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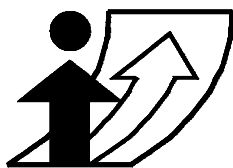
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# Location Choice in a Continuous Model

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## Abstract

This paper proposes a location choice procedure that is capable to handle long term and continuous location choice aspects. It integrates expected travel time, current location effectiveness, prospective location effectiveness, and individual unexplained location preference into a target-based model whose decision heuristic decides on the fly and with an open time horizon about future locations agents should visit. Several simulation runs illustrate agents' location choice behavior in different situations. We conclude by suggesting directions for future research.

## Keywords

location choice, seasonal effects, continuous model, multiday schedules, continuous activity generation and scheduling, microscopic travel demand simulation

## Preferred citation style

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# 1 Introduction

Microscopic travel demand simulation softwares simulate virtual people (referred to as agents) individually. This leads to high computational complexity which often results in computational performance and memory issues. Microscopic models typically introduce constraints to counter such issues. For instance, Balmer (2007) limits the maximum simulation horizon of standard size scenarios to a single day, making it difficult to investigate effects occurring over a period of days or weeks. Another limitation is that agents must commit themselves to a specific day-plan, making it challenging to simulate unexpected events realistically (Charypar *et al.* (2009) and Dobler *et al.* (2012)). As a consequence, a different simulation approach becomes necessary that is capable to model demand continuously, i.e. agents should be able to make decisions about upcoming activities on the fly and with an open time horizon.

We proposed a microscopic travel demand simulation in Märki *et al.* (2012a) and Märki *et al.* (2012b) that is capable to model demand continuously by using behavioral targets to represent agents' decision space. Targets can represent social and cultural norms and are closely related to observed behavior like execution frequency and time spent for an activity. Agents continuously track their performance and compare it to their behavioral targets using observation windows of different durations. Deviations from the desired behavior cause discomfort which is conveyed to a planning heuristic, making decisions about future activities agents should execute. This enables agents to react spontaneously to unexpected events. It also reduces memory consumption and computational complexity because agents do not need to keep track of complete daily schedules, making simulation periods of several months feasible.

The aim of this work is to address the question on how to integrate location choice into the continuous model while preserving its ability to simulate long periods in reasonable time and keeping its memory footprint acceptable. The envisaged procedure also needs to be able to consider long term and continuous location choice aspects like e.g. seasonal effects and weather conditions. We propose a combination of expected travel time, current location effectiveness, prospective location effectiveness, and individual unexplained location preference as the continuous location choice procedure. The combination of these elements not only allows investigations of long term and continuous aspects but also enables variety seeking and produces realistic location choice decisions.

The remainder of this paper is structured as follows: first, we introduce the target-based model and review the decision heuristic with a focus on relevant elements for location choice. The next section starts with a comparison of continuous location choice to location choice in other models. This is followed by an outline of the continuous location choice procedure, its components and their relevance in the decision process. The subsequent section validates the proposed continuous location choice procedure by considering seasonal aspects and weather conditions for leisure activities. We conclude

the paper with a perspective on future tasks.

## 2 Other Work

The target-based approach shows similarities to the need-based theory introduced by Arentze and Timmermans (2006, 2009). Whereas Arentze and Timmermans used needs as people's motivation to execute activities, we see the satisfaction of needs as one possible target in our model. Generally, we assume that people describe their desired performance through measures which are closer to data found e.g. in Swiss Federal Statistical Office (2006) or other travel diaries (e.g. Axhausen *et al.* (2002), Löchl *et al.* (2005), Schönfelder (2006)). We pick up Winston's (1982) suggestion to use time-dependent utilities for activities (also see Axhausen (1990, p. 34-38) for a summary or Gliebe and Kim (2010) for a recent work) and introduce time-dependent effectiveness functions, describing the effectivity of activities and locations towards discomfort reduction. Since different locations can provide different effectiveness definitions, location effectiveness becomes an important element of the location choice procedure. The individual unexplained preference for a certain location is modeled as a random variable similar to the proposal of Horni *et al.* (2011). The target-based model was introduced in Märki *et al.* (2012a) and validated in Märki *et al.* (2012b) using an existing six-week continuous travel diary (Löchl *et al.* (2005) and Schönfelder (2006)).

## 3 Introduction of Model and Decision Heuristic

Agents are the central component of our model and represent virtual people. Each agent has a motivation to execute activities and specifies its desired performance through behavioral targets. Deviations to behavioral targets result in discomfort which induces agents to take action against the deviation; higher deviations result in higher discomfort which in turn leads to a higher urge to take action. Agents can reduce discomfort through the execution of activities at different locations. We assume that agents prefer activity-location pairs that provide more discomfort reduction. This is similar to Arentze and Timmermans' work (Arentze and Timmermans (2009)), where they proposed activity utility as a function of need reduction.

## 3.1 Model

### 3.1.1 Targets

The core assumption of this work is that people have a motivation to execute activities and that they have a perception of their motivation in form of a desired performance. People specify this performance through *behavioral targets* and try to match with them across *observation windows* of different duration. For instance, a person would like to play  $2_{-1}^{+0.5}$  hours of tennis about  $2_{-1}^{+1}$  per week. This targeted behavior is transformed into following targets:

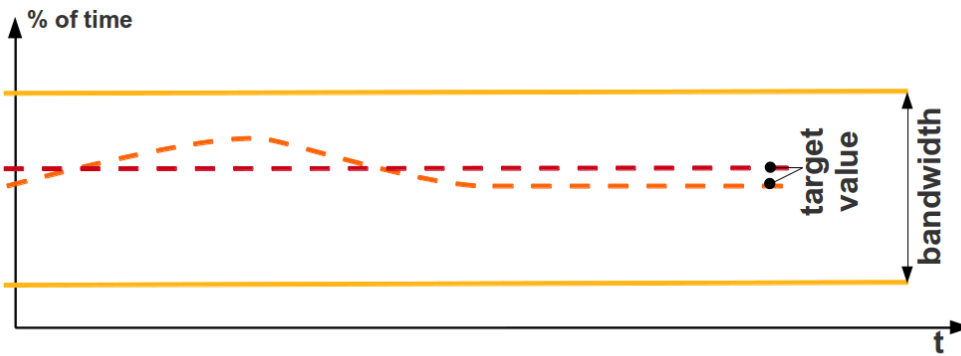
- The *percentage of time* target defines the time a person would like to spend for an activity within an *observation window*. In order to simplify modelers' task, it is possible to specify the total execution duration and the conversion to the percentage of time target is done internally. For the above example, the modeler would specify a *target value* of 2 hours of tennis, a *bandwidth* of  $_{-1}^{+0.5}$  hours (upper and lower bound of the target value) and an observation windows of one week (see Fig. 1(a)).
- The *frequency* target defines the number of activity executions a person would like to accomplish within an observation window. For the above example, the modeler would specify a *target value* of 2 executions of tennis with a *bandwidth* of  $_{-1}^{+1}$  executions and an observation windows of one week.

Agents monitor their performance during simulation and compare these *state values* to target values (see Fig. 1(b)). State values are exponentially discounted over the observation window of targets. This simulates a forgetting process where agents give recent behavior more weight and gradually forget their past performance.

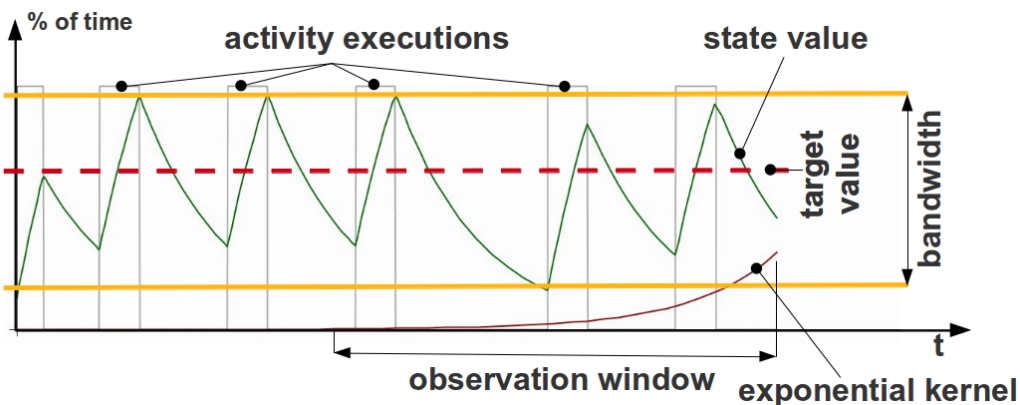
### 3.1.2 Effectiveness Functions

Effectiveness functions inform agents about the effectiveness of activities and locations towards discomfort reduction. This is similar to Winston (1982) who proposed time-dependent utilities for activities (also see Axhausen (1990, p. 34-38) for a summary or Gliebe and Kim (2010) for a recent work). Effectiveness functions are a broad concept and can model different effects. Possible examples are:

- **Shop opening hours for a *daily shopping* activity.** Agents can use this information to either determine if they can shop and for how long or how long it takes until they can shop next time. Since effectiveness functions can be location dependent, it is also possible to model location dependent shop opening hours.
- **Daylight intensity for a *sleep* activity.** This function specifies the light intensity. Agents can use this information e.g. as an indication of sleep effectiveness. Hereby,



(a) Schematic illustration of a target configuration that defines the average time a person would like to spend for an activity. *Target values* as well as upper and lower bounds (defining the *bandwidth*) can be static or dynamic (they can fluctuate) and are therefore modeled as functions in time.



(b) Schematic illustration of performance monitoring. The *state value* (green line) is calculated through a convolution of the *activity execution pattern* with an *exponential kernel* resulting in an exponentially weighted moving average. The *observation window*, in which the person tries to comply with the target, defines the kernel length.

Figure 1: Illustration of agent configuration and performance monitoring.

we assume that people sleep at night and have already adapted to their current timezone.

- **Business hours for a work activity.** This function can be seen as a cultural norm (cultures may have different business hours) and a social norm (social groups, e.g. professions, may have different business hours). Agents can use this information e.g. as an indication of work effectiveness. Hereby, we assume that people depend on co-workers to be able to do their work (the degree can differ depending on the profession).

## 3.2 Decision Heuristic

We consider a decision heuristic as a feasible approach to overcome limitations of alternative approaches like poor performance for large scenarios (Charypar and Nagel (2006)), high computational costs (Balmer (2007)) or inflexibilities when agents should spontaneously react to unexpected events (Kuhnimhof and Gringmuth (2009)). Since a heuristic aims to approximate a good solution, it is also possible to use incomplete knowledge about the state of mind and plans of other agents. This is helpful since complete knowledge generally induces high computational and memory costs.

The decision heuristic we proposed (Märki *et al.* (2012a)) combines several aspects which are derived from targets and effectiveness functions. The decision heuristic takes each promising activity-location pair, optimizes its variables to find the highest heuristic value, and decides to implement the activity-location pair which yields the highest heuristic value per invested time. The heuristic function is defined as

$$HF(t_{ts}, t_{es}, t_{ee}) = DR(t_{es}, t_{ee}) \cdot LA(t_{ee}) \cdot CEE(t_{es}, t_{ee}) \cdot ETQ(t_{ts}, t_{es}, t_{ee}) \quad (1)$$

the multiplication of the discomfort reduction  $DR(t_{es}, t_{ee})$  between execution start  $t_{es}$  and execution end  $t_{ee}$  with a look-ahead measure  $LA(t_{ee})$  at execution end multiplied by the current execution effectiveness  $CEE(t_{es}, t_{ee})$  and the execution time quota  $ETQ(t_{ts}, t_{es}, t_{ee})$ . Following list discusses the heuristic function with a focus on aspects relevant for the location choice procedure (we refer readers to Märki *et al.* (2012a) for a detailed explanation of the heuristic):

- **Discomfort:** Discomfort builds on targets and is a function of the difference between *target value* and *state value*. It takes longer to execute an activity at a location with low effectiveness because activity-location pairs with a low effectiveness have longer to increase their *state value* compared to pairs with high effectiveness (the calculation of the *state value* (see Fig. 1(b)) also takes effectiveness into account). Since the heuristic chooses the activity-location pair that yields the highest heuristic value per invested time, agents have a preference for effective locations.
- **Discomfort Reduction:** Discomfort reduction is the difference between the discomfort at execution start and execution end. We assume that people have a preference for activity-location pairs that yield the highest discomfort reduction and hence, we maximize the heuristic function.
- **Look-Ahead Measure:** The look-ahead measure builds on effectiveness functions and is calculated through the convolution of an effectiveness function with an exponential kernel that points into the future of the simulation. This gives an indication about prospective effectiveness and hence, about the flexibility to execute an activity at a later point in time. The decision heuristic uses this measure to postpone activities with more execution options/higher prospective effectiveness and favors other activities for current execution.



- **Current Execution Effectiveness:** The current execution effectiveness builds on effectiveness functions and is calculated through the integral of the effectiveness function between activity start and end normalized by the activity execution duration. This measure introduces a preference to execute activity-location pairs during efficient time windows, whereas efficiency is defined by whatever the effectiveness function represents (e.g. social or cultural norms).
- **Execution Time Quota:** The execution time quota introduces an aversion for traveling and a tendency for activity execution and is defined as the ratio between execution duration and the duration between travel start and execution end. Accordingly, it introduces a preference for accessible locations (locations that can be reached fast) and fosters activity chaining.

## 4 Continuous Location Choice

Location choice in a continuous model shares many aspects with location choice in other models. Accordingly, the proposed continuous location choice procedure also features a preference for accessible locations and the possibility to define an individual unexplained preference for certain locations. An additional requirement for continuous location choice is to consider long term aspects like seasonal effects or continuous aspects like recurrent visits. We provide this possibility through location effectiveness, informing agents about the effectiveness of locations towards discomfort reduction.

### 4.1 Preference for Accessibility

People show a preference to execute their activities (e.g. satisfy their daily shopping needs) in their surroundings. The decision heuristic considers this preference through the execution time quota, which is defined as

$$ETQ(t_{ts}, t_{es}, t_{ee}) = \frac{t_{ee} - t_{es}}{t_{ee} - t_{ts}} \quad (2)$$

the execution duration  $t_{ee} - t_{es}$  normalized by the duration between travel start and execution end  $t_{ee} - t_{ts}$ . The resulting factor is higher for alternatives with a lower travel share, introducing a preference for accessible locations without favoring short or long activity durations. It also fosters activity chaining since it introduces an aversion for traveling.

## 4.2 Location Effectiveness

A continuous model aims at the simulation of long periods like weeks or months. Accordingly, a continuous location choice procedure should be able to consider long term aspects like seasonal effects or continuous aspects like recurrent visits of e.g. relatives. Our model provides this ability for each individual location through the definition of an effectiveness function, informing agents about the effectiveness of this location towards discomfort reduction (also see Section 3.1.2 for a discussion of effectiveness functions).

Effectiveness functions can be static (e.g. precomputed measures like opening hours) or dynamic (e.g. measures computed on the fly coming from a sensor observing the environment) and are considered by the decision heuristic (see Section 3.2) through discomfort reduction, execution effectiveness and the look-ahead measure. The application of effectiveness function is manifold and only limited by the ability to express a measure in the range of  $[0..1]$ . Following list provides an overview of possible applications:

- Shop opening hours for a *daily shopping* activity could contain location dependent information about shop crowdedness. Hereby, we assume that shopping at overcrowded shops is less efficient and therefore takes longer than at less crowded shops. Shop crowdedness information could build on people's experience (in this case the function would be static) or on the number of agents currently visiting a shop (in this case the function would be computed dynamically). The decision heuristic provides agents with a preference for less crowded shops (because discomfort reduces faster) and it urges agents to go shopping before shops get crowded (through the look-ahead measure).
- Locations of a weather dependent activity could provide an effectiveness function containing weather forecast information. The decision heuristic prevents agents from executing weather dependent activities during rainy days (because discomfort reduces slower) and it urges agents to execute them ahead of bad weather fronts (through the look-ahead measure). A simulation run using weather dependent effectiveness functions could also provide insights about people's behavior for a coming long weekend, e.g. to get an indication about traffic conditions at an Easter weekend with bad weather in the north and good weather in the south of Europe.
- An activity modeling visits to relatives could have an effectiveness that is a function of the time since the last visit. Hereby, we assume that people have a repetitive meeting pattern and that the effectiveness of a visit increases as the time since the last visit increases. Since the decision heuristic provides agents with a preference for effective locations, the probability of an agent visiting a relative also increases as the time since the last visit increases. The effectiveness function could be assigned to the activity (to model the meeting pattern to relatives in general) or to a specific location (to model the meeting pattern to specific relatives like e.g. parents).
- An effectiveness function modeling seasonal effects for a *leisure* activity could

combine different effects like time of the year and weather conditions. As an example, a ski resort can have a high effectiveness during the winter months after a snowfall whereas the yacht club has a high effectiveness during the summer months with sunny weather and a good breeze. This enables agents to follow seasonal rhythms because they choose to ski at the ski resort during the winter and to sail at the yacht club during the summer.

- Agents could be matched to locations based on their income (e.g. for a *long term shopping* or *dine out* activity). Hereby, we assume that wealthier people prefer luxurious places/commodities which poorer people cannot afford. This could be modeled by a dynamic effectiveness function taking income and price level into account, resulting in a high effectiveness when levels match and decreasing effectiveness as the difference increases. Since the decision heuristic takes effectiveness into account, agents would with a preference for locations matching their income level.
- Habitual behavior could be modeled by an effectiveness function taking the number of past visits into account. Hereby, we assume that people's behavior has habitual elements, resulting in a preference for locations they already know. Accordingly, the effectiveness increases as the number of past visits increases. Explorative behavior (counteracting habitual behavior) could be integrated through a decay function, leading to decreasing effectiveness as the time since the last visit increases.

### 4.3 Individual Perception

Using a preference for proximity (see Section 4.1) and location effectiveness (see Section 4.2) results in a location choice with uniform characteristics where agents choose the most accessible and effective location, i.e. simulated variety seeking behavior is consistent between all agents. Clearly, this does not match the heterogeneity of observed behavior (Schönfelder (2006)).

A typical workaround to improve heterogeneity is to introduce an individual unexplained preference for certain locations, modeled as a random variable altering the perception of an alternative (Horni *et al.* (2011)). For utility maximization models, one has

$$U_{pi} = V_{pi} + \epsilon_{pi} \quad (3)$$

where  $p$  is the person/agent index and  $i$  the index of the alternative.  $V$  denotes the systematic part of the utility (identical to every agent -  $HF(t_{ts}, t_{es}, t_{ee})$  in our model),  $\epsilon$  the random offset, and  $U$  the resulting utility. Horni *et al.* used a Gumbel distribution and considered three approaches to calculate  $\epsilon_{pi}$  and thus, to improve the heterogeneity of their location choice procedure:

- (a) Freezing the applied global sequence of random number generation.

- (b) Computing and storing a separate  $\epsilon_{pi}$  for every combination of agent  $p$  and alternative  $i$ .
- (c) Re-calculating  $\epsilon_{pi}$  on the fly by using a random seed  $s_{pi} = f(p, i)$  that depends on agent  $p$  and alternative  $i$ .

Option (a) turned out to be infeasible because it is extremely difficult to freeze a drawing sequence (e.g. in a computer program that runs in parallel) and (b) exceeded memory resources for large-scale scenarios. This leaves (c) as the only feasible solution which we decided to adopt for our model. Accordingly, we extended the heuristic function with a random error term  $RET(p, i, t)$  that uses a seed depending on agent  $p$ , alternative  $i$ , and the current simulation day  $t$ . Including the current simulation day alters the variety seeking behavior between decisions while preserving deterministic behavior between simulation runs. This is necessary because in contrast to Horni *et al.*, we do not iteratively simulate the same day but perform a continuous simulation of longer periods where people might face the same decision at different days without choosing the same alternative.

## 5 Location Choice Validation

This section validates the proposed continuous location choice procedure using a model configuration focusing on seasonal aspects and weather conditions for leisure activities. We start with a description of the model configuration and then discuss simulation results.

### 5.1 Model Configuration

We use a grid of  $50 \times 50$  where each grid cell defines the home location of an agent. Each agent can choose between four locations (Fig. 4 shows their positioning on the grid) to execute leisure activities and as an alternative, agents can always choose to execute activities at home. The locations for leisure activities are separated into two summer locations (e.g. executed at the shore of a lake) and two winter locations (e.g. executed at a ski resort) whereas one location each is susceptible to weather conditions. Opening hours of each leisure location starts at 7 am and ends at 8 pm. The simulation focuses on 12 days, three days for each season (days 1-3 for summer, days 4-6 for autumn, days 7-9 for winter, and days 10-12 for spring). Travel times are calculated based on the euclidean distance between locations, simplifying recognition of effects due to the preference for accessible locations.

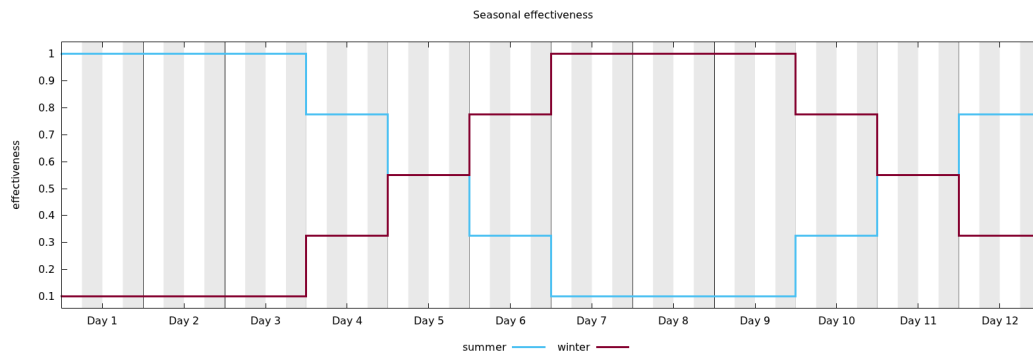
Fig. 2 illustrates the functions used by the simulation to create the effectiveness functions for the leisure locations shown in Fig. 3. Leisure locations either use the "summer"

or "winter" function of Fig. 2(a) dependent on being more effective in summer or winter, might integrate the function of Fig. 2(b) dependent on being susceptible to weather conditions, and use the function of Fig. 2(c) to integrate opening hours into their effectiveness function. This results in four different effectiveness functions, two for locations being more effective in summer with one with (*lake 1* - see Fig. 3(a)) and one without (*lake 2* - see Fig. 3(b)) susceptibility to weather conditions and two for locations being more effective in winter with one with (*ski 1* - see Fig. 3(c)) and one without (*ski 2* - see Fig. 3(d)) susceptibility to weather conditions.

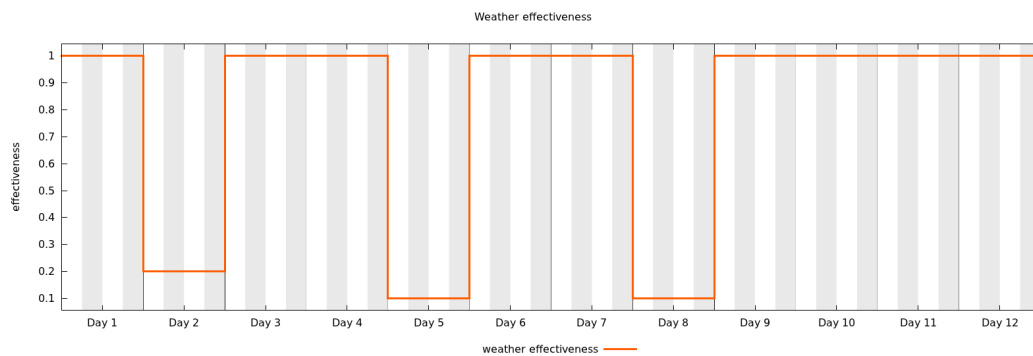
## 5.2 Simulation Results

We perform three simulation runs, one with deactivated individual perception (no randomness) and two with activated individual perception using a small and a large variance for the error term. Fig. 4 illustrates the simulation results of days 1, 5, 7, and 11. The first picture of each row shows results with deactivated and the second and third picture with activated individual perception (second using small and third using large variance in the error term). The home cell of an agent traveling to *lake 1* is colored orange, to *lake 2* yellow, to *ski 1* dark blue, and to *ski 2* light blue.

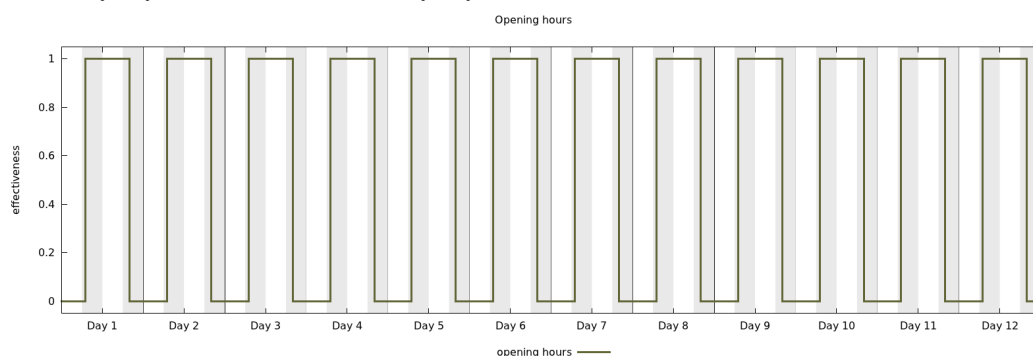
- Fig. 4(a) compares the simulation results of day 1. Since it is a sunny summer day, agents prefer locations with highest effectiveness in summer (*lake 1* and *lake 2*). With deactivated individual perception, agents choose the closest and most effective location (first figure). The decision border starts to blur as the variance of individual perception increases (second and third figure). These simulations show that agents choose the most effective location and that the influence of effectiveness decreases as individual perception increases.
- Fig. 4(b) compares the simulation results of day 5. Since it is a snowy autumn day, agents prefer locations *ski 2* and *lake 2* because they are insusceptible to weather conditions and because seasonal effects cancel out at day 5. With deactivated individual perception, agents choose the closest and most effective location (first figure). The decision border starts to blur as the variance of individual perception increases (second and third figure). Agents start to choose less effective locations (*lake 1* and *ski 1*) as the distance to the most effective locations (*ski 2* and *lake 2*) increases. This distance marks the point where the effect of individual perception exceeds the preference for accessible and effective locations (see left lower corner of second figure). These simulations show that agents react to weather conditions and choose locations insusceptible to weather when conditions are bad.
- Fig. 4(c) compares the simulation results of day 7. Since it is a sunny winter day, agents prefer locations with highest effectiveness in winter (*ski 1* and *ski 2*). With deactivated individual perception, agents choose the closest and most effective location (first figure). The decision border starts to blur as the variance of individual perception increases (second and third figure). These simulations show that agents follow seasonal rhythms and choose to execute winter activities



(a) Functions modeling seasonal effects (days 1-3 for summer, days 4-6 for autumn, days 7-9 for winter, and days 10-12 for spring). Locations more effective during summer use the "summer" function and locations more effective during winter use the "winter" function.



(b) Function modeling weather conditions. Location integrate this function into their effectiveness only if they are susceptible to weather conditions. Day 2 represents a rainy day, day 5 and 8 are snowy days, and all others are sunny days.

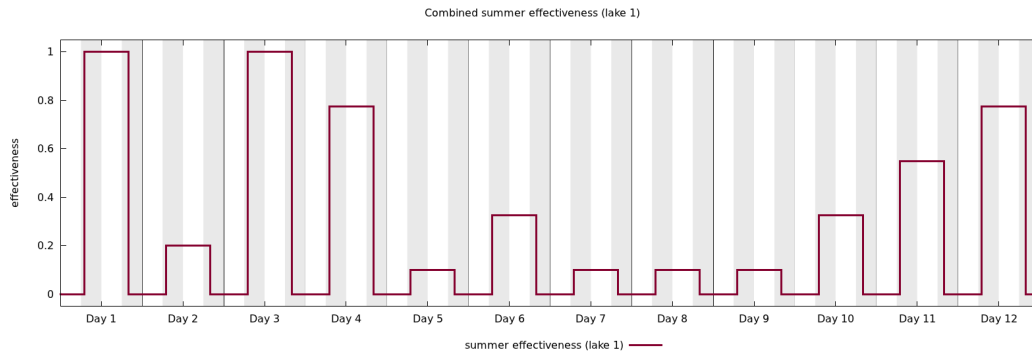


(c) Function modeling opening hours. All locations integrate this function into their effectiveness.

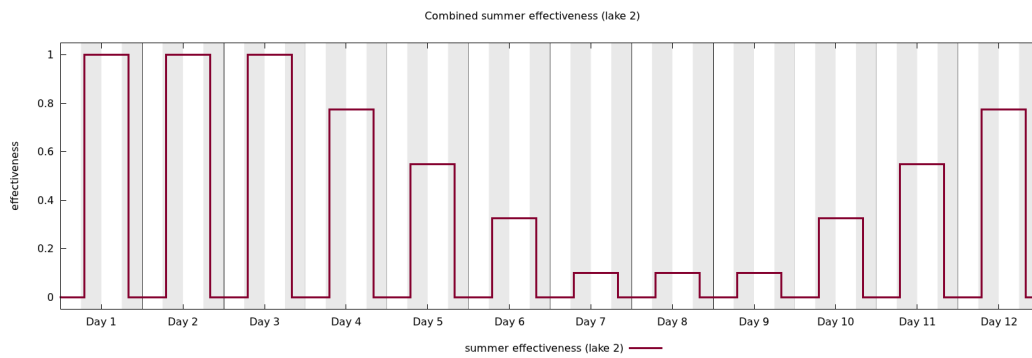
Figure 2: Illustration of the functions used by the simulation to create the effectiveness functions for the leisure locations shown in Fig. 3.

in winter and summer activities in summer (see Fig. 4(a) to compare to summer conditions).

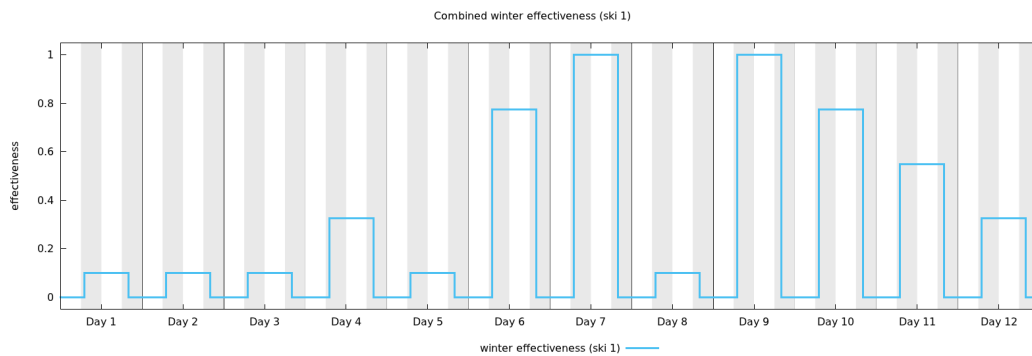
- Fig. 4(d) compares the simulation results of day 11. Since it is a sunny spring day and seasonal effects cancel out at day 11, all locations have the same effectiveness. Accordingly, agents choose the closest location (first figure) and the decision borders start to blur as the variance of individual perception increases (second and



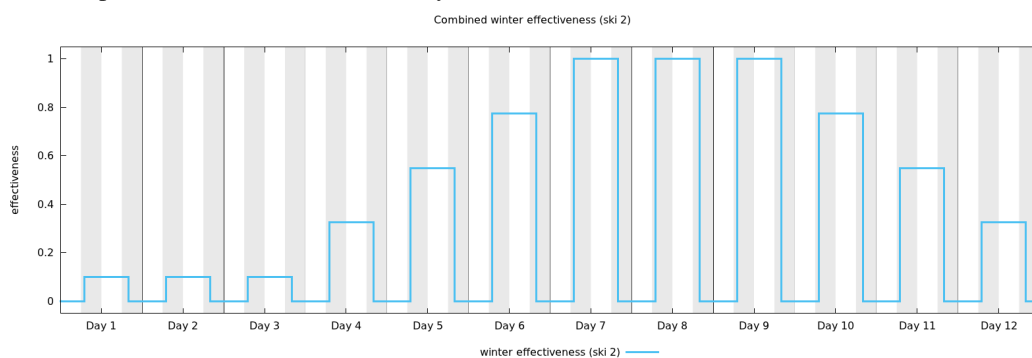
(a) Effectiveness function for the location (*lake 1*) that is more effective in summer. This location is susceptible to weather conditions (days 2, 5, and 8).



(b) Effectiveness function for the location (*lake 2*) that is more effective in summer. This location is insusceptible to weather conditions.



(c) Effectiveness function for the location (*ski 1*) that is more effective in winter. This location is susceptible to weather conditions (days 2, 5, and 8).



(d) Effectiveness function for the location (*ski 2*) that is more effective in winter. This location is insusceptible to weather conditions.

Figure 3: Illustration of the location effectiveness functions created by the simulation using the functions shown in Fig. 2.

third figure). These simulations show that agents base their decision on locations' accessibility when other effects cancel out.

In the above simulations, we use the euclidean distance between locations to calculate travel times (simplifying recognition of effects due to the preference for accessible locations). Accordingly, it is not surprising that increasing individual perception (higher variance in the error term) moves the travel time distribution towards longer travel times (see Fig. 5). This shows a possibility to calibrate the simulated travel time and travel distance distributions through altering the parameters of the error term. Horni *et al.* (2011) observed this effect as well and used it to calibrate their model to fit travel distance distributions of the Swiss National Travel Survey (Swiss Federal Statistical Office (2006)).

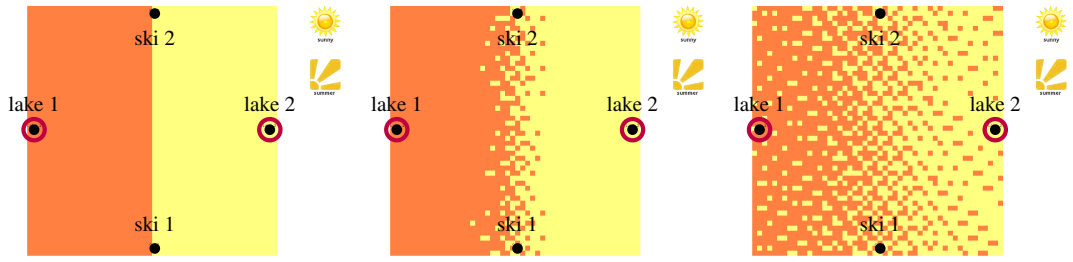
## 6 Outlook

We envision a project with the aim to compile a one year simulation scenario. This project should be capable to reproduce annual demand profiles (e. g. Bernard and Axhausen, 2008, 2010) and behavioral rhythms of individuals (e. g. Axhausen *et al.*, 2002, Schlich and Axhausen, 2003, Habib *et al.*, 2008). Apart from surveys focusing on long distance travel (Bieger and Lässer (2008), Bureau of Transportation Statistics (2012)), we are unaware of surveys covering such a long period. Accordingly, we will have to explore possibilities to generate effectiveness functions using available resources like historical data (e.g. weather conditions or daylight intensities) and options to combine them with information coming from surveys with shorter duration (we are not planning to conduct a new survey). It is also unclear how to recognize and model phase transitions in peoples life (i.e. abrupt changes like the birth of a child) and the time thereafter when this exceptional situation becomes everyday life. We will have to determine to what extent expert knowledge can help to overcome such ambiguities.

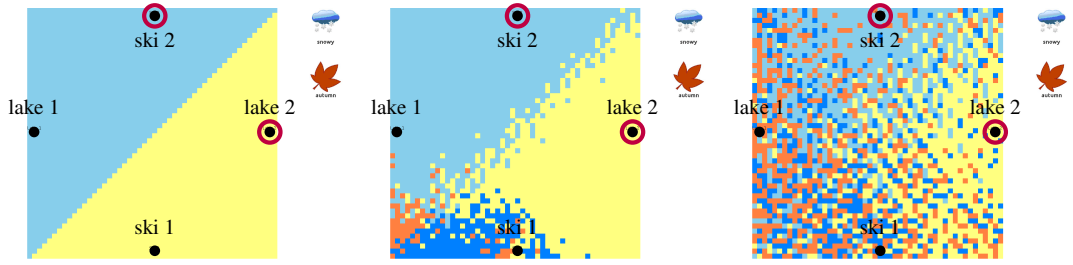
## 7 Conclusion

This paper proposes a continuous location choice procedure and integrates it into a target-based model whose decision heuristic decides on the fly and with an open time horizon about future locations agents should visit. The proposed location choice combines following elements. First, it integrates expected travel time as a *preference for accessible locations*, i.e. agents prefer close-by locations they can reach fast. Second, it utilizes effectiveness functions as an indication for locations' current and prospective effectiveness towards discomfort reduction. *Location effectiveness* is a broad concept that can model many aspects like e.g. susceptibility to weather conditions, recurrent

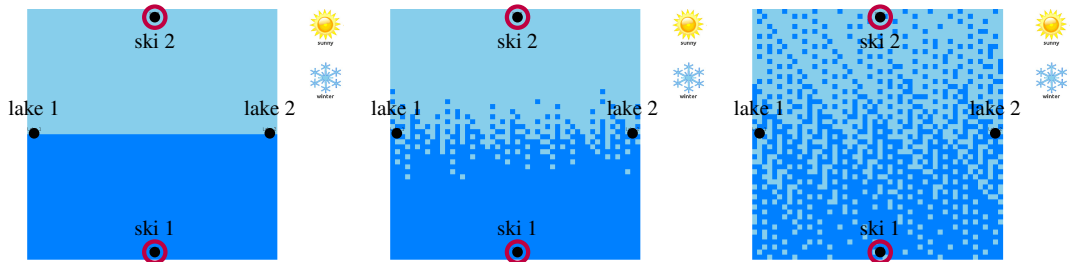




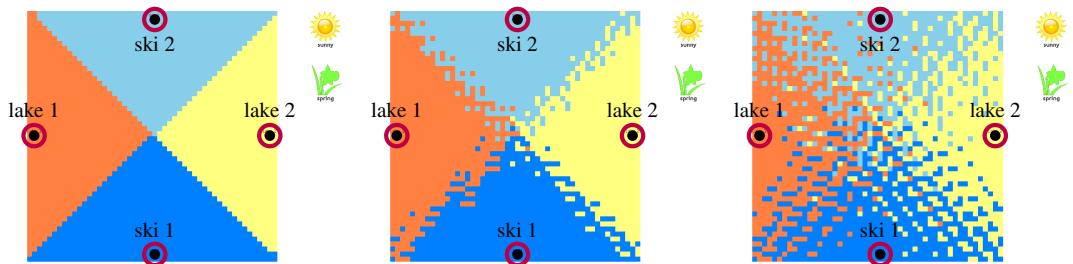
(a) Simulation results of day 1. A sunny summer day with a preference for summer locations (*lake 1* and *lake 2*).



(b) Simulation results of day 5. A snowy autumn day with seasonal effects canceling out and a preference for locations insusceptible to weather conditions (*ski 2* and *lake 2*).



(c) Simulation results of day 7. A sunny winter day with a preference for winter locations (*ski 1* and *ski 2*).



(d) Simulation results of day 11. A sunny spring day with seasonal effects canceling out (agents choose locations based on their accessibility).

Figure 4: Illustration of the simulation results of days 1, 5, 7, and 11 (see Section 5.2 for a detailed discussion). The first picture of each row shows results with deactivated individual perception, the second picture with activated individual perception using small variance in the error term, and the third picture using large variance. The home cell of an agent traveling to *lake 1* is colored orange, to *lake 2* yellow, to *ski 1* dark blue, and to *ski 2* light blue.

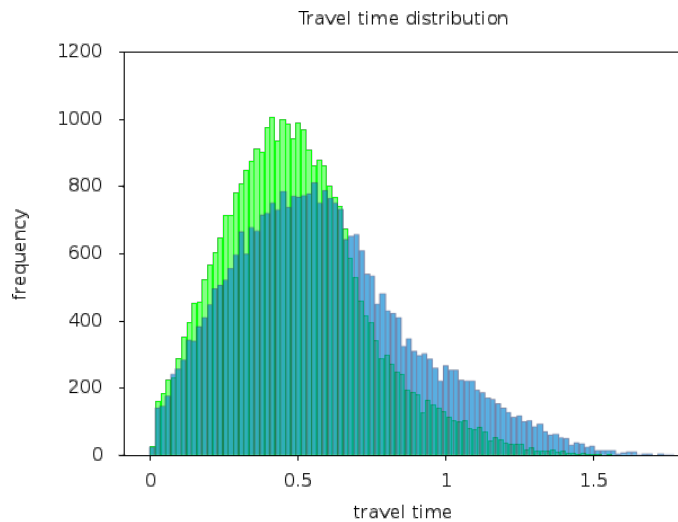


Figure 5: Illustration of the travel time distribution with activated individual perception using small (green) and high (blue) variance in the error term.

visiting patterns, and seasonal effects. Third, it uses *individual perception* to model unexplained preference for certain locations, resulting in an increase in heterogeneity for simulated location choice behavior. The combination of these elements results in a location choice procedure that is capable to handle long term and continuous location choice aspects, enables variety seeking, and produces realistic location choice patterns. Several simulation runs validate the continuous location choice procedure showing agents' behavior in different situations.

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