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MODELING SHORT-TERM DYNAMICS IN ACTIVITY-TRAVEL PATTERNS: FROM AURORA TO FEATHERS

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1. INTRODUCTION

Most operational models of activity-travel demand , including nested logit models (e.g., Vovsha *et al*. 2004), Cemdap (Bhat *et al*. 2004), Famos (Pendyala *et al*. 2005) and Albatross (Arentze and Timmermans 2000, 2005) have been developed to predict activity-travel patterns. The main contribution of these models is to offer an alternative to the four-step models of travel demand, better focusing on the consistency of the submodels and proving increased sensitivity to a wider range of policy issues. These models are most valuable for predicting the impact of land use and transportation policies on typical activity-travel patterns, allowing policy makers to assess the likely impact of such policies in terms of changing travel demand and a set of accessibility, mobility and environmental performance indicators.

In terms of short terms dynamics in activity-travel patterns, these activity-based models at their current state of development have much less to offer. For example, route choice and the aggregate impact of individual-level route choice decision on activity generation and rescheduling behaviour is not included in these models. Short term dynamics are really not addressed at all, while issues such as uncertainty, learning and non-stationary environments are also not considered. Of course, there is a wide variety of traffic assignment, route and departure choice models, but at their current state of development it is fair to say that the behavioural contents of these models from an activity-based perspective are still relatively weak and that comprehensive dynamic models are still lacking. Especially in the context of day-to-day management of traffic flows, such activity-based models of short-term dynamics in activity-travel patterns would serve their purpose.

To complement the Albatross system, the Urban Group has therefore started with the development of Aurora, a model focusing on the rescheduling of activity-travel patterns. The foundations of this model appear in Timmermans *et al.* (2001) and Joh *et al.* (2003, 2004) focusing on the formulation of a 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. Later, this model was extended to deal with uncertainty (Arentze and Timmermans, 2004), various types of learning (Arentze and Timmermans, 2005, 2006), and responses to information provision (Arentze, *et al*., 2005; Sun, *et al*., 2005). Finally, a framework to implement this model as a multi-agent simulation system has been developed and explored (Arentze *et al*., 2005). In 2005, a research programme coordinated by IMOB, was funded by IWT, Belgium. The goal of this program, in addition to exploring the potential use of new technology on collecting travel data, is to develop a

prototype, activity-based model of transport demand for Flanders, Belgium. The basis of this model, which has been given the acronym Feathers, will be the extended version of Aurora, complemented with some additional concepts.

This paper reports the current development of this 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. It summaries some concepts and discusses a series of projects and activities that will be conducted to further operationalize the models for Flanders.

2. AURORA

2.1 Key Characteristics

Aurora is an agent-based micro-simulation system in which each individual of the population is represented as an agent. It is also an activity-based model in the sense that the model 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. It is also dynamic in that (i) perceived utilities of scheduling options depend on the state of the agent, and implementing a schedule changes this state; (ii) 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, and (iii) 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. This may happen because an agent's expectations may differ from reality. This may be the result from imperfect knowledge, but it may also be 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.

2.2 Basic Concepts

The utility function

The model is based on a set of utility functions, where the utility of a schedule is defined as the sum of utilities across the sequence of travel and activity episodes it contains. Formally:

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

(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:

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

(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:

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

where t_a, l_a and q_a are the start time, location and position in the sequence of activity a, $0 \leq f(x) \leq 1$ 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:

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

where $t_a^1 \leq t_a^2 \leq t_a^3 \leq t_a^4$ 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.

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. 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.

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.

Schedule implementation

It is assumed that an activity schedule is implemented sequentially during the day. To allow for possible rescheduling behaviour, it is assumed that agents decide to reschedule their activities or not at every node of the transportation network and after completing each activity. 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. 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.

Learning

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.

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 (Arentze and Timmermans, 2005, 2006). The strength of a memory trace of a particular item in the choice set is modelled as follows:

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

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, $0 \leq \gamma \leq 1$ is a parameter representing a recency weight and $0 \leq \lambda \leq 1$ is a parameter representing the retention rate. The coefficients γ and λ determine the size of reinforcement and memory retention respectively and are parameters of the system.

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:

$$P(H_i^t) = P(G^t)P(H_i^t \mid G^t) \tag{7}$$

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):

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

where, V_i^t is the utility of location i according to some measure and τ is a parameter determining the degree of randomness in the selection of new locations, but which can also be interpreted in terms of a degree of agent uncertainty (Han and Timmermans, 2006). The higher the tau parameter the more evenly probabilities are distributed across alternatives and, hence, the higher the randomness and vice versa. 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:

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

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

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.

3. FEATHERS

3.1 Scope

This model is part of a wider research program, involving a number of other Belgian research institutes. This program aims at examining a series of issues, pertinent in the development of an activity-based model of travel demand for Flanders, Belgium. For example, new technology for collecting vehicle data will be explored, as well as the application of combined GPS/PDA technology for collecting activity-travel data (PARROTS: Pda system for Activity Registration and Recording Of Travel Scheduling, see Bellemans *et al.*, 2005; Kochan *et al.*, 2006). Feathers (Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS) is the acronym given to the model, which will be based on the current status of the extended Aurora model, as explained above. However, because Aurora to date is largely based on theory only and on some numerical experiments to assess the face validity of the model, further empirical testing and operationalisation will be required. It is to be expected therefore that certain elements will be further refined and that other new elements will be added. In the remainder of this section, we will shortly address some of these issues.

3.2 The utility functions

The core of the model are the S-shaped utility functions (Equations 2 and 3). To date, this shape which is quite different from other models of activity-time allocation, is derived from theory. No specific data to test the shape of the functions and assess its relevance has been collected to date. Therefore, one of the subprojects is concerned with collecting data on how individuals change their activity-travel patterns and test whether the assumed S-shaped utility functions represent such change, or if not, what

alternative functional forms are required. This project will also examine and estimate the effect of context variables that influence the maximum utility (Eq. 3) that can be derived. Note that the results will be critical in that unlike other models, we assume that utility functions are context-dependent. Finally, it will be tested whether the assumed addition of activity and context-specific utility functions to represent the overall utility of a daily activity-travel schedule can be corroborated or that more complex forms are required.

3.3 Learning

It follows from the foregoing that an agent's beliefs about the system he/she interacts with play a role in scheduling and are updated each time a schedule is implemented. Learning may involve many different mechanisms. First, we assume that as explained above when implementing their activity schedules, agents will learn about the attributes or states of their environment (e.g. travel times) from experiences. Experiences with respect to the state of a variable will change the subjective probabilities and hence the agent's beliefs. If the actual situation is consistent with outcomes perceived as most probable, uncertainty in beliefs will be reduced and the individual will be more confident in predicting outcomes on future occasions. In contrast, if outcomes are contrary to expectations, uncertainty will increase and difficulty of prediction and perceived value of information of future events increases. Secondly, in addition to this *attribute learning*, we assume that agents have an inherent desire to make sense of the world around them. One of the mechanisms involved is to identify the conditions that allow them to explain away differences in attributes of the environment (*condition* learning). For example, differences in travel times can be explained in terms of day of the week, departure time, weather conditions, an accident, etc. The condition set is not necessarily constant over time, but may grow or shrink. These two forms of learning would imply that only after many personal experiences, agents will have gained sufficient knowledge about their environment. Reality suggests otherwise, and therefore we assume that agents also are capable of *analogue* learning and reasoning: they draw inferences about attributes of certain objects in analogy to other similar objects. Finally, in addition to these personal styles of learning, we assume that agents learn from being part of a social network: they learn from word of mouth from members of their social network.

Similar Bayesian updating equations (see Arentze and Timmermans, 2006) will be used to estimate these learning processes. This is the topic of another project.

3.4 Impact of life trajectory events

In the above, we have assumed that the household context is stationary. However, in reality the household context change over time as a function of life trajectory events, such as a new child, another job, etc and this may bring about changes in one or more facets of the activity agenda and preferences for choice alternatives. The potential relevance and impact of such events in an activity framework has been explored by van der Waerden, Borgers and Timmermans (2003a,b), and has led to the formulation of a Bayesian decision network model, applied to transport mode choice decisions (Verhoeven, *et al.*, 2005a, 2005b). The approach will be further evaluated and extended to multiple facets of activity-travel patterns in the context of Feathers. It constitutes another project in the program.

4. CONCLUSIONS AND DISCUSSION

This paper has reported progress and plans in the development, testing and implementation of a multi-agent activity-based model of (re)scheduling behaviour, called Aurora. An operational and extended version of this model will be developed specifically for Flanders, Belgium under the acronym,

Feathers. Data collection for estimating the various components is on its way. We plan to report the first empirical results in the near future.

Unlike the activity-based models mentioned in the introduction of this paper, the potential value of this model is to simulate short term dynamics. As such it should be primarily relevant to simulate dynamics in day-to-day traffic flows and their environmental impacts. Developing it into a model that can be used for longer-term assessment would require additional components. Such projects are on their way as well, but at this stage not part of Feathers. The future will then tell whether even more complexity that is implied by these and other extensions will be feasible, not only from a modelling and computational point of view, but also in terms of acceptance by practitioners and policy-makers.

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