IMPLEMENTATION OF A MODEL OF DYNAMIC ACTIVITY-TRAVEL RESCHEDULING DECISIONS: AN AGENT-BASED MICRO-SIMULATION FRAMEWORK

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Abstract: Recent progress in activity-based analysis has witnessed the development of dynamic models of activity-travel rescheduling decisions. This paper discusses issues of implementation of the *Aurora* model in an agent-based system that allows one to simulate activity-travel rescheduling decision in space and time. The implementation is illustrated using activity-travel diary data collected in the Eindhoven region that was collected originally to better understand the choice of urban parks in the study area.

Keywords. Activity-based modelling, micro-simulation, dynamic systems.

1 INTRODUCTION

Over the last years, several research teams have focused on building activity-based models of transport demand (e.g., Roorda and Miller 2004, Vovsha *et al*. 2004, Bhat *et al*. 2004, Arentze and Timmermans 2005, Pendyala *et al*. 2005). The interest in these models stems from increased complexity in society and the realization that transport demand is a derivative from how individuals and households organize their daily life within the boundaries set by their physical environment and institutional contexts. In terms of application, the primary focus has been on predicting and analysing the effects of travel demand measures as part of transport policies. However, the models also have a clear relevance for spatial planning. By taking time budgets and temporal preferences of individuals into account as well as their locational preferences, the models are able to give a more fundamental account of opportunities an urban structure offers his inhabitants compared to more traditional accessibility studies (Miller 2003).

Recent progress in activity-based analysis has witnessed the development of some dynamic models of activity-travel scheduling. One aspect of dynamics concerns within-day rescheduling behavior. Most of the work in that area involved descriptive analyses (Garling *et al.* 1999). Timmermans *et al.* (2001) and Joh *et al.* (2003, 2004) elaborated this work and developed a more comprehensive theory and model of activity rescheduling and re-programming decisions as a function of time pressure. Apart from duration adjustment processes, their *Aurora* model incorporates also other potential dynamics such as change of destination, transport mode, and other facets of activity-travel patterns.

A second recent interest in the field of activity-based modeling concerns the development of multi-agent systems for micro-simulation (e.g., Rindt *et al*. 2003, Rindsfüser and Klügl 2004, Raney and Nagel 2005, Salvini and Miller 2003). Representing individuals and households individually as agents in the system allows simulating interactions between agents and dynamics based on short-term adaptations as well as learning processes. Furthermore, an important advantage of micro-simulation is that users can extract any information from the activity patterns generated and, hence, consider any segmentation of the data they are interested in.

This paper reports the development of an agent-based micro-simulator that allows one to simulate activity-travel scheduling decisions, within day re-scheduling and learning processes in high resolution of space and time. The implementation is illustrated using activity-travel diary data, pertaining to the Eindhoven region that was collected originally to better understand the choice of urban parks in the study area.

2. THE *AURORA* MODEL

2.1 Characteristics of the Model

To position the model against the background of existing approaches, we mention the following characteristics of the model. First, *Aurora* is a micro-simulation system. This means that each individual of the population is represented individually as an agent. The agents of a base-line situation are synthesized as a first step of a simulation. Second, *Aurora* is an activity-based model. This implies that the system simulates the full pattern of activity and travel episodes of each agent and each day of the simulated time period. At the start of the day, the agent generates a schedule from scratch and during the day he executes the schedule in space and time. The residential location of each agent is given and determined as part of the population synthesis procedure. Finally, *Aurora* is a dynamic model in three aspects. First, perceived utilities of scheduling options are dependent of the state of the agent, and implementing a schedule changes this state. Particularly, an agent keeps a record of the history of each activity in his activity agenda to determine the urgency of each optional activity at the time of scheduling. Second, long-term adaptions are based on learning processes. Each time after having implemented a schedule, an agent updates his knowledge about the transportation and land use system and develops habits for implementing activities. Third, at each time an agent arrives at a node of the network or has completed an activity during execution of a schedule, he may reconsider scheduling decisions for the remaining time of the day. An agent considers this option only if the episode's end time deviates from the scheduled end time. Such a mismatch can occur because an agent's expectations may differ from reality. But even if the knowledge of the agent is generally correct, the actual travel or activity time may still be different due to the non-stationarity of the environment. As a result of the decisions of all other agents, congestion may cause an increase in travel times on links or transaction times at activity locations. Furthermore, random events may cause a discrepancy between schedule and reality. In sum, within-day re-planning is a central characteristic of the *Aurora* model and congestion is the mechanism by which agents interact.

2.2 Basic Concepts

The scheduling method

The model assumes that individuals' abilities and priorities to optimize a schedule are limited by cognitive constraints and the amount of mental effort they are willing to make. To find reasonable solutions within the constraints, the model uses a heuristic scheduling method. Many specifications of such an heuristic are possible and methods used in reality may differ between individuals and situations. Nevertheless, we assume that a realistic model has the following characteristics. First, scheduling processes consist of step-wise making (small) improvements to an existing schedule. Generating an initial schedule from scratch is a special case of re-scheduling where the existing schedule consists of doing nothing the entire day. In each step, optional and elementary operations on the current schedule are tried and the one that maximizes the improvement is implemented if that improvement is positive. The value of a schedule is measured as a numeric utility value. An activity episode is the building block of a schedule and adaptations are defined in terms of changes of attributes of activity episodes, such as location, timing, duration, trip chaining and transport mode. Travel episodes are not directly determined by scheduling decisions, but rather follow logically from the specification and sequencing of activities. If an activity episode is added to the schedule, default settings are assumed for its attributes.

The utility function

The utility of a schedule is defined as the sum of utilities across the sequence of travel and activity episodes it contains. Formally:

$$U = \sum_{a=1}^{A} U_a + \sum_{j=1}^{J} U_j \tag{1}$$

where, U_i is the utility of episode i, A is the number of activity episodes and J is the number of travel episodes in the schedule. The functional form of utilities differs between activity and travel episodes. For activity episodes, utility is defined as a continuous, S-shape function of the duration of the activity. This form reflects the notion that with increasing values duration is at first a limiting factor in ‘producing’ utility and after some point other factors become limiting. In particular:

$$U_a = \frac{U_a^{\max}}{1 + (\gamma_a \exp[\beta_a(\alpha_a - v_a)])^{1/\gamma_a}} \tag{2}$$

where v_a is the duration of episode a; $U_a^{\max}$ is the asymptotic maximum of the utility the individual can derive from the activity and α_a , β_a and γ_a are activity-specific parameters. The alpha, beta and gamma parameters determine the duration, slope and degree of symmetry at the inflection point respectively. In turn, the asymptotic maximum is defined as a function of schedule context, attributes and history of the activity, as:

$$U_a^{\max} = f(t_a) * f(l_a) * f(q_a) * \left[\frac{U_{x_a}}{1 + \exp[\beta_{x_a}(\alpha_{x_a} - T_a)]}\right] \tag{3}$$

where t_a, l_a and q_a are the start time, location and position in the sequence of activity a, $0 \le f(x) \le 1$ are factors representing the impact of activity attributes on the maximum utility, U_{x_a} is the base level of the maximum utility and T_a is the time elapsed since the last implementation of activity a. The position variable, q_a, takes into account possible carrying-over effects between activities leading to preferences regarding combinations or sequences of activities (e.g., shopping after a social activity). Note that for this function we assume the same functional form (an S-shape) as for the duration function (Equation 2). Thus, we assume that the urgency of an activity increases with an increasing rate in the low range and a decreasing rate in the high range of elapsed time (T).

The start-time factor of the maximum utility is a function of attributes of the activity:

$$f(t_a) = \begin{cases} \dfrac{t_a - t_a^1}{t_a^2 - t_a^1} & if\ \ t_a \ge t_a^1 \wedge t_a < t_a^2 \\ 0 & if\ \ t_a \ge t_a^2 \wedge t_a < t_a^3 \\ \dfrac{t_a^3 - t_a}{t_a^3 - t_a^4} & if\ \ t_a \ge t_a^3 \wedge t_a < t_a^4 \\ 1 & otherwise \end{cases} \tag{4}$$

where $t_a^1 \le t_a^2 \le t_a^3 \le t_a^4$ are the cut-off points dividing the day into four intervals. The intervals define start times where the activity would not generate any utility (the first and last interval), the utility is at a maximum (the third interval) and the utility is some fraction of the maximum.

Travelling involves effort and sometimes monetary costs, depending on the transport mode used. Assuming that travel time is not intrinsically rewarding, the utility of a travel episode is modelled as a negative function of duration.

3 IMPLEMENTATION IN A DYNAMIC MICRO-SIMULATION SYSTEM

In this section we describe the implementation of Aurora in a dynamic micro-simulation system. The system is programmed in an object-oriented way using the programming language C++. We will, however, discuss the system at a more abstract level than programming solutions. The agents of the system represent individuals rather than households. In the system, households are represented as objects where household level data and, in particular, data about activities are stored. The agents belonging to the same household own the same household object and through this object they have access to household-level data as well as to the other agents with which they form the household.

The main components of the system relate to the main steps in a simulation run. These include 1) synthesizing a population, 2) generating a schedule for each agent for the first day, 3) simultaneous execution of the schedules of agents and 4) updating the knowledge of each agent. Whereas the first step is an initialisation step, Steps 2-4 are repeated for each day in the simulated period. The synthesis of a population involves generating households and individuals within households. Apart from socio-demographic attributes, the knowledge of each agent at the first day of the simulation is also synthesized. The knowledge relates to activity history, choice-sets, default settings of activities (i.e., habits) and relevant attributes of the transport and land-use system. Although the problem of synthesizing a representative population in all these aspects is far from trivial, in the present section we will focus on the other behavioural components. Before discussing each of these components in turn, we will first consider in some detail the most central data component of the system, that is, the activity list.

3.1 The Activity List

Defining activities

The activity list represents the exhaustive set of possible activities that members of a household could consider. Although the list is an attribute of a household, it may include activities that only particular members can conduct. Since the person is included as an attribute of the activity, we define such cases simply as a special case where the person choice-set consists of a single individual (i.e., agent). The activities in the list do not have class labels but are generically defined by a set of parameters. The parameters represent fundamental characteristics of activities so that almost any activity can be modelled. Furthermore, an activity list is specified for each household separately meaning that heterogeneity within a population can be represented. The lists are generated in the population-synthesis stage and do not change during the simulation. This reflects the present system’s focus on individuals’ short-term decisions.

A classification of activities

A three-way classification of activities is the only exception on the rule that activity definitions do not include class labels. A distinction is made between fixed activities, flexible activities and the home activity. Fixed activities are mandatory activities that are fixed in space and time at the moment the schedule for a day is generated. Typical examples are work and school where existing commitments may dictate the times and locations of conducting the activities. In reality, this distinction may not be dichotomous and the degree of flexibility may even vary between the choice facets of a single activity. The system allows one to model this. In case of a discrete choice facet – person, location and transport mode – the degree of flexibility is encoded by means of a choice set. Fixedness is simply the case where the choice set includes only a single item. As for continuous attributes – urgency, start time and duration – the degree of flexibility is defined by the slope parameter of the urgency function (Equation 3), the slope parameter of the duration function (Equation 2) and the parameters of the timing function (Equation 1).

Yet, the system does maintain a distinction between fixed and flexible in terms of both the parameters used to define the activities and the way they are treated in the scheduling process. Fixed activities are defined as the activities of which the urgency (i.e., frequency), duration and start time are fixed. These activities are scheduled first and constitute the so-called schedule skeleton. The times between fixed activities determine the slots available for all other, flexible activities, which are scheduled next. Because there is no decision making involved, a fixed activity has no utility function associated to it. That is, fixed activities have a zero utility in the model. We emphasize that, alternatively, fixed activities can be defined as flexible activities with sufficiently high values for the slope parameters of the time-related utility functions. The qualitative distinction between fixed and flexible is maintained for reasons of efficiency of encoding and scheduling.

The home activity is special in several ways. First, the activity represents an aggregate of all home-stay episodes of the individual across the day. This means that the utility of this activity is a function of a sum of durations across home-stay episodes. Being a slack activity, the (total) duration is equal to the difference between 24 hours and the sum of all travel and non-home activity episodes (including wait times). All activities are directly competing with the home activity in the sense that increasing their duration means reducing the duration of the home activity. Because the home activity necessarily is included each day, its U^{max} is a constant rather than a function of a history.

Encoding activities

Given these definitions, each activity in the list is encoded in terms of the following variables and parameters: Type (fixed versus flexible), History, Interval time (if fixed), Person choice-set and default, Location choice-set and default, Mode default, Trip-chaining default (origin location, destination location), Default duration (= fixed duration, if fixed), Default start time (= fixed start time, if fixed), Urgency function parameters (if flexible), Duration function parameters (if flexible) and Timing function parameters (if flexible). History represents the number of days elapsed since the activity was performed the last time. The interval time is relevant in case of a fixed activity and defines the number of days between two episodes of the activity. Thus, in combination with history the interval time determines whether or not the activity will be included in the schedule of the current day. If the history is equal to the interval time, the activity is included and otherwise it is postponed. We emphasize that even in case a fixed activity has irregular time intervals, it is still possible to encode its pattern based on these variables. For example, a 5-day working week displays an irregular pattern in the sense that on Monday the activity has an interval time of two days and on all other working days it has an interval time of one day. The pattern can be encoded by including each working day as a separate activity – e.g., Monday work, Tuesday work, etc. – having an interval time of 7 days.

The variables related to persons, locations and modes are references to objects in the system where more detailed attribute data is stored. The history as well as choice-set and default values are all dynamic in the sense that they are updated each time after having executed a schedule, as explained later. The home activity is defined at the person level and, given its special characteristics, is encoded by means of the following smaller set of parameters: Duration default, U^{max} parameter, Duration function parameters and Timing function parameters.

3.2 The Scheduling Heuristic

The heuristic assumes an existing schedule (which may be empty) as given. The schedule should be consistent and the result of the heuristic is again a consistent schedule with a higher or equal utility value. The heuristic searches for and implements improvements by considering one operation at a time. In the order in which they are considered, these include: (i) inserting activities; (ii) substituting activities; (iii) re-positioning activities; (iv) deleting activities, (v) changing locations; (vi) changing trip-chaining choices; (vii) changing transport modes. A single operation is repeated until no more improvement has been made. If the schedule has changed in any one of these steps, the process is repeated. Each step in this procedure is in itself an iterative process that can be written as:

1. For all options of <Operation>
   a. Implement the option
   b. Make the schedule consistent
   c. Optimise durations
   d. Optimise start times
   e. Evaluate the schedule's utility
   f. Restore the schedule (i.e., undo Step a)
2. If <Best option> improves the schedule, then
   a. implement <Best Option>
   b. Repeat from 1

Where <Operation> denotes a specific operation considered in Steps 1 – 7. As implied by this procedure, operations are always evaluated under conditions of consistency and optimal duration and timing decisions. Table 1 represents the number of options considered for each operation. We emphasize the heuristic nature of this method. In none of the steps the evaluation of options is exhaustive. By iteratively applying the search procedure, the method may still find good solutions. Some pairs of operations, such as for example mode and location choices, may interact strongly. It is possible to extend the heuristic with a limited number of simultaneous choices, to reduce the risk of getting trapped in a local optimum.

Table 1: Number of Options Considered in each Operation

Operation	Number of options	Operation	Number of options
Insert	$(N + 1) \times M$	Location	$\sum_i^N L_i$
Substitute	$N \times M$	Trip-chaining	N
Re-position	$N \times (N - 1) / 2$	Transport mode	$\sum_i^N M_i$
Delete	N		

N is the number of activities in current schedule, M is the number of optional activities not included in the current schedule, L_i is the location choice set and M_i the mode choice set of activity i.

Travel episodes are scheduled as part of activity episodes. The trip to the location and the trip to home after having conducted the activity are considered as attributes of an activity. The return-home trip is empty if the agent decides to travel to the next activity location directly without returning home in-between (this is referred to as trip chaining). Default settings are used for each activity attribute when it is inserted in the schedule by an insertion or a substitution operation.

Making the schedule consistent (Step 1b) is a subroutine which implements minimal adaptations needed to make a schedule consistent with constraints, such as that the individual should return home at the end of the day, start from home at the beginning of the day, use the same transport mode (if vehicle-based) for trips that are chained and so on. Travel times are initially set to defaults and updated each time the destination location, origin location or transport mode changes.

3.3 Optimising Durations and Start Times of Activities

Durations and start times of activities are optimised each time a schedule operation is evaluated keeping the composition and sequence of activities fixed. Although optimal durations of activities may be dependent on start times and, vice versa, the two facets are optimised sequentially (as opposed to simultaneously) to reduce computation times. Duration optimisation is conducted first and start-time optimisation is implemented next.

Duration optimisation

Given that the sum of episodes in a consistent schedule equals the total time of a day, duration adjustment can take place only by re-allocating time between activity episodes. The optimality condition states that the marginal utilities of the activities are equal, because, if this is not the case, the utility could be improved by exchanging time units between activities. It is noted, however, that the condition does not necessarily hold if fixed activities are present. If the sum of durations of episodes in a time slot equals the available time, then the activities in that time slot cannot receive extra time units and, consequently, the marginal utility levels of these activities may be higher than those of activities from other time slots, while the schedule is in equilibrium. To take this into account, the optimization is conducted in two steps. In the first step, the equilibrium is found ignoring time limitations within slots. Then, in the next step, those slots where the time used exceeds the time available are identified and optimised isolated from the rest of the schedule and respecting the time available time in that slot. As a result the marginal utilities may differ between slots.

The duration optimisation in Step 1 (the complete schedule) and Step 2 (a particular slot) are based on the same procedure. Rather than exchanging time units between activities, which would be the most straightforward way, the method determines the equilibrium by searching for the level of the marginal utility (MU) where the sum of durations across activities equals the available time (in the slot or the complete schedule). On the S-shape curve there are two durations meeting a given MU, one on the left side and one on the right side of the inflection point. If the MU exceeds the maximum at the inflection point, there is no duration that meets the MU. The search method uses rules to determine whether to search on the left or the right side and which action to take when there is no such point. Given such rules, a unique duration value exists for each given value of MU. Starting with an arbitrary low value, MU is increased if the sum of durations exceeds the available time and decreased if this sum is smaller than the available time. This process is continued until the sum of durations is equal to the available time, within some level of precision. A possible result of the procedure is a zero duration for one or more activities. Zero-duration activities are removed from the schedule, as part of the optimisation.

Start time optimisation

Start-time adjustments are possible because the duration of home-stay episodes between out-of-home activities are flexible. The start-time optimisation method evaluates possible shifts of start times on the time axis within temporal constraints given by fixed activities and opening hours of facilities. A simple heuristic is used which creates a solution by shifting start times as much as possible towards positions in the preferred time zones for activities while respecting all temporal constraints. The heuristic used is efficient in terms of computation time and seems to give plausible results.

3.4 Schedule Execution

Having determined an activity schedule for each agent, the system executes the schedules of all agents simultaneously in time steps. The time-step size is a system parameter set by the user. The smaller the time step, the more accurately the degree of congestion of links and locations and corresponding delays can be determined. However, accuracy should be traded off against computation time, which obviously increases with decreasing step size. For example, 2 minutes could be a typical setting of time step size. The possible influence of congestion on activity time is not yet implemented. On the other hand, travel times on links are estimated as a function of the number of agents using the link simultaneously for a given time step, using the well-known method:

$$t_i = t_i^f [1 + \alpha (v_i / c_i)^\beta] \tag{5}$$

where t_i is the updated travel time on link i, t_i^f is the free floating travel time, v_i is the traffic intensity, c_i is the capacity of the link and α and β are parameters. The estimates are used to determine actual travel times in that time step.

Travel episodes are decomposed into as many episodes as there are links in the (planned) path through the network. A schedule starts at three o'clock in the morning and ends at three o'clock in the morning of the next day. Simultaneous execution means that all agents are processed in a given time step before going to the next time step. Within time steps the order in which agents are processed is fully arbitrary. The algorithm controlling the simultaneous execution of schedules can be written as follows (initially, t = 0 and i = 1):

1. For time step t and agent i: Progress Time until the end of the time step or until an episode is completed (whichever one comes first)
2. If an episode is completed, then if a situation of 'time surplus' or 'time lack' exists, then:
    a. Solve Time Conflict
    b. Reschedule
    c. Repeat from 1 for the remaining time in time step t
3. Repeat from 1 for agent i + 1
4. Update the travel speed for each link on the road network
5. Repeat from 1 for the time step t + 1 and agent i = 1

The terms Progress Time, Solve Time Conflict, Reschedule and Recompile refer to methods of agents. Re-schedule refers to the (re-)scheduling heuristic described earlier. Progress Time has two functions. First, it updates for each link the number of agents making use of that link in the current time step. On the basis of these counts and the size of the time step link travel times are updated using Equation 5 (in Step 4). Second, it simulates possible unforeseen events as positive or negative delays in the execution of activities. Delay times are randomly generated with given probability and distribution.

Thus, unexpected travel times and unforeseen events are two possible causes for a mismatch between a scheduled and actual end time of an episode. A time-surplus or time-lack situation at the moment of completing an episode triggers rescheduling. Before applying the scheduling heuristic, Solve Time Conflicts is activated first to identify and correct possible inconsistencies in the schedule. This method assumes a hierarchy of operations. For example, changing the start time of an activity is preferred over changing its duration and so on. Note that the definition of this hierarchy is somewhat arbitrary, but at the same time also not that critical because the subsequent optimisation of the schedule may undo choices that turn out to be non-optimal. It is also worth noting that since re-scheduling may occur at the moment the agent arrives at a link, the system can simulate revising an agent's route as well as all other possible schedule adaptations.

3.5 Updating Knowledge

After having executed the schedule, an agent updates his knowledge regarding choice-sets, default settings of activities and expected values of attributes of the transportation and land-use system. Choice-set updating is relevant for choices where the choice-set is a subset of the universal choice-set and does not necessarily include the optimal choice for each possible schedule. This generally holds for location choice and route choice. In the present system, route choice is based on a least-cost path finding algorithm. Expected travel times by car are stored in a collective memory rather than for each agent individually to save storage capacity demands (in large-scale applications). The travel times are disaggregated to time of day: morning peak, afternoon peak and off-peak. Updating also occurs at this collective level by taking the average of realized travel speeds at each link as an added observation.

The location choice-set consists of all locations known by the individual. ‘Known’ in this context means that the agent not only knows the physical location but also the attributes that are potentially relevant for evaluating utility values for all potential activities. Nevertheless, location choice-sets are dynamic. Changes follow from processes of knowledge decay, reinforcement and exploration. Following concepts from the field of reinforcement learning, the strength of a memory trace of a particular item in the choice set is modelled as follows:

$$W_i^{t+1} = \begin{cases} W_i^t + \gamma U_i^t & \text{if } I_i^t = 1 \\ \lambda W_i^t & \text{otherwise} \end{cases} \quad (6)$$

where W_i^t is the strength of the memory trace (awareness) of location i at time t and $I_i^t = 1$, if the location was chosen at time t, and $I_i^t = 0$, otherwise, U_i^t is the utility attributed to location i, $0 \le \gamma \le 1$ is a parameter representing a recency weight and $0 \le \lambda \le 1$ is a parameter representing the retention rate. Thus, at each time step the strength is reinforced or decays depending on whether it has been chosen in the last time step. The coefficients γ and λ determine the size of reinforcement and memory retention respectively and are parameters of the system. Based on the current value of memory strength, the system determines whether or not the item is included in the choice set in the next time step based on the simple rule stating that it is included if it exceeds a threshold level and is not included, otherwise.

Exploration on the other hand is a process by which new elements can enter the choice set. The probability that a certain location i is added to the choice set in a given time step is modelled as:

$$P(H_i^t) = P(G^t) P(H_i^t \mid G^t) \quad (7)$$

where $P(G^t)$ is the probability that the individual decides to explore and $P(H_i^t \mid G^t)$ is the probability that location i is discovered during exploration and tried on a next choice occasion. Whereas the former probability is a parameter of the system to be set by the modeller, the latter probability is modelled as a function of attractiveness of the location based on the Boltzman model (see Sutton and Barto 1998):

$$P(H_i^t \mid G^t) = \frac{\exp(V_i^t / \tau)}{\sum_i \exp(V_i^t / \tau)} \quad (8)$$

where, V_i^t is a the utility of i according to some measure and τ is a parameter determining the degree of randomness in the selection of new locations. The higher the tau parameter the more evenly probabilities are distributed across alternatives and, hence, the higher the randomness and vice versa. The parameter can be interpreted as the general (lack of) quality of information sources available to the individual, such as social network, public and local media and own observations during travel. More than one location may be added to the choice set in a given time step. A new location has priority over known locations in location choice and cannot be removed from the choice-set before it has been tried once. Once tried, the new location receives a memory-trace strength and is subject to the same reinforcement and decay processes that hold for memory traces in general. As a consequence of the above mechanisms, higher-utility locations have a higher probability of being chosen for three reasons: 1) they have a higher probability of being discovered; 2) if discovered they have a higher probability of being chosen and 3) if chosen they are more strongly reinforced. At the same time, they do not have a guarantee of staying in the choice-set because of two other mechanisms: 1) if the utility decreases due to non-stationarity in the system (e.g., they do not longer fit in changed schedules), the decay process will make sure that they vanish from the choice-set and 2) if more attractive locations are discovered, they will be outperformed and, therefore, will decay.

Finally, learning involves updating default settings of activities, such as duration, start time, transport mode and location. For this, each agent keeps a record of the probability distribution across each choice set. For start time and duration, which are continuous variables, a reasonable subrange is identified and subdivided into *n* rounded values. For each choice facet the following, Bayesian method of updating is used:

$$P_i^{t+1} = \begin{cases} \dfrac{P_i^t M^t + 1}{M^t + 1} & \text{if } I_i^t = 1 \\ \dfrac{P_i^t M^t}{M^t + 1} & \text{otherwise} \end{cases} \tag{9}$$

$$M^{t+1} = \alpha M^t + 1 \tag{10}$$

where P_i^t is the probability of choice *i* at time *t*, *M* is a weighted count of the number of times the choice is made in the past, I_i^t indicates whether or not *i* was chosen at time *t* and $0 \leq \alpha \leq 1$ is a retention rate of past cases. As implied by Equation 9, more recent cases have a higher weight in the update (if $\alpha < 1$), to account for possible non-stationarity in the agent's choice behaviour. Having defined the probability distribution of each choice facet at the current time step, the default is simply identified as the option having the highest probability across the choice set.

A potential weakness of the choice-set as well as default updating processes above is that expected values are all unconditional. In reality, however, probabilities and values may be conditional upon contextual factors such as day of the week and schedule context. Methods of learning conditions that have an impact on choice exist and can be incorporated in a possible future extension of the model.

4 ILLUSTRATION

In this section we discuss an application of the model in a decision support system for urban green-space planning, named GRAS (Greenspace Assessment System), to illustrate the model system. Arguably, the activity-based approach is particularly relevant in the area of green-space planning, because temporal factors are generally influential in opportunities consumers have to conduct green activities in their (urban) environment. Green space activities tend to be highly flexible and, therefore, probably more subject to temporal constraints than most other activities. As a case, we consider the application of the system to Eindhoven, a city with approximately 200,000 inhabitants, in the Netherlands. For a detailed description of this application, readers are referred to Pelizaro (2005).

This application uses the concept of scenarios, which is defined in terms of an appropriate geo-referenced database that represents the urban system in terms of greenspace amenities, the transportation network, the land use configuration, the zonal system, the work facilities, and individuals of the entire study area. To capture the effect of individuals' time pressure on greenspaces usage we apply the *Aurora* model. As output, this model generates individuals' schedules of activities, for a given day. Individuals' generated schedules are an essential ingredient to capture some important performance indicators for scenario-based evaluations, such as frequencies with which individuals participate in green activities, the duration, timing, combination with other activities, the transport mode used and the distance (time) that individuals are willing to travel to reach greenspaces, given the time pressure.

4.1 Settings and Initialization

Given the purpose of illustration, a limited activity list of each household was assumed. Besides the green activity, only the work activity of individuals working part time or full time was included. We emphasize that this reduction does not mean that all other activities are left out of consideration. Rather it means that the home activity, which is a fixed component and slack activity in the model, will represent an aggregate of all other activities (in and out of home), i.e. should be interpreted as the category Other.

Being a fixed activity, the settings of the work activity of each individual was synthesized as part of a more-encompassing synthesis of the population. Using an iterative proportional fitting approach, the method of synthesis was designed to reproduce the known marginal distributions for each zone in the area as well as the odd ratios provided by a large sample of the Eindhoven population. On the other hand, green activities are considered flexible implying that decisions to include the activity in the schedule and start time and duration are based on the scheduling model. The parameter settings of the utility functions of urgency, duration and start time were manually calibrated using activity diary data from the same sample of the Eindhoven population. For the green activity the parameters are set to $U_x = 20$, $\alpha_x = 7$, $\beta_x = 1$ (urgency function) and $\alpha = 10$, $\beta = 0.07$ and $\gamma = 1.5$ (duration function) and $t^1 = 540$, $t^2 = 620$, $t^3 = 1440$ and $t^4 = 1440$ (start-time function), whereas for the home activity the settings are $U^{\max} = 60$, $\alpha = 600$, $\beta = 0.0065$ (duration function). The assumed travel-time weights are –0.2 and –0.1 for car and slow mode respectively (whereby travel time is measured in units).

The location choice for each green activity included in schedules was determined using an MNL model estimated on revealed and stated choice data again from the same population. Learning processes related to location choice and choice-sets were not simulated in this application. Concerning route choice, agents consistently choose the fastest route across the network with the transport mode chosen. Since the public transport network was not modelled, the transport mode choice set did not include public transport implying that a choice between car and slow mode remained.

Finally, the initialization of the population of agents requires determining the initial values regarding the days ago a green activity was conducted the last time. The history factor is derived from the activity parameter settings. The α_x parameter can be interpreted roughly as the normal amount of days that passes without including the activity in the individuals' schedule. Therefore, the day that an individual last performed a green activity is arbitrary set by a random number generated between [0, α_x]. The average history thus equals approximately half of the normal interval time between green activities, which is appropriate.

4.2 Some Results

To illustrate the type of results one can obtain from the *Aurora* model, we compare the outcomes of two runs of the model on several performance indicators. The runs considered are based on the activity parameter settings, discussed above, and a scenario where the alpha parameter of the Home (read Other) activity category has a higher value, i.e. from 600 (baseline situation) to 700. The latter setting simulates a scenario where the average agent experiences a higher time pressure, i.e. where there is less flexibility to substitute other activities by the green space activity. The performance indicators considered include: average frequency of green activities, average duration of green activities, and the total utility derived from executing the activities.

For the baseline situation, the model predicts that, approximately, 25% of individuals of the synthetic population have scheduled a green activity for the day simulated. From these 25%, 47% also have scheduled a work activity. The average duration of green activities for an agent without a work activity is 82 minutes with a standard deviation of 11.4 minutes. For the agents with a work activity, the average duration of the green activity is 55 minutes and the standard deviation is 10.3 minutes. Although the standard deviations are approximately the same, agents with a work activity spend on average almost 30 minutes less on green activities than agent without a work activity.

Under the increased time-pressure scenario, the model predicts that 22% of the agents in the synthetic population would include a green activity in their schedule, i.e. 3% less than in the baseline situation. In this case, 58% of the agents with a green activity in their schedule do not have a work activity scheduled for that day. In the new situation only 6.9% of the agents having a workday scheduled a green activity, against 12.2% in the situation before. Hence, we observe a drop in the number of working agents conducting green activities. As expected, agents with a work activity are more affected by the higher pressure situation than agents without a work activity. We also observe a drop in the average duration of green activities. Agents with work and green activities in the schedule spend, on average, 49 minutes (with a standard deviation of 10.3 minutes) on green activities, compared to 55 minutes in the situation before. Agents without a work activity show a drop in the green activity duration as well. In the scenario, these agents would spend, on average, 74 minutes on green activities, i.e., about 8 minutes less than before.

As a final performance indicator, the average utility agents derive from their schedule is 53.12 for the baseline situation against 49.33 in the increased time pressure situation. It is noted that the decrease in average schedule utility is not only caused by the decrease in frequency and duration of green activities. Increasing the alpha parameter means that for a given duration of the home activity the utility level will be lower especially in schedules including a work activity. In other words, the scenario assumes that the extra activities causing the increase in time pressure do not generate a utility themselves.

5 CONCLUSIONS AND DISCUSSION

This paper has discussed some issues in the implementation of a multi-agent activity-based model of (re)scheduling behaviour, called *Aurora*. The application shows that activity plans can be simulated in time and space, offering the possibilities to address in more detail questions of transport demand management and land use planning that are more difficult to address with conventional transport models. Although *Aurora* already is a rich model of activity scheduling behaviour, several problems for future research remain. First, the model does not consider scheduling over a longer time horizon than a day. In reality, people may schedule at least part of their activity agendas on a week basis or even consider a longer time horizon. Second, although it considers the household as the unit of decision making, the current system does not model within-household interactions between individuals. Such interactions may occur in the form of joint activity or travel participation and task (re-)allocation between members of the household. Also, social interactions in a broader sense are not incorporated in the system. Week planning, within-household interaction and social interaction are included in the agenda for future extensions of the system.

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