Destination and Mode Choice in an Agent-Based Simulation of Long-Distance Travel Demand

Maxim Janzen

Kay W. Axhausen

Institute for transport planning and systems

May 2017

STRC | **17th Swiss Transport Research Conference**
Monte Verità / Ascona, May 17 – 19, 2017

Institute for transport planning and systems

Destination and Mode Choice in an Agent-Based Simulation of Long-Distance Travel Demand

Maxim Janzen
IVT
ETH Zurich
CH-8093 Zurich
phone: +41-44-633 33 40
email: maxim.janzen@ivt.baug.ethz.ch

Kay W. Axhausen
IVT
ETH Zurich
CH-8093 Zurich
phone: +41-44-633 39 43
email: axhausen@ivt.baug.ethz.ch

May 2017

Abstract

Analysis of long-distance travel demand has become more relevant in recent times. The reason is the growing share of traffic induced by journeys related to remote activities, which are not part of daily life. In today's mobile world, these journeys are responsible for almost 50 percent of the overall traffic. Consequently, there is a need of reliable long-distance travel forecasting tools. A potential tool is agent-based simulation. Due to the complex task of destination choice modelling, there are just few agent-based simulations available. This paper presents a continuous target-based simulation that simulates long-distance travel behavior for a long period of time. It is shown how destination choice and mode choice is modelled in this agent-based simulation. Destination and mode are chosen simultaneously along with activity type and activity duration. The presented approach uses a heuristic to reduce the choice set since the underlying multi-dimensional optimization problem is too hard to be solved directly with acceptable computational effort. Afterwards the best combination of destination, mode and activity is determined based on the agents' projected discomfort.

Keywords

long-distance travel demand; destination choice, agent-based simulation; C-TAP

1 Introduction

To date, travel demand generation focuses on reproducing and predicting daily life behavior. This stands in contrast to the significant part of traffic volume caused by long-distance journeys related to activities not usually undertaken during daily life. Studies report that long-distance journeys account for almost half of all vehicle miles travelled (e.g. 40% in France, 2008 (Grimal, 2010) or 45% in Germany, 2014 (Frick et al., 2014)). This fact is valid even without accounting for freight traffic. Therefore, analysis of long-distance travel behavior has become more important recently.

Destination choice is a crucial part of travel demand models. Wrong destination models lead to substantial over-estimates of miles travelled. Therefore, destination choice is included in statistical travel demand models (He et al., 2009; Zheng and Guo, 2008; Bekhor and Prashker, 2008) as well as in microsimulations (Horni et al., 2012; Jonnalagadda et al., 2001; Horni, 2013). The same applies to mode choice analysis (Johansson et al., 2006; Chorus et al., 2008; Miller et al., 2005; Rieser et al., 2009). Nevertheless, the focus of these models and simulations is usually daily life. Holiday destination choice has been investigated as well in the past (Crompton, 1992; Karl et al., 2015), but due to the enormous size of the choice set the analysis is difficult. Researchers have to introduce an additional structure, like hierarchy of destination classes in the choice set, in order to estimate models.

Just few microsimulations focus on long-distance travel behavior. Thus, not many destination choice implementations in long-distance agent-based simulations are known. Long-distance journeys are the core interest of the microsimulation presented in this paper. We will introduce a model for long-distance destination choice. The proposed model is divided in two parts: a heuristic pre-processing part and an optimization part. The destination will be optimized simultaneously with the duration of the activities.

An estimator for long-distance travel demand is valuable, because it introduces a new possibility to evaluate political decisions in this policy domain. An application might be the evaluation of big infrastructural investments, like new bridges, tunnels or airports, which is very useful for the cost-benefit analysis of this investments. Additionally, results for long-distance travel demand can be combined with short-term traffic simulations to get a complete image of total demand for travel.

2 Related Work

Agent based simulations have a long tradition in analysis and explanation of social behavior. Schelling (1971) is often referred to be the first developer of an agent based simulation. Agent based simulations were also used to estimate travel demand (Axhausen and Herz, 1989; Pendyala et al., 1997) or to generate an activity-based travel forecast (e.g. Bhat et al. (2003) or Miller (1996)). Nowadays agent based simulations make a notable contribution to the field of transportation research (e.g. Balmer (2007), Arentze et al. (2010), Kuhnimhof and Gringmuth (2009), Erath et al. (2012)).

The target-based approach is related to the need based theory which was introduced by Arentze and Timmermans (2006). They developed also a model for activity generation with the assumption of utilities described as dynamic function of needs (Arentze and Timmermans, 2009). Targets instead of needs were used as an explanation of human behavior (Märki et al., 2012b) and validated by Märki et al. (2012c) for short distance travel generation.

Long-distance trips have been the focus of recent literature. Long-distance travel behavior has been analyzed several times, e.g. for the UK and the Netherlands (Limtanakool et al., 2006). Some statistical long-distance travel demand models have been developed (e.g. Erhardt et al. (2007)) and used for traffic forecast (e.g. Beser and Algers (2001)). Recently, different surveys were also analyzed to derive an outlook on the future of long distance travel demand (Frick and Grimm (2014), Outwater et al. (2015a)).

The usage of a continuous target-based model for a long-term simulation of long-distance travel demand was introduced recently by Janzen and Axhausen (2015b). This adaptation is beneficial, because the statistical models of long-distance travel behavior focus on the current state of the world, which is not always sufficient. Thus, there is a need of a tool to predict travel demand after major infrastructural or cost changes.

Destination choice has been the focus of a vast amount of studies. Statistical models have been the tools used to explain destination choices (Outwater et al., 2015b; He et al., 2009; Zheng and Guo, 2008; Adler and Ben-Akiva, 1976; Bekhor and Prashker, 2008; Southworth, 1981). Nevertheless, most of the studies focus of daily life, e.g. shopping locations. Destination choices in daily-life have been also modelled in microsimulations (Horni et al., 2012; Jonnalagadda et al., 2001; Horni, 2013). Holiday destination choice with a focus on choice set generation has been studied as well (Crompton, 1992; Crompton and Ankomah, 1993; Karl et al., 2015; Seddighi and Theocharous, 2002). Modelling vacation destination choice is a problem tackled recently (Van Nostrand et al., 2013; Bhat et al., 2016; LaMondia et al., 2010). However, long-distance destination choice has not yet been implemented in an agent-based simulation.

Furthermore, a variety of models has been implemented to model the mode choice (Vovsha, 1997; Klöckner and Matthies, 2004; Johansson et al., 2006; Chorus et al., 2008). The mode choice in the scope of long-dist travel has been investigated (Bhat, 1995; De Lapparent et al., 2013) as well as mode choice in other agent-based transport simulations (Miller et al., 2005; Rieser et al., 2009; Meister et al., 2010). Finally, combined mode and destination choice has been focus of research (Anas, 1981; Timmermans, 1996).

3 Continuous Target-Based Model

We introduce a microscopic travel demand model, which is used to generate long-term and long-distance travel demand, namely the **C**ontinuous **T**arget-based **A**ctivity **P**lanning (C-TAP) model. The core of microscopic models is built with agents representing virtual people. In contrast to iteration-based models (like the one used by Balmer (2007)) a continuous planning model does not iterate to a steady state, but generates continuously an activity schedule without a systematic replaning. One of the main advantages is the capability of the simulation to generate arbitrarily long activity plans in linear runtime. Thus, it is a better basis for the generation of long-term, long-distance travel demand. Finally, we choose an event-driven simulation, which is more effective for our issues than a time-driven simulation, because the action between two events is not crucial to the simulation and maintaining a single event queue can be implemented simply in our simulation.

The simulation presented in this section was introduced by Märki et al. (2012b,a, 2013). The extension to a long-term simulation was presented by Janzen and Axhausen (2015b) and improved by Janzen and Axhausen (2015c,a). We explain in this section the main ideas of C-TAP, i.e. the behavioral targets, the activities and their interaction within the simulation algorithm. Afterwards, we will show how the destination choice is incorporated in the activity planning.

3.1 Behavioral Targets

The core idea of (Long-Term) C-TAP is the usage of behavioral targets, which represent the motivation of the agents to perform an activity. The focus in C-TAP are activities that take place outside of the agents environment and are planned in advance. An example of such a long-distance and long-term motivation is vacation. In this case an agent might have the motivation to go on vacation for two weeks twice a year.

There are several options to define targets. In the following we present the two types that are used in C-TAP and were proposed by Märki (2014):

- Percentage-of-time target: indicates how much relative time within an observation window an agent would like to spend on a specific activity (e.g.the motivation to spend a specific amount of time on vacation within one year).
- Duration target: indicates how much time an agent would like to spent for a single execution of a specific activity (e.g. the motivation to spend a specific amount of time on each vacation).

Note that the first target type include the definition of an observation window. But in case of the simulation presented here it is not necessary to include additional parameters to the calibration of the simulation, because it is sufficient if the observation window just equals the simulated time, i.e. one year. However, the users can give some of the targets a bigger weight, if they shorten the observation window.

3.2 Activities and State Values

Activities are necessary to complete the concept of a target-based simulation, because the targets/ motivations described above are satisfied by the execution of a corresponding activity. Activities also mark the trip purposes. The decision on the executed activities is based on state values. For each target we define a state value, which is necessary to measure the satisfaction. We need to introduce two types of state values:

- for the percentage-of-time targets: the state value is the result of a convolution of the activity execution pattern with an exponential kernel, which is restricted to the length of the observation window. So it increases during the execution of the relevant activity, respectively decreases during non-execution.
- for duration targets: the state value is defined as the activity duration.

The level of satisfaction now is measured by the quadratic difference of state value and target value. This measurement is called *discomfort* and its influence within the model is described in detail in the next section.

3.3 Core Algorithm

We will now present and discuss the main implementation issues of the Long-Term C-TAP model. The core algorithm of the Long-Term C-TAP simulation has a simple structure and is shown in algorithm 1.

Algorithm 1 Core C-TAP Algorithm (Pseudo Code)

```
1: while simulation end not reached do
2:     for all agent with no activity do
3:         state ← UpdateAgentState(agent)
4:         nextActivity ← MakeDecision(agent, state)
5:         agent.execute(nextActivity)
6:     end for
7:     nextTimeStep = minimum( all execution endpoints)
8:     proceed to nextTimeStep
9: end while
```

The main procedure is a continuous, event-driven iteration over discrete points of time. This iterative process is implemented by the outer while-loop including the incremental computation of the consecutive time points in lines 7 and 8. Whenever an agent finishes the execution of an activity, the function *MakeDecision* (line 4) computes the next activity based on its current state, which has to be updated before (line 3). After that, the activity is executed until the computed execution end. Activity execution also includes traveling to the location of the activity. Recording these trips we obtain the travel demand. The simulation stops after a predefined stopping condition is reached. This condition is usually a time period, which has to be simulated. In case of long term simulations a time period of one year is reasonable. The implementation of the *MakeDecision* function, which describes the activity planning, is discussed in the following subsection.

3.4 Activity Planning

In order to make decisions on the next performed activities one needs a measurement to value different options of activity performance. This valuation is the core of the decision process and should be simple and fast to compute. Given this, we can compare different activities (including different durations and locations) and choose the best option. In the case of C-TAP the quality of a potential decision is measured by the *discomfort value*

$$D(t) = \sum_{\omega \in A} (f^{\omega}_{target}(t) - f^{\omega}_{state}(t))^2 * \gamma_{\omega}, \tag{1}$$

where γ_{ω} a bandwidth normalization factor. The function $f^{k}_{target}(t)$ describes the target value at a given point of time t, while $f^{k}_{state}(t)$ describes the state value at t. The set of all activities is named A.

The decision procedure is the following. Whenever a decision about the next activity of an agent has to be made, all possible combinations of next activities are computed. The number of planned activities is called planning horizon and is a parameter of the simulation. The next step is the calculation of the activity duration minimizing the discomfort value at the end of the planning horizon. Finally, the first activity of the optimal activity combination is chosen to be the next executed activity. We assume in the following that the planning horizon is one activity, i.e. just a single activity is planned. This assumption is made in order to simplify the discussion of the problem presented in this paper. The implementation of C-TAP plans several activities in advance as it was shown by Janzen and Axhausen (2015a). The crucial part of this procedure is the minimization of the discomfort value, which is an exponential multi-dimensional optimization problem.

3.5 Decision Making

The discomfort minimization problem for a specific agent is discussed in detail in this subsection. Following the description above, we assume that for every activity ω there exist two targets, namely a duration target $T^{\omega}_{dur} \in \mathbb{R}^{+}$ and a percentage-of-time target $T^{\omega}_{perc} \in [0, 1]$. For simplicity we keep both types of T fixed, but an extension to a function of time is applicable.

Given an activity duration t, the discomfort of a single agent for an activity a can be expressed as

$$D(t, a, l, v_0) = \overbrace{\sum_{\omega \in A} (T^{\omega}_{perc} - v^{\omega}(t, v_0(\omega)))^2}^{\text{percentage-of-time targets}} + \overbrace{\sum_{\omega \in A} (T^{\omega}_{dur} - t)^2 * \gamma_{\omega}}^{\text{duration targets}}, \tag{2}$$

where $v^{\omega}(t)$ is the state value of the percentage-of-time target corresponding to the activity ω after execution of activity a with a duration of t. $v_0(\omega)$ is the state value of an activity ω before the execution of a. The first sum consists of the discomfort arising from percentage-of-time targets, while the second part sums the discomfort of the duration targets. The first part does not include normalization factors, because its parts are already normalized to the [0, 1]-interval.

The remaining question in the discomfort calculation is the computation procedure of the v^{ω}-values, i.e. how do the state values change during the execution of the activities. The state values are described by two exponential functions. First, there is a state value increasing function:

$$\hat{v}_a(t, v_0(a)) = 1 + (v_0(a) - 1)e^{-\tau_a \cdot t}. \tag{3}$$

Second, we define also a state value decreasing function:

$$\check{v}_a(t, v_0(a)) = v_0(a) \cdot e^{-\theta_k \cdot t}. \tag{4}$$

In both cases v_0 is the state value before the increase or decrease applies. τ_k and θ_k are constants, which are computed for every activity subject to multiple other variables. These values are not explained in detail here. Note also that valid values of v are between 0 and 1. Whenever an activity a is executed for a duration t, the corresponding state value increases by $\hat{v}_a(t)$. Whenever an activity is not performed for a duration t (the agent either travels or performs another activity), its state value decreases by $\check{v}_a(t)$. Note that $\hat{v}_a(t_1, \hat{v}_a(t_2, v)) = \hat{v}_a(t_1 + t_2, v_0(a))$. The same applies to the $\check{v}_a$-function. This property simplifies the computation of a single discomfort value.

The discomfort function D can be now phrased as follows:

$$\begin{aligned}
D(t, a, l, v_0) &= \overbrace{\sum_{\omega \in A} (T^{\omega}_{perc} - v^a(t, v_0(\omega)))^2}^{\text{percentage-of-time targets}} + \overbrace{\sum_{\omega \in A} (T^{\omega}_{dur} - t)^2 * \gamma_{\omega}}^{\text{duration targets}} && (5)\\
&= \sum_{\omega \in A \setminus a}^{n} (T^{\omega}_{perc} - v^{\omega}(t, v_0(\omega)))^2 + (T^{a}_{perc} - v^a(t, v_0(a)))^2 + (T^{a}_{dur} - t)^2 * \gamma_a && (6)\\
&= \sum_{\omega \in A \setminus a}^{n} (T^{\omega}_{perc} - \check{v}_a(t, v_0(\omega)))^2 + (T^{\omega}_{perc} - \hat{v}_a(t, v_0(a)))^2 + (T^{a}_{dur} - t)^2 * \gamma_a && (7)
\end{aligned}$$

In equation (6) all duration discomforts other than corresponding to activity a are excluded, because duration targets apply just to actually performed activities. Equation (7) uses the state value evolution functions. Finally, Equation (7) is also the function optimized in each activity planing step. Note that all state values are decreasing, when the agent is travelling to the next activity.

The decision on the next activity and the execution duration is made as follows. For every activity and location the optimal duration is computed. The optimal duration is the one minimizing the discomfort D. Afterwards, the activity minimizing the discomfort is executed. Nevertheless, the discomfort definition above does not include any location attributes. We describe in the next section how the destinations influence the activity planning.

4 Modelling Long-Distance Destination Choice

The activity planning as described above does not imply a destination choice. The destination has to be chosen simultaneously with the activity since it influences the discomfort of the agents directly. Thus, the optimal activity and the optimal duration are dependent on the locations of the activities performed.

Destination choice is based on several parameters, destination parameters as well as individual parameters. Research has been studying intensively these parameters and their influence (Karl et al., 2015; Crompton and Ankomah, 1993). Destination specific parameters that are included are the following:

- Type: Type of activity at this destination. It influences the destination choice indirectly via some of the following parameters.
- Location: Coordinates or a node in a network defining distance and travel duration.
- Quality: A measure for the appreciation for this destination.
- Price: Costs for this destination, which are dependent on type, distance, quality and duration of the considered activity.
- Seasonal Penalty: A function lowering the quality in dependence of the season, e.g. beaches are not appreciated in cold months.

Other parameters have been studied, but are not included here. For example, the need of a visa for specific countries or the question whether the destination is domestic or international may influence destination choices.

Besides these destination parameters, individual parameters play a substantial role in the decision process. The following parameters are included in the destination choice module:

- Awareness: Binary function indicating whether the person is aware of the destination.
- Second Home: Potentially, a link to a destination. Reducing the costs of vacation at this destination.
- Budget: A person's limit for the costs.

- Targets: Percentage-of-time and duration targets as described above.
- Perception: An individual function reducing or increasing the (perceived) quality of each destination.
- Mode Availability: A set of modes that is accessible to the agent (potentially, also the access time to the mode).

Awareness has been shown to be an important part in the decision process (Karl et al., 2015; Seddighi and Theocharous, 2002) since most of the people are actually not aware of all destinations. This phenomenon applies also to daily life's destination choices and is referred to as mental map (Narayana and Markin, 1975; Hannes et al., 2008; Ordóñez Medina, 2015). Parameters, which are not included so far, are socio-demographics like age or education. Income is modelled indirectly with the budget parameter. Additionally, a certain destination loyalty can be observed in recent studies (Niininen et al., 2004; Oppermann, 2000; Oom do Valle et al., 2006), but is not taken into account here, but one could extend the model for even longer duration simulations.

A further set of paramters is needed to charactarize the available modes. Mode paramaters include speed and costs per kilometer. A multi-modal network is needed in order to get travel times and total travel costs for each route. Potentially, comfort of the mode can be added to the set of parameters.

The destination choice model of C-TAP includes all the parameters above. Before the heuristic implementation of the model is shown, the problem needed to be solved is described in detail in the following.

4.1 Mathematical Formulation

The attributes of agents and locations described above have to be included in the activity planning since the destination is part of the activity choice. Some of the attributes reduce the probability to visit a specific location l. Since a probability can be quantified, we introduce an attractiveness factor ϕ. The attractiveness factor includes the quality of a location $q(l) \in [0, 1]$, the agents perception for the location $\varepsilon(l) \in [0.9, 1.1]$ and the seasonal influence on the location $s(l, u) \in [0, 1]$ at time u. The perception can be above 1.0, i.e. the perceived quality of a location might be higher than the actual quality. The three attributes $s(l, t)$, $q(l)$ and $\varepsilon(l)$ measure independently the attraction of the location. Assuming an activity starting time t_s and an activity ending time t_e, we incorporate $\phi(l, t_s, t_e) = q(l) * \varepsilon(l) * \int_{t_s}^{t_e} s(l, u)\mathrm{d}u/(t_e - t_s)$ in the state value increasing function:

$$\hat{v}_a(t_e - t_s, v_0(a)) = 1 + (v_0(a) - 1)e^{-\tau_a \cdot \phi(l, t_s, t_e) \cdot (t_e - t_s)} = 1 + (v_0(a) - 1)e^{-\tau_a \cdot q(l) \cdot \varepsilon(l) \cdot \int_{ts}^{te} s(l,u) \mathrm{d}u} \quad (8)$$

A higher value ϕ will increase the slope of $\hat{v}_a$. Thus, the state value will raise faster for the considered activity. Consequently, the activity is more likely to be executed at locations with high ϕ-values. A ϕ-value close to zero (e.g. due to the season effect) will prevent the corresponding state value from rising. Therefore, an activity execution at these locations would not contribute to a discomfort reduction and, consequently, the execution will not take place there.

There are also hard restrictions other than the soft restrictions included in ϕ. Hard restrictions limit the solution space and can be expressed as constraints of an optimization problem. The main constraints of the decision choice problem are budget constraints and awareness constraints. Both were discussed above. Consequently, the discomfort minimizing problem can be expressed as

$$\min_{t,\, a,\, l\; m} D(t, a, l, m, v_0) + \gamma_B \cdot \overbrace{\frac{B - p_l(l, t) - p_m(l, m)}{B}}^{\text{Budget Reduction Discomfort}}$$

$$\begin{aligned} s.t. \quad & l \in L(a) \\ & l \in AW \\ & m \in M \\ & p_l(l, t) + p_m(l, m) \leqslant B \\ & t \in \mathbb{R}^+ \end{aligned} \quad (9)$$

As before, the optimized variables are activity a, activity duration t and activity location l. The location choice is limited to the set of available activity locations $L(a)$ and the location set the agent is aware of AW. The mode choice m is limited to the set of available modes M. Additionally, the budget B limits the choice set with respect to a location price p_l and a mode price p_m that depends on the location and the duration. The price of a destination takes into account whether the corresponding agent has a second home at the considered destination. In other words, the price is lower for locations with a second home. The weighted budget reduction discomfort ensures that agents choose the cheaper option, if there are two similar location. Long-Term C-TAP solves this optimization problem every time an agent has to decide on his next activity. Thus, activity type, activity location, activity duration and mode are optimized simultaneously. The computation of the solution has to be fast, because the number of agents is sizable and a reasonable time simulated is a year. Therefore, a heuristic approach is needed.

4.2 Heuristic Approach

The mathematical problem formulated above can not be solved optimally in a reasonable time. Note that the set of destinations is discrete, unordered and potentially enormous. Though, the problem has to be solved every time an agent has to make an activity decision. Thus, it is necessary to have a solver that provides a result fast. Therefore, we propose an heuristic approach. The main idea is a reduction of the set of valid locations using the constraints of the equation (9). A location set reduction leads to a reduced set of feasible solutions and simplifies the optimization problem.

Before a computation of the optimal location (and duration) for an activity, we introduce a check whether the agent is aware of a location, whether he can afford it and whether it attracts him. The remaining locations form the set of feasible locations. The following steps are performed for each considered activity during an agents activity decision process:

1. Availability: Find all locations that provide the chosen activity and all modes that are available.
2. Awareness: Remove all locations that are not part of the agents awareness.
3. Affordability: Compute the maximal duration t_{max} that the agent can afford. Remove the locations where t_{max} is lower than $min_T[in\%]$ of the duration target corresponding to this activity.
4. Attractiveness: Compute the location attractiveness values ϕ. Remove the locations where ϕ is lower than min_F (Note: $\phi \in [0, 1.1]$).
5. Optimality: Solve the optimization problem (9) for the remaining set of locations. Apply the optimal location and duration.

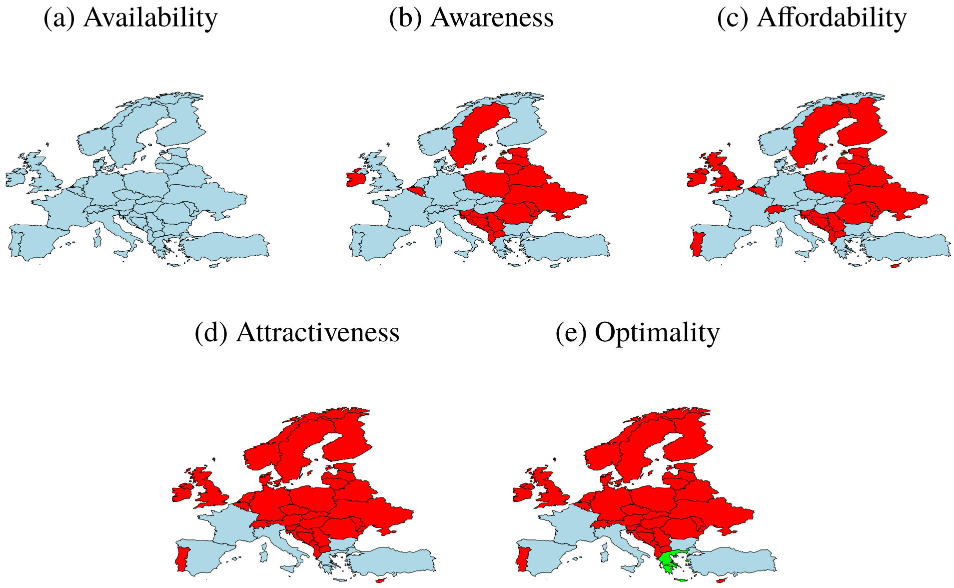
The steps 2-4 reduce the size of the solution space before the optimum within the reduced solution space is computed. As described in the previous section, the attractiveness includes location quality, season influence and agents' perception. The parameters min_T and min_F are parameters of the simulation. We propose to use $min_T = 75\%$ and $min_F = 0.9$ in order to reduce the set of locations sufficiently. The distance or travel time is not mentioned explicitly in the proposed approach since it influences the decision indirectly via the discomfort. The discomfort of an agent increases, while he is travelling. Therefore, longer distances are avoided if it is possible. A more detailed description of the discomfort minimization approach can be found in Janzen and Axhausen (2015a).

The five steps of the approach are illustrated in Figure 1 [1]. Blue destinations are in the choice

[1] Country border shapes from `http://thematicmapping.org/downloads/world_borders.php`

set, red destinations are excluded and the green destination is the one chosen due to discomfort minimization. Assume that the destination for summer vacation is optimized and the considered location choice set is limited to Europe (at country level). Thus, step 1 will generate a set of all European countries (1 (a)). Afterwards, all countries, which are not in the awareness set of the agent, are removed. In case of Europe, these countries are usually in Eastern Europe (1 (b)). The next step removes all non-affordable destinations, i.e. all countries that are expensive (1 (c)). Then, non-attractive countries are removed, e.g. due to seasonal effects (1 (d)). Eventually, the optimal destination among the remaining options is computed and used.

Figure 1: Illustration of the destination choice: Summer vacation within Europe



5 Discussion

A major concern of this approach is data availability, and thus, calibration of the simulation. Microsimulations as C-TAP need individual data for calibration and validation of the software. In case of long-distance travel, these data sources are very rare and usually have a small sample size. The lack of individual data was not an issue in this paper since the presented scenario was artificial. Nevertheless, alternative data sources (e.g. GPS or GSM data) have to be taken into account in order to increase the value of the microsimulation presented in this work

Due to the heuristic steps implemented before the activity planning, the number of possible destinations is higher than usually in activity-based simulations. Nevertheless, handling thousands of destinations (as it is the case in real world) is still impossible. Additionally, there might be several C-TAP destinations at the same location (e.g. a cheap and an expensive one) leading to a further increase of the complexity. However, the approach is applicable to the top-level of a hierarchical destination choice problem, e.g. choice of a country or region before the choice of the actual destination.

6 Conclusion

We have presented a destination choice algorithm that can be used within a continuous target-based microsimulation for long-distance travel demand. Two stages were implemented. Firstly, a heuristic reduces the number of considered destinations. Secondly, the discomfort minimizing solution is computed among the remaining destinations. The impact of season, quality, price, budget, awareness, second homes and perception has to be evaluated. Realistic evaluation scenarios are needed for the future. However, the destination choice module presented is an important step towards a tool that forecasts long-distance travel demand.

7 Acknowledgements

We would like to acknowledge the Swiss National Science Foundation (SNSF) for providing funds to the authors under grant 205120_165900 *Long Distance Travel Demand Simulation*.

8 References

Adler, T. J. and M. E. Ben-Akiva (1976) Joint-choice model for frequency, destination and travel mode for shopping trips, *Transportation Research Record*, **569**, 136–150.

Anas, A. (1981) The estimation of multinomial logit models of joint location and travel mode choice from aggregated data, *Journal of Regional Science*, **21** (2) 223–242.

Arentze, T. A., T. A. Pelizaro and H. J. P. Timmermans (2010) An agent-based micro-simulation framework for modelling of dynamic activity-travel rescheduling decisions, *International Journal of Geographical Information Science*, **24** (8) 1149–1170.

Arentze, T. A. and H. J. P. Timmermans (2006) A new theory of dynamic activity generation, paper presented at the *85th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2006.

Arentze, T. A. and H. J. P. Timmermans (2009) A need-based model of multi-day, multi-person activity generation, *Transportation Research Part B: Methodological*, **43** (2) 251–265.

Axhausen, K. W. and R. Herz (1989) Simulating activity chains: German approach, *Journal of Transportation Engineering*, **115** (3) 316–325.

Balmer, M. (2007) Travel demand modeling for multi-agent traffic simulations: Algorithms and systems, Ph.D. Thesis, ETH Zurich, Zurich, May 2007.

Bekhor, S. and J. N. Prashker (2008) GEV-based destination choice models that account for unobserved similarities among alternatives, *Transportation Research Part B: Methodological*, **42** (3) 243–262.

Beser, M. and S. Algers (2001) Sampers - the new swedish national travel demand forecasting tool, in L. Lundqvist and L.-G. Mattsson (eds.) *National Transport Models: Recent Developments and Prospects*, Advances in Spatial Science, 101–118, Springer, Stockholm.

Bhat, C. R. (1995) A heteroscedastic extreme value model of intercity travel mode choice, *Transportation Research Part B*, **29** (6) 471–483.

Bhat, C. R., S. Astroza and A. C. Bhat (2016) On allowing a general form for unobserved heterogeneity in the multiple discrete–continuous probit model: Formulation and application to tourism travel, *Transportation Research Part B*, **86**, 223–249.

Bhat, C. R., S. Srinivasan, J. Y. Guo and A. Sivakumar (2003) Activity-based travel-demand modeling for metropolitan areas in Texas: A micro-simulation framework for forecasting, *Final Report*, Texas Department of Transportation, University of Texas, Austin, February 2003.

Chorus, C. G., T. A. Arentze and H. J. P. Timmermans (2008) A comparison of regret-minimization and utility-maximization in the context of travel mode choices, paper presented at the *87th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2008.

Crompton, J. L. (1992) Structure of vacation destination choice sets, *Annals of Tourism Research*, **19** (3) 420–434.

Crompton, J. L. and P. K. Ankomah (1993) Choice set propositions in destination decisions, *Annals of Tourism Research*, **20** (3) 461–476.

De Lapparent, M., K. W. Axhausen and A. Frei (2013) Long distance mode choice and distributions of values of travel time savings in three European countries, *European Transport*, **53**, 1–31.

Erath, A. L., A. Chakirov, P. J. Fourie, S. A. Ordóñez Medina, M. Shah, M. A. B. van Eggermond and K. W. Axhausen (2012) A large-scale agent-based transport travel demand model for Singapore: The implementation of MATSim, *Working Paper*, Future Cities Laboratory, Singapore-ETH Centre (SEC), Singapore.

Erhardt, G. D., J. Freedman, A. Stryker, H. Fujioka and R. Anderson (2007) Ohio long-distance travel model, *Transportation Research Record*, **2003**, 130–138.

Frick, M., B. C. Belart, M. Schmied, B. Grimm and D. Schmücker (2014) Zukunftsperspektiven der Langstreckenmobilität - Grundlagenstudie, *Final Report*, Institut für Mobilitätsforschung, Berne.

Frick, M. and B. Grimm (2014) Langstreckenmobilität: Aktuelle Trends und Zukunftsperspektiven, *Research Report*, Institut für Mobilitätsforschung, Munich.

Grimal, R. (2010) Mobilité à longue distance : plus de voyages s'effectuent en train, mais les seniors restent adeptes de la voitur, *Technical Report*, Setra, Paris, December 2010.

Hannes, E., D. Janssens and G. Wets (2008) Destination choice in daily activity travel: The mental map's repertoire, paper presented at the *87th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2008.

He, M., M. He and S. Gao (2009) Destination choice modeling for home-based non-commute trips: Some improvements in utility function and a case study in China, paper presented at the *88th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2009.

Horni, A. (2013) Destination choice modeling of discretionary activities in transport microsimulations, Ph.D. Thesis, ETH Zurich, Zurich.

Horni, A., K. Nagel and K. W. Axhausen (2012) High-resolution destination choice in agent-based demand models, paper presented at the *91st Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2012.

Janzen, M. and K. W. Axhausen (2015a) Activity Planning in a Continuous Long-Term Travel Demand Microsimulation, paper presented at the *15th Swiss Transport Research Conference*, Ascona, April 2015.

Janzen, M. and K. W. Axhausen (2015b) Long-Term-C-TAP Simulation: Generating Long Distance Travel Demand for a full Year, paper presented at the *94th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2015.

Janzen, M. and K. W. Axhausen (2015c) Population Generation for Continuous, Long-Distance Travel Demand Simulations, paper presented at the *14th International Conference on Travel Behaviour Research (IATBR)*, Windsor, July 2015.

Johansson, M. V., T. Heldt and P. Johansson (2006) The effects of attitudes and personality traits on mode choice, *Transportation Research Part A*, **40** (6) 507–525.

Jonnalagadda, J., N. Freedman, W. A. Davidson and J. D. Hunt (2001) Development of microsimulation activity-based model for San Francisco: Destination and mode choice models, *Transportation Research Record*, **1777**, 25–35.

Karl, M., C. Reintinger and J. Schmude (2015) Reject or select: Mapping destination choice, *Annals of Tourism Research*, **54**, 48–64.

Klöckner, C. A. and E. Matthies (2004) How habits interfere with norm-directed behaviour: A normative decision-making model for travel mode choice, *Journal of Environmental Psychology*, **24** (3) 319–327.

Kuhnimhof, T. and C. Gringmuth (2009) Multiday multiagent model of travel behavior with activity scheduling, *Transportation Research Record*, **2134**, 178–185.

LaMondia, J. J., T. Snell and C. R. Bhat (2010) Traveler Behavior and Values Analysis in the Context of Vacation Destination and Travel Mode Choices, *Transportation Research Record*, **2156**, 140–149.

Limtanakool, N., M. Dijst and T. Schwanen (2006) On the participation in medium. and long-distance travel: A decomposition analysis for the uk and the netherlands, *Tijdschrift voor economische en sociale geografie*, **97** (4) 389–404.

Märki, F. (2014) An Agent-Based Model for Continuous Activity Planning of Multi-Week Scenarios, Ph.D. Thesis, ETH Zurich, Zurich.

Märki, F., D. Charypar and K. W. Axhausen (2012a) Location choice in a continuous model, paper presented at the *13th International Conference on Travel Behaviour Research (IATBR)*, Toronto, July 2012.

Märki, F., D. Charypar and K. W. Axhausen (2012b) Target driven activity planning, paper presented at the *91st Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2012.

Märki, F., D. Charypar and K. W. Axhausen (2012c) Validation of a continuous simulation model for daily travel, paper presented at the *12th Swiss Transport Research Conference*, Ascona, May 2012.

Märki, F., D. Charypar and K. W. Axhausen (2013) Integration of Household Interaction with a Continuous Simulation Model, paper presented at the *13th Swiss Transport Research Conference*, Ascona, April 2013.

Meister, K., M. Balmer, F. Ciari, A. Horni, M. Rieser, R. A. Waraich and K. W. Axhausen (2010) Large-scale agent-based travel demand optimization applied to Switzerland, including mode choice, paper presented at the *12th World Conference on Transportation Research*, Lisbon, July 2010.

Miller, E. J. (1996) Microsimulation and activity-based forecasting, paper presented at the *Activity-Based Travel Forecasting Conference*, New Orleans, June 1996.

Miller, E. J., M. J. Roorda and J. A. Carrasco (2005) A tour-based model of travel mode choice, *Transportation*, **32** (4) 399–422.

Narayana, C. L. and R. J. Markin (1975) Consumer behavior and product performance: An alternative conceptualization, *Journal of Marketing*, **39** (4) 1–6.

Niininen, O., E. Szivas and M. Riley (2004) Destination loyalty and repeat behaviour: An application of optimum stimulation measurement, *International Journal of Tourism Research*, **6** (6) 439–447.

Oom do Valle, P., J. A. Silva, J. Mendes and M. Guerreiro (2006) Tourist Satisfaction and Destination Loyalty intention: A Structural and Categorical Analysis, *International Journal of Business Science and Applied Management*, **1**, 25–44.

Oppermann, M. (2000) Tourism Destination Loyalty, *Journal of Travel Research*, **39** (1) 78–84.

Ordóñez Medina, S. A. (2015) Recognizing personalized flexible activity patterns, paper presented at the *14th International Conference on Travel Behaviour Research (IATBR)*, Windsor, July 2015.

Outwater, M., M. A. Bradley, N. Ferdous, C. R. Bhat, R. M. Pendyala, S. Hess, A. J. Daly and J. J. LaMondia (2015a) Tour-Based National Model System to Forecast Long-Distance Passenger Travel in the United States, paper presented at the *94th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2015.

Outwater, M., M. A. Bradley, N. Ferdous, S. Trevino and H. Lin (2015b) Foundational knowledge to support a long-distance passenger travel demand modeling framework, *Technical Report*, Transport Studies Unit, University of Oxford.

Pendyala, R. M., R. Kitamura, A. Chen and E. I. Pas (1997) An activity-based microsimulation analysis of transport control measures, *Transport Policy*, **4** (3) 183–192.

Rieser, M., D. Grether and K. Nagel (2009) Adding mode choice to multiagent transport simulation, *Transportation Research Record*, **2132**, 50–58.

Schelling, T. C. (1971) Dynamic models of segregation, *The Journal of Mathematical Society*, **1** (2) 143–186.

Seddighi, H. R. and A. L. Theocharous (2002) A model of tourism destination choice: a theoretical and empirical analysis, *Tourism Management*, **23** (5) 475–487.

Southworth, F. (1981) Calibration of multinomial logit models of mode and destination choice, *Transportation Research Part A: Policy and Practice*, **15** (4) 315–325.

Timmermans, H. J. P. (1996) A stated choice model of sequential mode and destination choice behaviour for shopping trips, *Environment and Planning A*, **28** (1) 173–184.

Van Nostrand, C., V. Sivaraman and A. R. Pinjari (2013) Analysis of long-distance vacation travel demand in the United States: a multiple discrete-continuous choice framework, *Transportation*, **40** (1) 151–171.

Vovsha, P. (1997) Cross-Nested Logit model: An application to mode choice in the Tel-Aviv metropolitan area, *Transportation Research Record*, **1607**, 6–15.

Zheng, J. and J. Y. Guo (2008) Destination choice model incorporating choice set formation, paper presented at the *87th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2008.