Integration of Household Interaction with a Continuous Simulation Model

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Abstract

This paper presents an approach to integrate social interactions with a agent based simulation model for continuous activity planning. It describes an interface to the underlying target-based model providing the possibility to influence agents' behavior by manipulating targets and effectiveness functions. It proposes tasks as the mean for exogenous modules to interact with agents and describes a module for managing social interactions among agents. This module uses the interface to ensure agents adhere to appointments and meet at arranged locations and specified dates. The validation of the approach focuses on activities shared among household members requiring regular meetings to arrange future responsibilities. We conclude by suggesting directions for future research.

Keywords

household interaction, social interaction, target based planning, traffic simulation

1 Introduction

Microscopic travel demand simulation software uses a direct representation of virtual people (usually referred to as agents) to generate demand in terms of activity plans. 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), Dobler *et al.* (2012)). To model such flexible behavior, a different simulation approach becomes necessary that is capable of modeling demand continuously, i.e. agents should be able to make decisions about upcoming activities on the fly and with an open time horizon (see also the empirical insights from the work of Doherty (2005)).

We proposed a microscopic travel demand simulation in Märki *et al.* (2012a) and Märki *et al.* (2012b) that is capable of modeling demand continuously by using behavioral targets to guide agents through their decision space. These targets are closely related to observed behavior like e.g. execution frequency or time spent for an activity and can consider exogenous effects like social and cultural norms. Our 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 schedules, making simulation periods of several months feasible.

The aim of this work is to address the question on how to integrate social interactions with the continuous model while preserving its ability to simulate long periods in reasonable time and keeping its memory footprint small. We describe an interface to the underlying target-based model providing the possibility to influence agents' behavior by manipulating target and effectiveness functions. Arbitrary exogenous modules can use this interface to manipulate agents according their purpose. We propose to use this interface for a module managing social interactions among agents. This module influences agents' behavior to ensure they adhere to their appointments and meet at arranged locations and specified dates.

The remainder of this paper is structured as follows: first, we introduce the target-based model and review the decision model with a focus on relevant elements for manipulating agents' behavior. This is followed by a description of the interface and an illustration on how to use it to influence agents' behavior. The subsequent section validates the approach by focusing on activities shared among household members requiring regular meetings to arrange future responsibilities. We conclude the paper with a perspective on future tasks.

2 Related 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 (BFS) (2006) or other travel diaries (e.g. Axhausen *et al.* (2002), Schönfelder (2006), Axhausen *et al.* (2007)). We pick up Winston's (1982) suggestion to use time-dependent utilities for activities (see also Axhausen (1990, p. 34-38) for a summary or Gliebe and Kim (2010) for a recent work in this tradition) and introduce time-dependent effectiveness functions, describing the effectivity of activities and locations with respect to discomfort reduction. 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 (Schönfelder (2006), Axhausen *et al.* (2007)).

3 Target-Based Model

Agents, representing virtual people, are the central component of our model. Each agent has the motivation to execute activities and specifies its desired performance through behavioral targets. Deviations to behavioral targets result in discomfort which primes agents for taking 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 and 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 Targets

The core assumption of this work is that people are motivated to execute activities and that they have a conception of their motivation in form of a performance they want to achieve. 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 exercise roughly two hours of sport about twice per week. This person would still agree on 1 hour of exercise once per week and states that up to 2.5 hours of exercise three times per week would still be compatible with his weekly schedule. 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 exercise, a *bandwidth* of $^{+0.5}_{-1}$ 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 with a *bandwidth* of $^{+1}_{-1}$ executions and an observation windows of one week.

Play tennis, swim and hike are possibilities to exercise. At the same time, playing tennis is also a chance to socialize or even a mean to maintain business relations (see e.g. Arentze and Timmermans for a discussion on multi purpose activities). Our model allows for activities to serve multiple targets and it is possible to assign a target to several activities. This facilitates configuration of interacting effects as outlined above.

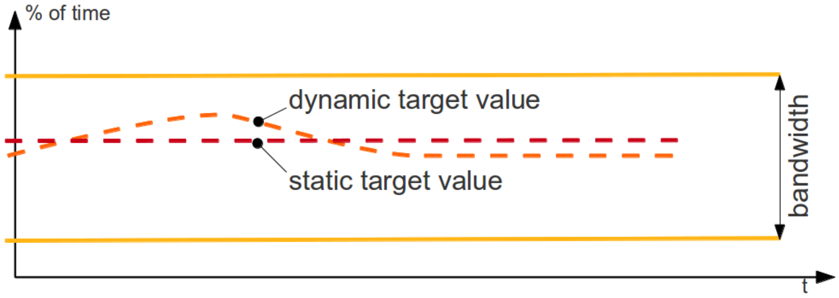
Agents monitor their performance during simulation and compare these *state values* to target values (see Fig. 1(b)). State values are exponentially discounted over the observation window of targets. This simulates a forgetting process where agents give more weight to recent behavior and gradually discount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

3.2 Effectiveness Functions

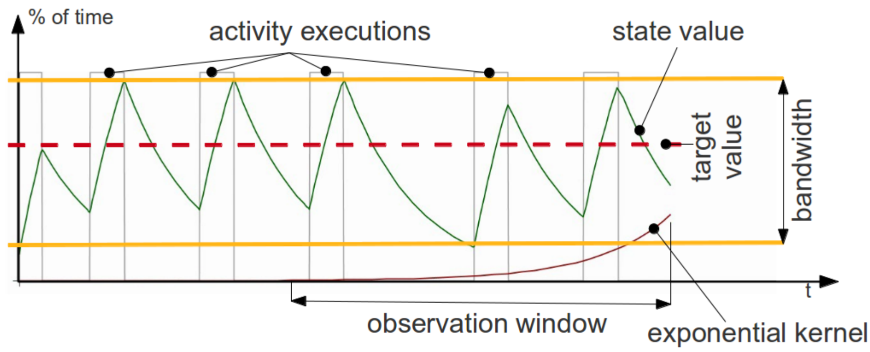
People seem to have a time-dependent preference to execute activities and/or visit locations. Reasons for this behavior can be manifold and vary from constraints (e.g. opening hours)

Figure 1: Illustration of agent configuration and performance monitoring.

(a) Schematic illustration of a target configuration that defines the average time a person would like to spend on executing an activity. *Target values* as well as upper and lower bounds (defining the *bandwidth*) can be static or dynamic 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.



over norms (e.g. business hours) and dependencies (e.g. weather conditions) to combinations of such effects. Effectiveness functions are a simple but comprehensive concept to describe such interdependencies and are expressed in percentage of execution effectivity. Effectiveness functions inform agents about the effectiveness of activities and locations with respect to discomfort reduction. This is similar to Winston (1982) who proposed time-dependent utilities for activities (see also Axhausen (1990, p. 34-38) for a summary or Gliebe and Kim (2010) for a recent work in this tradition). Possible effects that can be modeled by effectiveness functions 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 as an indication of sleep effectiveness. Hereby, 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 (different 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 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).
- **Seasonal effects for a *sport* activity.** This function is location dependent and combines different effects like time of the year and weather conditions. As an example, a ski resort can have a hight effectiveness during the winter months after a snowfall whereas the yacht club has a hight 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.

4 Decision Model

Other approaches to agent-based microsimulations revealed various disadvantages. Balmer (2007) re-planned the same day until the algorithm produced an optimal state. This procedure led to high computational costs. Kuhnimhof and Gringmuth (2009) struggled with inflexibilities when agents should spontaneously react to unexpected events. Charypar and Nagel (2006) formulated the planning procedure as a reinforcement learning problem and reported that this approach performs poorly for large scenarios. We use a decision heuristic to overcome the limitations described above. The proposed heuristic uses a continuous decision procedure, enabling agents to spontaneously react to unexpected events. 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. One could argue that people seek optimal day plans and applying a heuristic makes this infeasible. However, other authors (e.g. Simon (1955) and Schlich (2004)) doubt that behavior can be explained as a utility maximization function.

The decision heuristic we proposed in 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 $ETQ(t_{ts}, t_{es}, t_{ee})$. The following list discusses the heuristic function with a focus on aspects relevant for the location choice procedure (see Märki *et al.* (2012a) for a more 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 it takes longer for activity-location pairs with a low effectiveness 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 preference 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.

5 Behavior Modification Interface

Agents base their decisions on the heuristic function value HF (see Eq. (1)). This value is influenced primarily by the *discomfort* value being the difference of *state values* and *target values* of behavioral targets (see Section 3.1) and time-dependent effectivenesses of activities and locations (see Section 3.2). Consequently, it is possible to influence agents' behavior by manipulating behavioral targets and effectiveness functions. The application of these manipulations is manifold and ranges from stimulating agents to execute activities (by manipulating the frequency target) over stimulating agents to spend time for an activity (by manipulating the percentage of time target) to changing agents' likelihood executing a specific activity and/or visiting a specific location (by manipulating effectiveness functions). Table 1 illustrates different manipulation combinations and how they influence the behavior of agents. The aim of these manipulations is to introduce additional tasks an agent has to execute. Consequently, the described manipulations are only visible for this specific agent and only during the specified time.

5.1 Target Modification

Target modifications temporarily influence behavior, e.g. by temporarily increasing target values, lower bounds, and upper bounds of targets (in this work we focus on target values). This is a mechanism to stimulate agents to e.g. temporarily spend time for an activity (by modifying the *percentage of time* target) and/or to temporarily perform activity executions (by modifying the *frequency* target). Consequently, a target modification defines the time when the modification takes place and how targets should be modified during that time. Lets assume a person executes an activity (e.g. *daily shopping*) every other day for two hours (Fig. 2(a) illustrates the configuration of this activity). Furthermore, we assume that this activity can be executed at any time (there are no opening hours or other execution constraints). This is necessary to guarantee that changes in behavior are a result of the target modification and is not influenced by other elements. Based on these assumptions, we produce a base configuration and apply different modifications resulting in new configurations. For each of these configurations, we generate 100 identical agents and run a 10 week simulation.

- Fig. 2(a) illustrates the base configuration. In average, the activity should be executed every second day (3.5 times per week - orange plot) for two hours ($3.5 \cdot 2h / (7 \cdot 24h) = 4.17\%$ - dark red plot). Fig. 2(b) shows that agents execute the activity in average slightly more than 0.5 times per day (about every other day - blue plot) and spend in average about one hour for this activity per day (every other day two hours - green plot). Consequently, agents follow the configuration and behave as expected.

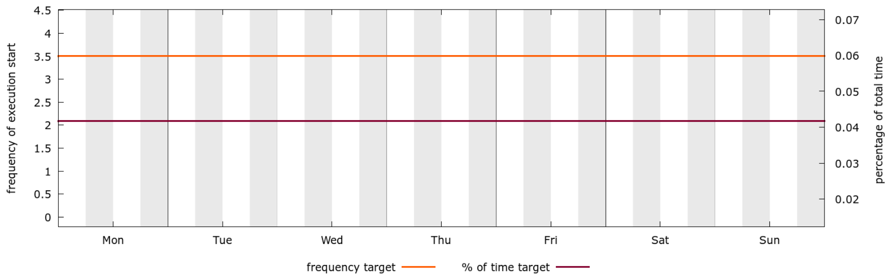
Table 1: Illustration of different manipulation combinations with the aim to introduce tasks an agent should execute.

Task	Parameters	Description
buy extra food	Activity: daily shopping Duration: $+0.5h$ Frequency: $+0\times^{+1}_{-0}$ Time: 24/04/2013 between 9:00 am to 4:00 pm	This agent invited guests for dinner and needs to do extra *daily shopping* to buy groceries. The agent needs to spend 0.5 extra hours (since these groceries are in addition to daily needs) and is free to combine it with other shopping duties or to do an extra shopping trip (increase of upper bound of frequency). The task should be done on Wed 24th Apr, 2013 between 9 am and 4 pm (before preparation of dinner) and hence, manipulations on behavioral targets are active during this time.
extra sport	Activity: sport Duration: $+2.0h^{+0}_{-0}$ Frequency: $+2\times^{+1}_{-1}$ Time: 24/04/2013 to 26/04/2013	This agent decided to spend extra time for sport during e.g. a conference taking place from Wed 24th Apr, 2013 to Fri 26th Apr, 2013. The agent would like to spend 2 extra hours (parameter duration) and favors to split this time in 1 to 3 additional sessions (parameter frequency). Manipulations on behavioral targets are active while the conference takes place.
get a hair-cut	Activity: personal care Duration: $+1.0h^{+0}_{-0}$ Frequency: $+1\times^{+0}_{-0}$ Location: hair dresser *flying scissors* Time: 24/04/2013 from 2:30 pm to 3:30 pm	This person has a hair dresser appointment on Wed 24th Apr, 2013 from 2:30 pm to 3:30 pm. Manipulations on behavioral targets are active while the appointment takes place. Additionally, the location effectiveness of the hairdresser *flying scissors* is set to 100% whereas the location effectiveness of all other locations are set to 0% while the appointment takes place. This forces the agent to visit the location of the hairdresser *flying scissors*.

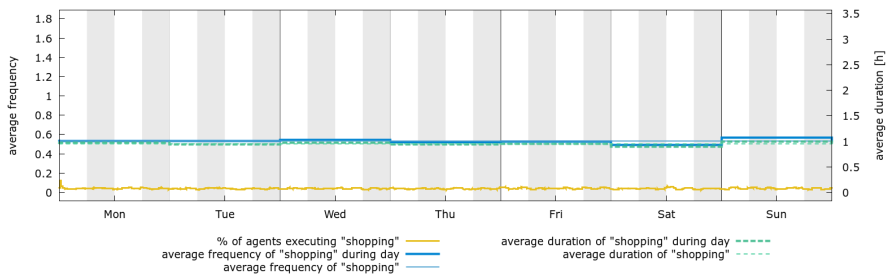
- In a second configuration (see Fig. 3(a)), we stimulate the agent to temporarily spend two hours (dark red plot) for the activity by performing an execution of the activity (orange plot) on Tuesdays between 9 am and 6 pm. This figure also illustrates that modifications of target values are discounted (through a convolution with an exponential kernel of one week) as it is done for *state values* (see Section 3.1). This is necessary because abrupt changes would result in a sudden increase of the difference between target and state values, leading to an instantaneous discomfort increase leaving agents with no time to

Figure 2: Illustration of the base configuration and simulation outcome.

(a) In average, the activity should be executed every second day (3.5 times per week) for two hours (3.5 · 2h / (7 · 24h) = 4.17%).



(b) Agents execute the activity in average slightly more than 0.5 times per day (about every other day) and spend in average about one hour for the activity per day (every other day for two hours).



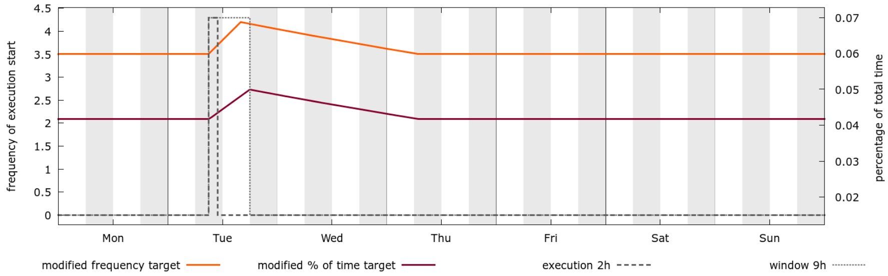
react. Fig. 3(b) shows that every agent executes the activity at least once during Tuesdays (about 20% of the agents even twice - blue plot) and that agents spend slightly more than two hours for the activity (green plot). The average frequency and average duration (blue and green plot) stays constant during the rest of the week. This shows that the execution during Tuesdays does not influence agent's behavior besides Tuesdays. Interesting to note is the wavelike form of the execution pattern (yellow plot) during Tuesdays. This indicates that some agents execute the activity right at the beginning of the execution window while others wait until its end or even execute it thereafter.

5.2 Effectiveness Modification

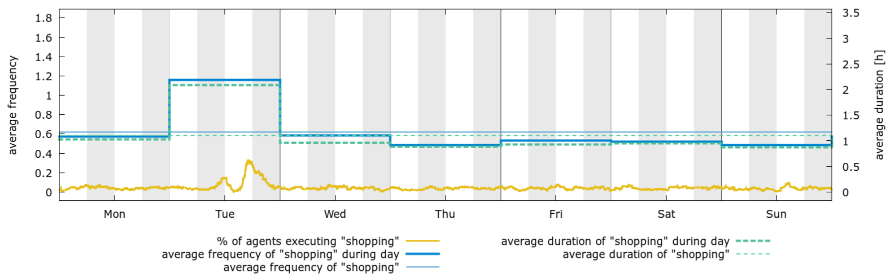
Effectiveness functions inform agents about the effectiveness of activities and locations with respect to discomfort reduction (see Section 3.2). By modifying effectiveness functions, it is possible to change agents' preference for activities and locations (since effectiveness functions can be activity and location specific). Accordingly, it is possible to influence the likelihood of activity executions and/or the likelihood of location visits. By introducing an opening window

Figure 3: Illustration of the second configuration and simulation outcome.

(a) Modification of the base configuration for an execution on Tuesdays between 9 am and 6 pm for two hours.



(b) Every agent executes the activity during Tuesdays at least once for about two hours. Agents behavior during the rest of the week is not affected by the extra execution on Tuesdays. Interesting to note is that agents tend to execute the activity at the start, at the end, or even after the execution window (yellow plot).

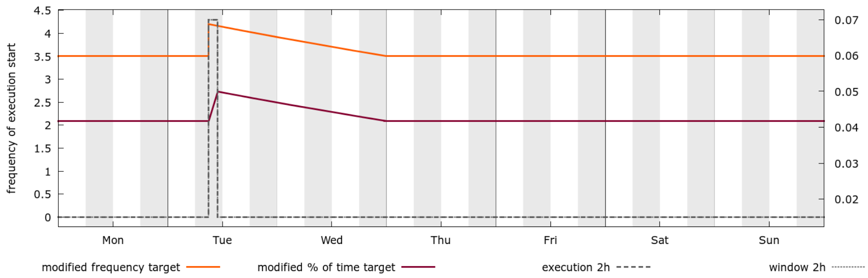


for an activity/location and a closing window for all other activities/locations, it is even possible to force agents to execute a specific activity/visit a specific location. By combining target modifications and effectiveness modifications, it is possible to ensure agents execute activities on time and at an arranged meeting location. This feature is of importance for social interactions, where groups of people meet at specific locations to execute specific activities together.

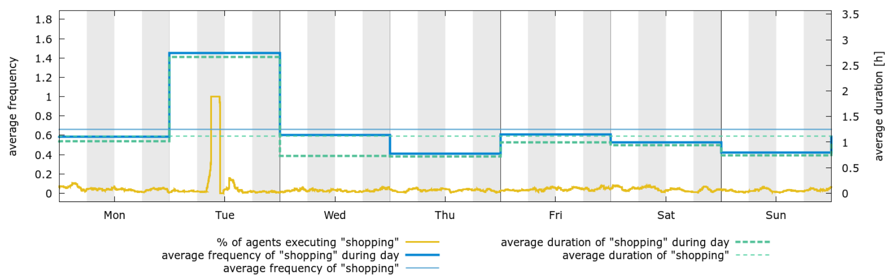
In a third configuration (see Fig. 4(a)), we reuse the second configuration and limit the execution window from 9 am to 11 am (resulting in an execution window having the same duration as the time the agent should spend for the activity). Additionally, we modify the effectiveness function and introduce closing windows between 9 am and 11 am for all activities (except the considered activity). Fig. 4(b) shows that all agents execute the activity on Tuesdays between 9 am and 11 am (yellow plot). In comparison to the second configuration (see Fig. 3(b)), agents execute the activity slightly more often and longer during Tuesdays. This probably originates from the additional increase in agents executing the activity right after the execution window (yellow plot) and is probably also the reason why less agents execute the activity on Wednesdays and Thursdays (green plot).

Figure 4: Illustration of the third configuration and simulation outcome.

(a) Modification of the base configuration for an execution on Tuesdays between 9 am and 11 am for two hours (resulting in an execution window having the same duration as the time the agent should spend for the activity). Additionally, we modify the effectiveness function and introduce closing windows between 9 am and 11 am for all activities (except the considered activity).



(b) All agents execute the activity on Tuesdays between 9 am and 11 am (yellow plot). In comparison to the second configuration, slightly more agents execute the activity twice during Tuesdays. This is probably the reason why less agents executing the activity during Wednesdays and Thursdays (green plot)



5.3 Interaction Model

Apart from periodically executed activities (e.g. sleep or daily shopping), people can also have a motivation to execute activities which are limited to a certain time period and in that sense extra to their life rhythm. The motivation and the time period is thereby defined by a special event. An simple example is the plan to give a party and the necessity to buy extra food before the party starts. In this case, it is the event of having a party that drives people to the shop. We envisage a concept building on projects to model such events. Axhausen (1998) and Schönfelder and Axhausen (2009) define projects as a coordinated set of activities, tied together by a common goal or outcome. We described tasks as the basic component of projects (Märki *et al.* (2011)). Tasks are linked to activities and temporarily modify targets and effectiveness functions during a specific time period (see also Section 5).

We envisage that exogenous modules can manipulate agents' behavior by defining projects and tasks, which in turn interact with the target-based model through the *behavior modification interface* (see Section 5). In this work, we focus on a household interaction module and use a conceptual implementation building on tasks to manipulate agents' behavior. We understand it as a proof of concept showing how the envisaged approach works correctly.

6 Household Interaction

Household interactions range from coordination meetings (e.g. to coordinate activities serving a common goal like *daily shopping* or to assign duties like *pick up children* from school) to ordinary social interactions (as observable in other social groups). All these interactions have in common that people agree to meet at a predefined location and time to execute activities together. Consequently, the target-based model also needs to provide agents the possibility to agree on meetings and to specify activities they want to execute together. The interaction model described in Section 5.3 offers the necessary means. In this work, we provide a proof of concept by focusing on coordination meetings among household members. However, we think it is possible to generalize coordination meetings to other social interactions since all interactions require that agents can define meeting location and date and that the model ensures that agents adhere to these appointments.

6.1 Shared Activities

We introduce shared activities to validate the proposed approach. A shared activity serves a common goal among people of a social group like e.g. household members. *Daily shopping* acts as an example because it supplies all household members with daily goods and potentially every member could be in charge of this activity. Accordingly, we ensure that household members meet on a regular bases to interact and negotiate about the responsibility for shared activities based on their *work load*. We define *work load* as the total amount of time necessary to reduce an agent's discomfort level of the *percentage of time* target to zero (assuming a concurrent execution of all activities) and weight it with an agent specific value of time. This is defined by

$$WL_i = VT_i \cdot \sum_{j=0}^{n} \Delta t_{i,j} \tag{2}$$

$$\Delta t_{i,j} = solve(D(t + \Delta t_{i,j})_{i,j} = 0, \Delta t_{i,j}) \tag{3}$$

agent i's specific value of time VT_i multiplied by the sum of the duration $\Delta t_{i,j}$ necessary to reduce activity j's discomfort $D(t)_{i,j}$ to zero.

Since every activity contributes to the *work load*, it is of interests to find an allocation which leads to an equally distributed *work load* among all household members. *Work loads* dynamically change over time due to a changing environment (e.g. changing obligations of people). Thus, agents need to meet on a regular basis and renegotiate the shared activity allocation. We ensure this by introducing a periodic coordination meeting task for all household members. We utilize a variation of the greedy approximation algorithm proposed by Dantzig (1957) to find a dynamic activity allocation providing a fair *work load* distribution for all household members (see Algorithm 1). Shared activities are sorted in decreasing order according their contribution to the *work load*. Thereafter, one activity after another is assigned to the agent with the lowest *work load* until all shared activities are allocated to an agent.

Algorithm 1 Distribute shared activities among involved agents

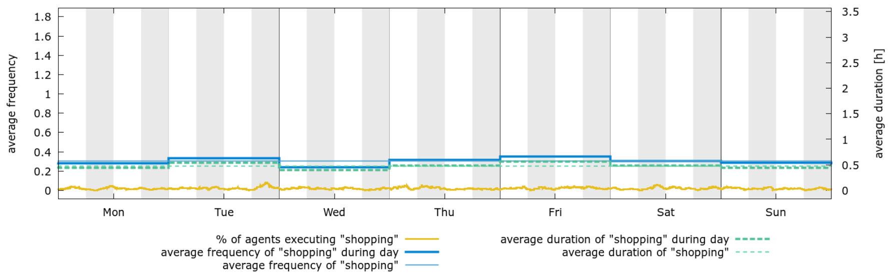
```
sortedSharedActivities ← getAllSharedActivitiesSorted()
agents ← getAllInvolvedAgents()
for all activity in sortedSharedActivities do
    agent ← getAgentWithLowestWorkLoad(agents)
    agent.add(activity)
end for
```

By showing that this algorithm provides an equally distributed activity allocation, we can show that the model ensures that agents adhere to their coordination meetings and hence, that the model supports social interactions among any group of people (by providing the possibility to define meeting location and time and ensuring agents adhere to appointments).

6.2 Interaction Validation

We pair agents used for the base-configuration simulation in Section 5.1 together into households. This results in 50 households with two members per household. Each member has the same configuration and thus the same *work load*. We remove the shopping activity and reintroduce it as a shared household activity. Furthermore, we introduce a coordination meeting task on Sundays when household members meet and renegotiate the allocation of shared activities (see Section 6.1 for a description of the negotiation protocol). Fig. 5 shows that agents execute the

Figure 5: Illustration of the simulation outcome when two agents share a shopping activity. Agents perform the activity every forth day (compared to every second day in Fig. 2(b)) and in average execute the activity for 0.5 hours per day (compared to an average of one hour per day in Fig. 2(b)).



activity in average slightly more than 0.25 times per day (about every forth day compared to every second day in Fig. 2(b)) - blue plot) and spend in average about 0.5 hours per day for this activity (every forth day two hours compared to every second day two hours in Fig. 2(b)) - green plot).

7 Future Work

It is on our long term agenda to extend the household interaction approach presented in this work to arbitrary social interactions. We think this should be straight forward since we could show that the proposed behavior modification interface already provides the necessary means to support interactions among other social groups.

In this work, we use a conceptual implementation of tasks and their interaction with the behavior modification interface of the target-based model. We understand it as a proof of concept showing that the proposed approach works correctly. The long term goal is to provide a framework allowing a dynamic generation and allocation of tasks. This would provide an interaction interface for exogenous modules of arbitrary purpose.

8 Summary

This paper proposes a behavior modification interface to the target-based model allowing exogenous modules to influence agents' behavior. This interface builds on tasks defining the behavior modification and the time period when it takes place. The application of such tasks are manifold and can represent different things like e.g. definitions of special events being extra to people's life rhythm or meetings to coordinate activities serving a common goal among people of a social group like e.g. household members. Tasks influence agents' behavior by modifying target values in order to influence the execution frequency and execution duration of an activity and by modifying effectiveness functions in order to influence the likelihood of activity executions and/or the likelihood of location visits. We demonstrate the behavior modification interface by using different modification configurations for a shopping activity and present the resulting behavioral changes. We conclude by describing and validating a module to manage social interactions and use it to coordinate activities serving a common goal among household members.

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