation Research Part B* 38, pp. 767–787.

Bradley, M. and P. Vovsha (2005). "A model for joint choice of daily activity pattern types of household members". In: *Transportation* 32, pp. 545–571.

Bricka, S. and C. R. Bhat (2006). "Comparative Analysis of Global Positioning System-Based and Travel Survey-Based Data". In: *Transportation Research Record* 1972, pp. 9–20.

Carrasco, J. A. (2006). "Social activity-travel behaviour: A personal network approach". PhD thesis. University of Toronto.

Charypar, D. and K. Nagel (2005). "Generating complete all-day activity plans with genetic algorithms". In: *Transportation* 32.4, pp. 369–397.

Federal Office for Spatial Development and Swiss Federal Statistical Office (2007). *Mobilität in der Schweiz, Ergebnisse des Mikrozensus 2005 zum Verkehrsverhalten.* Neuchâtel, Bern.

Habib, K. M. N. and J.-A. Carrasco (2011). "Investigating the Role of Social Networks in Start Time and Duration of Activities". In: *Transportation Research Record* 2230, pp. 1–8.

Hackney, J. and F. Marchal (2011). “A coupled multi-agent microsimulation of social interactions and transportation behavior”. In: *Transportation Research Part A* 45, pp. 296–309.

Horni, A., K Nagel, and K. Axhausen (2012). *High-resolution destination choice in agent-based demand models*. Annual Meeting Preprint 12-1989. Washington D.C.: Transportation Research Board.

Illenberger, J., K. Nagel, and G. Flötteröd (accepted). “The role of spatial interaction in social networks”. In: *Networks and Spatial Economics*. doi: 10.1007/s11067-012-9180-4. DOI: 10.1007/s11067-012-9180-4.

Kemperman, A., T. Arentze, and H. Timmermans (2006). “Social Commitments and Activity-Travel Scheduling Decisions”. In: *Transportation Research Record* 1977, pp. 242–249.

Kowald, M., J. Koot, C. Dobler, and K. W. Axhausen (2012). *Soziales Verhalten in grossräumigen Evakuierungsereignissen in der Schweiz*. Tech. rep. 711. Institute for Transport Planning and Systems, ETH Zürich.

Kowald, M. and K. W. Axhausen (2012). “Focussing on Connected Personal Networks: Selected Results from a Snowball Sample”. In: *Environment and Planning A* 44.5, pp. 1085–1100.

Larson, J., J. Urry, and K. W. Axhausen (2006). *Mobilities, Networks, Geographies*. Ashgate, Aldershot.

Marchal, F. and K. Nagel (2005). “Modeling Location Choice of Secondary Activities with a Social Network of Cooperative Agents”. In: *Transportation Research Record* 1935, pp. 141–146.

Middelkoop, M. van, A. Borgers, and H. Timmermans (2004). “Merlin – Microsimulation System for Predicting Leisure Activity-Travel Patterns”. In: *Transportation Research Record* 1894, pp. 20–27.

Ohnmacht, T., K. Götz, and H. Schad (2009). “Leisure mobility styles in Swiss conurbations: construction and empirical analysis”. In: *Transportation* 36, pp. 243–265.

Páez, A., D. M. Scott, and E. Volz (2008). “A discrete-choice approach to modeling social influence on individual decision making”. In: *Environment and Planning B* 35, pp. 1055–1069.

Ronald, N., T. Arentze, and H. Timmermans (2012). “Modeling social interactions between individuals for joint activity scheduling”. In: *Transportation Research Part B* 46, pp. 246–290.

Schlich, R., S. Schönfelder, S. Hanson, and K. W. Axhausen (2004). “Structures of Leisure Travel: Temporal and Spatial Variability”. In: *Transport Reviews* 24.2, pp. 219–237.

Silvis, J., D. Niemeier, and R. D’Souza (2006). “Social networks and travel behaviour: Report from an integrated travel diary”. In: *Proceedings of the meeting of the International Association for Travel Behavior Research (IATBR)*. See www.iatbr.org. Kyoto, Japan.

Srinivasan, S. and C. R. Bhat (2008). “An exploratory analysis of joint-activity participation characteristics using the American time use survey”. In: *Transportation* 35, pp. 301–327.

Swiss Federal Statistical Office (2005). *Abschlussbericht zur Volkszählung 2000*. Neuchâtel.

— (2007). *Betriebszählung 2005 – Die wichtigsten Ergebnisse in Kürze*. Neuchâtel.

Tarigan, A. K. M. and R. Kitamura (2009). “Week-to-Week Leisure Trip Frequency and Its Variability”. In: *Transportation Research Record* 2135, pp. 43–51.

Train, K. (2003). *Discrete choice methods with simulation*. Cambridge University Press.

Vrtic, M., N. Schüssler, A. Erath, M. Bürgle, K. Axhausen, E. Frejinger, M. Bierlaire, R. Rudel, S. Scagnolari, and R. Maggi (2008). *Einbezug der Reisekosten bei der Modellierung des Mobilitätsverhaltens*. Schriftenreihe 1191. Final Report for Project SVI 2005/004. Bern, CH: Bundesamt für Strassen, UVEK.