Conference Paper

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Publication Date: 2017

Permanent Link: https://doi.org/10.3929/ethz-b-000118791

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Holiday Destination Choice in a Continuous Activity-Based Microsimulation

Date of submission: 2016-08-1

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Words: 6675 words + 1 figure + 1 table = 7175 word equivalents
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 forecast tools. A potential tool is an 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 is modelled in this agent-based simulation. We focus on the holiday destination choice, because it dominates the long-distances trips for the average traveler. The presented approach uses a heuristic to reduce the solution space. Afterwards, the optimal activity duration and activity location is computed simultaneously. This technique ensures a fast computation.
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 (1) or 45% in Germany, 2014 (2)). 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 (3–5) as well as in microsimulations (6–8). Nevertheless, the focus of these models and simulations is usually daily life. Holiday destination choice has been investigated as well in the past (9, 10), 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 focus lies on holiday destination choice, because holidays are the activities least restricted in terms of 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 holidays.

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.

The paper is structured as follows. After a literature review we describe in detail the continuous target-based simulation used to generate long-distance travel demand. The activity planning within the model will be presented with a focus on holiday destination choice. The methodology will be then applied to a simple scenario in order to proof the concept. The paper finishes with a discussion and a conclusion.

RELATED WORK

Agent based simulations have a long tradition in analysis and explanation of social behavior. Schelling (11) is often referred to be the first developer of an agent based simulation. Agent based simulations were also used to estimate travel demand (12, 13) or to generate an activity-based travel forecast (e.g., Bhat et al. (14) or Miller (15)). Nowadays agent based simulations make a notable contribution to the field of transportation research (e.g., Balmer (16), Arentze et al. (17), Kuhnimhof and Gringmuth (18), Erath et al. (19)).

The target-based approach is related to the need based theory which was introduced by Arentze and Timmermans (20). They developed also a model for activity generation with the assumption of utilities described as dynamic function of needs (21). Targets instead of needs were used as an explanation of human behavior (22) and validated by Märki et al. (23) 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 (24). Some statistical long-distance travel demand models have been developed (e.g., Erhardt et al. (25)) and used for traffic forecast (e.g., Beser and Algers (26)). Recently, different surveys were also analyzed to derive an outlook on the future of long-distance travel demand (Frick and Grimm (27), Outwater et al. (28)).

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 (29). 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.

Finally, destination choice has been the focus of a vast amount of studies. Statistical models have been the tools used to explain destination choices (30, 3, 31, 32). Nevertheless, most of the studies focus of daily life, e.g., shopping locations. Destination choices in daily-life have been also modelled in microsimulations (6–8). Holiday destination choice with a focus on choice set generation has been studied as well (9, 33, 10, 34). Modelling vacation destination choice is a problem tackled recently (35–37). However, holiday destination choice has not yet been implemented in an agent-based simulation.

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 Continuous Target-based Activity Planning (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 (16)) a continuous planning model does not iterate to a steady state, but generates continuously an activity schedule without a systematic replanning. 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. (22, 38, 39). The extension to a long-term simulation was presented by Janzen and Axhausen (29) and improved by Janzen and Axhausen (40, 41). 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.

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 holidays 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 (42):
• 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 holidays within one year).

• Duration target: indicates how much time an agent would like to spend for a single execution of a specific activity (e.g., the motivation to spend a specific amount of time on each holiday trip).

Note that the first target type includes 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.

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.

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 \textit{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 \textit{MakeDecision} function, which describes the activity planning, is discussed in the following subsection.

### 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

\begin{equation}
D(t) = \sum_{\omega \in A} (f_{\ target}^\omega (t) - f_{\ state}^\omega (t))^2 \ast \gamma_\omega,
\end{equation}

where \( \gamma_\omega \) a bandwidth normalization factor. The function \( f_{\ target}^k(t) \) describes the target value at a given point of time \( t \), while \( f_{\ state}^k(t) \) 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 (41). The crucial part of this procedure is the minimization of the discomfort value, which is an exponential multi-dimensional optimization problem.

### 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 \( \omega \) there exist two targets, namely a duration target \( T_{dur}^\omega \in \mathbb{R}^+ \) and a percentage-of-time target \( T_{perc}^\omega \in [0, 1] \). 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

\begin{equation}
D(t, a, l, v_0) = \sum_{\omega \in A} (T_{perc}^\omega - v^\omega (t, v_0(\omega)))^2 + \sum_{\omega \in A} (T_{dur}^\omega - l)^2 \ast \gamma_\omega,
\end{equation}

where \( v^\omega (t) \) is the state value of the percentage-of-time target corresponding to the activity \( \omega \).
after execution of activity \( a \) with a duration of \( t \). \( v_0(\omega) \) is the state value of an activity \( \omega \) 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 \( v^\omega \)-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:  

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

(3)

Second, we define also a state value decreasing function:  

\[
\check{v}_a(t, v_0(a)) = v_0(a) \cdot e^{-\theta_k \cdot t}.
\]  

(4)

In both cases \( v_0 \) is the state value before the increase or decrease applies. \( \tau_k \) and \( \theta_k \) 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 \( \hat{v}_a(t_1, \check{v}_a(t_2, v)) = \hat{v}_a(t_1 + t_2, v_0(a)) \). 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:

\[
D(t, a, l, v_0) = \sum_{\omega \in A} \left( \frac{(T^\omega_{perc} - v^\omega(t, v_0(\omega)))^2}{\gamma_\omega} \right) + \sum_{\omega \in A} \left( \frac{(T^\omega_{dur} - t)^2}{\gamma_\omega} \right) \]

(5)

\[
= \sum_{\omega \in A} \left( (T^\omega_{perc} - v^\omega(t, v_0(\omega)))^2 + (T^\omega_{perc} - \check{v}_a(t, v_0(\omega)))^2 + (T^\omega_{dur} - t)^2 \right) \gamma_\omega
\]  

(6)

\[
= \sum_{\omega \in A} \left( (T^\omega_{perc} - \hat{v}_a(t, v_0(\omega)))^2 + (T^\omega_{perc} - \check{v}_a(t, v_0(\omega)))^2 + (T^\omega_{dur} - t)^2 \right) \gamma_\omega
\]  

(7)

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 planning 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.
MODELLING HOLIDAY 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. We will focus on the holiday destination choice in the remainder of the paper, because it is the travel purpose that is the least restricted in terms of destination choice. For example, commuting tours usually do not imply any choice of destination.

Holiday destination choice is based on several parameters, destination parameters as well as individual parameters. Research has been studying intensively these parameters and their influence (10; 33). Destination specific parameters that are included are the following:

• Type: Type of vacation 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 vacation destination.
• Price: Costs for this destination, which are dependent on type, distance, quality and duration of the vacation trip.
• 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.

Awareness has been shown to be an important part in the decision process (10; 34) since most of the people are actually not aware of all vacation destinations. This phenomenon applies also to daily life’s destination choices and is referred to as mental map (43–45). 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 (46–48), but is not taken into account here, but one could extend the model for even longer duration simulations.

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.

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. Since a probability can be quantified, we introduce an efficiency factor \( \phi \). The efficiency factor includes the quality of a location \( q(l) \in [0, 1] \), the seasonal influence on the location \( s(l) \in [0, 1] \) and the agent's perception for the location \( \epsilon(l) \in [0.9, 1.1] \). 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 \( s(l), q(l) \) and \( \epsilon(l) \) measure independently the attraction of the location. We incorporate \( \phi = s(l) \cdot q(l) \cdot \epsilon(l) \) in the state value increasing function:

\[
\hat{v}_a(t, v_0(a)) = 1 + (v_0(a) - 1) e^{-\tau_a \cdot \phi(l) \cdot t}.
\]  (8)

A higher value \( \phi \) 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 \( \phi \)-values. A \( \phi \)-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 \( \phi \). 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

\[
\min_{t, a, l} D(t, a, l, v_0)
\]

s.t.  
\[
\begin{align*}
  l &\in L(a) \\
  l &\in AW(a) \\
  p(l, t) &\leq B \\
  t &\in \mathbb{R}^+
\end{align*}
\]  (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 \( AW(a) \). Additionally, the budget \( B \) limits the choice set with respect to a price \( p \) 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. Long-Term C-TAP solves this optimization problem every time an agent has to decide on his next activity. Thus, activity type, activity location and activity duration 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.

**Heuristic Approach**

The mathematical problem formulated above can not be solved optimally in a reasonable time. Note that the set of holiday locations 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 a 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 is efficient for him to visit it. The remaining locations form the set of feasible locations. The following steps are performed for each considered activity during an agent’s activity decision process:

1. Availability: Find all locations that provide the chosen activity.
2. Awareness: Remove all locations that are not part of the agent’s awareness.
3. Affordability: Compute the maximal duration $t_{\text{max}}$ that the agent can afford. Remove the locations where $t_{\text{max}}$ is lower than $\min_T[\text{in} \%]$ of the duration target corresponding to this activity.
4. Efficiency: Compute the location efficiency values $\phi$. Remove the locations where $\phi$ is lower than $\min_F$ (Note: $\phi \in [0,1]$).
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 efficiency 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 five steps of the approach are illustrated in Figure 1. Blue destinations are in the choice 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

PROOF OF CONCEPT

The destination choice model in C-TAP has to be validated. Therefore, we created a toy scenario covering the attributes included in the activity planning. One year of long-distance travel behavior was simulated, from 1. January to 31. December. The year was divided in two seasons, in order to measure a seasonal effect. Summer takes place from April to August, while the other months are considered to be winter months. We will describe the setup of the scenario as well as the simulation results in the following.

Scenario

As described above, there are two different types of parameters that influence the holiday destination choice. On the one hand, attributes of the destination itself are considered. On the other hand, the agent itself has attributes influencing his decision. Destinations were defined considering the following variables:

- **Type / Season influence:** Two different types of holiday destinations are considered. Beach places that have high attraction $s(\text{Beach}) = 1.0$ in summer and moderate attraction $s(\text{Beach}) = 0.8$ in winter. The second type Mountain has the opposite attraction values.
- **Quality / Price:** We link quality and price and define three different quality-price levels. Luxury destinations (Lux) have a price of 200$ per day and quality value of $q(\text{Lux}) = 1.0$. Cheap destinations (Cheap) have a price of 50$ per day and quality value of $q(\text{Cheap}) = 0.8$. Overpriced destinations (OP) have a price of 200$ per day and quality value of $q(\text{OP}) = 0.8$.
- **Location:** All holiday destinations are assumed to have the same distance to the agents and fixed travel time of 5 hours from all home locations. In other words, the influence of distance is not evaluated in this scenario.

In total, there are six possible combinations of destination attributes. We generate two destinations for each combination. Thus, 12 holiday destinations were implemented in this scenario. Additionally, an identifier A or B is mapped to each location, in order to distinguish the two destinations with the same attributes.

Agents were defined based on the following parameters:

- **Awareness:** Some agents are not aware of all B destinations, i.e. there choice set is limited to A destinations.
- **Second home:** Some of the agents have a second home at Beach-Lux-B, i.e. they pay just 20$ per night at this place (instead of 200$).
- **Budget:** The budget of each agent is growing each month by a certain savings rate. The rate is either 150$ per month (Poor) or 1000$ per month (Rich).
- **Perception:** Each agent has a location perception factor $\varphi \in [0.9, 1.1]$ that is fixed for each location.
- **Targets:** The targets are defined such that all agents have the motivation to go on holidays three times a year. Twice for a single week and once for two weeks. No other targets are defined, i.e. the agents do not have long-distance trips other than vacations.
- **Home location:** All agents have the same home location with a fixed distance to all holiday destinations.

Considering this variables, eight agent types are defined (3 variables, each has two levels). Two agent types are excluded, namely the ones that are not aware of B destinations, but have a second home at Beach-Lux-B. 1000 agents are generated for each of the remaining six types.
Simulation Results
C-TAP was used to simulate one year of holiday travel demand using 12 holiday destinations and 6000 agents. The travel behavior of the agents is analyzed in order to validate the destination choice module of C-TAP. The destination choices of the agents is shown in Table 1.

Table 1: Holiday destination choices in the scenario

<table>
<thead>
<tr>
<th>Awareness</th>
<th>Agents</th>
<th>Sec home</th>
<th>Salary</th>
<th>Full set</th>
<th>not aware of B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No</td>
<td>High</td>
<td>Low</td>
<td>at Beach-Lux</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>High</td>
<td>Low</td>
<td>No</td>
<td>Low</td>
</tr>
</tbody>
</table>

| Beach     | Lux | Summer | A | 514 | – | 498 | – | 968 | – |
| Winter    | A   | 19     | 8 | 21  | 34 | 95 | 49 |
|           | B   | 19     | 7 | 18  | 255| –  | –  |
| Cheap     | Summer | A | 1 | 226 | – | 22 | 9 | 341 |
|           | B   | –  | 250| –   | 16| –  | –  |
| OP        | Summer | A | – | 224 | – | 18 | 12 | 338 |
|           | B   | –  | 237| –   | 21| –  | –  |
| Winter    | A   | –  | –  | –   | – | –  | 4  |
|           | B   | –  | –  | –   | – | –  | –  |
| Mountains | Lux | Summer | A | 928 | 481| 959| 404| 1725| 840|
|           | B   | 959 | 482| 932 | 372| –  | –  |
| Cheap     | Summer | A | – | 1  | – | – | – | – |
|           | B   | –  | –  | –   | – | –  | –  |
| OP        | Summer | A | 16 | 283 | 19 | 269| 94 | 704 |
|           | B   | 19 | 291| 14  | 235| –  | –  |
| Winter    | A   | –  | 1  | –   | – | –  | 3  |
|           | B   | –  | 1  | –   | – | –  | –  |
|           |        |        |        |        |        |        |        |        | 4  |
|           |        |        |        |        |        |        |        |        | –  |
|           |        |        |        |        |        |        |        |        | –  |

In total, 18,013 trips to holiday destinations were simulated for the agents. Almost all of the 6000 agents did two short trips (around one week) and a long trip (around two weeks). One can see that the simulated destination choice meets the expectations. Awareness was taken into account. None of the agents, which were not aware of B destinations, went to these places. Agents with a second home went to the second home more often than to other places. This applies mainly to the poorer agents since they have tighter budget restrictions. The budget plays also an important role for all other agents. One can see that rich agents are attracted by the luxury locations. Finally, the seasonal effect is obvious. While the beach is the preferred destination in summer, mountains attract agents in winter. Due to our setup, the number of trips in winter are higher than in summer, because agents tend to do the two short vacations in winter.
and the single long vacation in summer.

**DISCUSSION**

The simulation results above suggest that the presented destination choice approach is valuable. We have shown that a variety of attributes can be included in the destination choice of a continuous agent-based simulation. The main task of the scenario was a proof of concept. Therefore, the structure was simple. Especially, the number of attribute levels was limited. Two or three discrete levels per attribute were available. Further validation of the approach should include continuous attributes as well as distance variation.

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. 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.

**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 approach was validated with a toy scenario simulating holiday destination choices. The impact of season, quality, price, budget, awareness, second homes and perception has been evaluated and shown to be working. More realistic evaluations are needed for the future. However, the destination choice module presented is an important step towards a tool that forecasts long-distance travel demand.

**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*.

**REFERENCES**


