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Decision Making in an Agent-Based Simulation of Long-Distance Travel Demand

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Abstract

Analysis of long-distance travel demand has become more relevant in recent times due to the growing share of traffic induced by journeys related to remote activities. Consequently, there is a need of reliable long-distance travel forecasting tools like agent-based simulations. This paper presents a target-based simulation that simulates long-distance travel behavior for a long period of time. It is shown how decisions are modelled in this simulation. Activity type, duration, destination and mode are chosen simultaneously with respect to time and monetary budgets. The presented approach uses a heuristic to reduce the choice set followed by optimizing a discomfort function.

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Keywords: agent-based simulation; long-distance travel demand; continuous simulation; target-based approach; decision making; C-TAP

1. Introduction

To date, just few agent-based simulations focus on long-distance travel behavior. Long-distance journeys, which are defined by the trip distance (e.g. at least 50 km), are the core interest of the simulation presented in this paper. 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.

Agent based simulations have a long tradition in analysis and explanation of social behavior and were also used to estimate travel demand [1,2] or to generate an activity-based travel forecast [3,4]. Nowadays, agent-based simulations make a notable contribution to the field of transportation research [5,6,7,8]. The target-based approach presented in this paper is related to the need-based theory which was introduced by Arentze and Timmermans [9]. They developed a model for activity generation with the assumption of utilities described as dynamic function of needs [10]. Targets instead of needs

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were used as an explanation of human behavior[11] and validated for short distance travel generation[12]. The usage of a continuous target-based model for a long-term simulation of long-distance travel demand was introduced recently[13].

2. 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 (e.g. MATSim[5]) 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. The simulation presented in this section was introduced as a weekly simulation[11,14,15] and extended to a long-term simulation[13,16].

2.1. Behavioral Targets, Activities and State Values

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. Two types of targets are used to define the agents desires to travel:

- Percentage-of-time target: indicates the relative time within an observation window an agent would like to spend on a specific activity
- Duration target: indicates the time an agent would like to spent for a single execution of a specific activity

Activities are necessary to complete the concept of a target-based simulation, because the targets (or motivations) described above are satisfied by the execution of a corresponding activity, which induces travel. The decision on the executed activities is based on state values. Each target corresponds to a state value, which is necessary to measure the satisfaction. We need to introduce two types of state values. Firstly, the state value of a percentage-of-time target is the result of a convolution of the activity execution pattern with an exponential kernel. Therefore, it increases during the execution of the relevant activity, respectively decreases during non-execution. Secondly, the state value of a duration target defined as the actual activity duration. The level of satisfaction 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.

2.2. 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[17]. The crucial part of this procedure is the minimization of the discomfort value, which is an exponential multi-dimensional optimization problem.

2.3. Discomfort Function

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 an 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:

$$D(t, a, l, v_0) = \sum_{\omega \in A \setminus a}^{n} (T^{\omega}_{perc} - \check{v}_a(t, v_0(\omega)))^2 + (T^{\omega}_{perc} - \hat{v}_a(t, v_0(a)))^2 + (T^{a}_{dur} - t)^2 * \gamma_a \tag{5}$$

In principle, 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. The destination influence on the activity planning is described in the following.

2.4. Decision Variables

Various variables are involved in the decision process of C-TAP. The variables involved can be divided in three groups: destination-based, mode-based and personal variables. The destination-based variables include the actual location (implicitly defining the distance) and certain attractiveness values for each activity type. Vacation activities are connected to a (seasonal) price and a seasonal penalty potentially lowering the attractiveness at each location. Mode variables that are considered are the (average) speed of a mode and the price per kilometer, which are the main variables driving the mode choice. Personal variables play the most important role since they drive the activity

type decision, which is mainly controlled with the targets of an agent as described above. Additionally, the destination choice is affected by personal location awareness and location perception. Awareness has been shown to be an important part in the decision process[18,19] 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[20,21,22]. Furthermore, car availability and second homes of agents can be modelled here.

One major constraint in the planning of long-distance trips is the given budget. Two types of budget constraints are taken into account within the C-TAP activity planning, when a non-business activity is considered. Firstly, a monetary budget is used to implicitly model income effects on the decision. Secondly, a budget of vacation days is modelled in order to make weekends more attractive for private long-distance tours.

2.5. Mathematical Formulation

The variables described above are included in the activity planning. Some of the variables reduce the probability to visit a specific location l. In order to model this probability, we introduce a pull factor ϕ. The pull 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:

$$\hat{v}_a(t_e - t_s, v_0(a)) = 1 + (v_0(a) - 1)e^{-\tau_a \cdot \phi(l,t_s,t_e)\cdot(t_e - t_s)} = 1 + (v_0(a) - 1)e^{-\tau_a \cdot q(l)\cdot \varepsilon(l)\cdot \int_{t_s}^{t_e} s(l,u)\mathrm{d}u} \tag{6}$$

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

$$\begin{aligned} \min_{t,\, a,\, l\, m} D(t, a, l, m, v_0) + \overbrace{\gamma_B \cdot \frac{B - p_l(l, t) - p_m(l, m)}{B}}^{\text{Budget Reduction Discomfort}} \\ s.t. \quad & l \in L(a) \\ & l \in AW \\ & m \in M \\ & p_l(l, t) + p_m(l, m) \leq B \\ & t \in \mathbb{R}^+ \end{aligned} \tag{7}$$

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 added here to the equation 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.

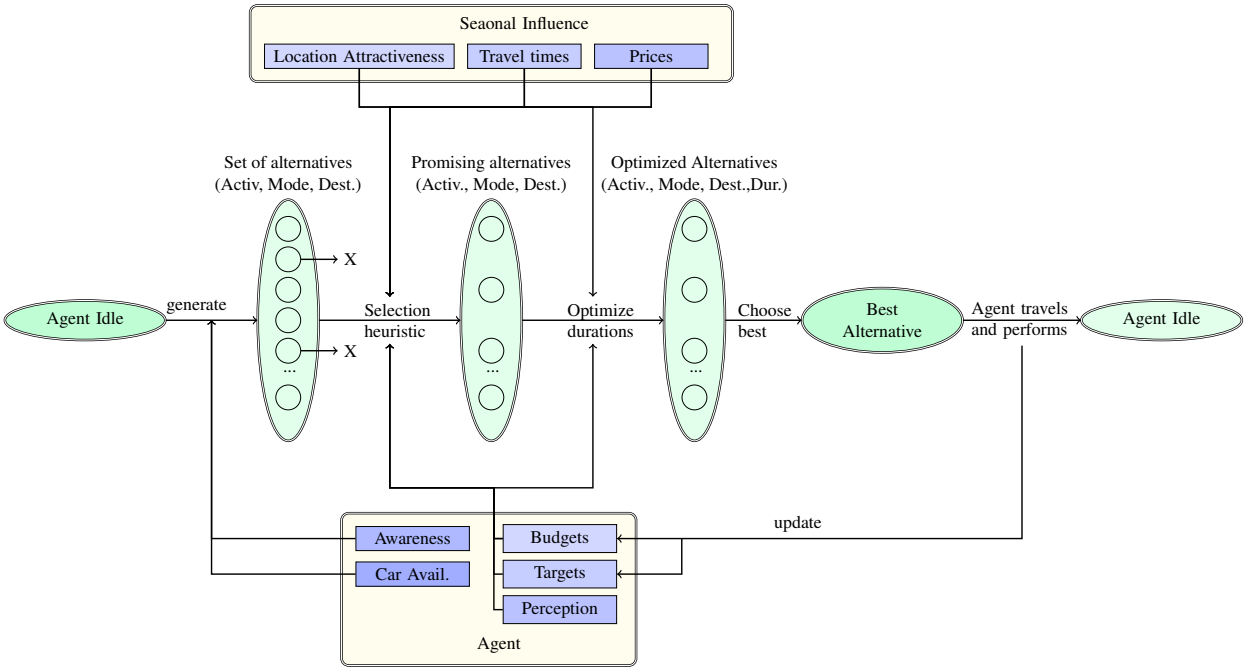

Fig. 1. Sketch of an agents decision process.

2.6. 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 that is sketched in Figure 1.

When an agent finishes his activity and becomes idle, a set of alternatives for his next action is created. An alternative consists of an activity plus an activity location and a travel mode. In this first step, the agents' awareness and mode availability is taken into account. Though, the set of alternatives is usually large. Therefore, the non-promising alternatives are removed from the set. Non-promising alternatives include alternatives, which can not be afforded by the agent, and alternatives with a low pull factor ϕ. Subsequently, the optimal duration is computed for each alternative in the remaining set (see Equation (7)). A detailed description of the discomfort minimization approach can be found in [17]. Finally, the agent performs the best alternative from the optimized set and the targets and budgets are updated.

3. 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. Therefore, 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.

4. Conclusion

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

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