Multi-Day Activity Scheduling Reactions to Future Events in a Dynamic Agent-Based Model of Activity-Travel Behaviour

Linda Nijland, Theo Arentze and Harry Timmermans
Eindhoven University of Technology

Key words: Travel Demand, Activity-Based Modelling, Activity Generation, Activity Scheduling, Needs, Multi-Day Activity Planning

Abstract: In the context of activity-based transport simulation models, multi-day activity planning is receiving increasing attention. The aim of this paper is to develop and illustrate an extension of a needs-based model of activity generation that takes into account possible influences of pre-planned activities and events. This paper describes the theory and shows the results of simulations of the extension. The simulation was done for six different activities and different parameter values. The results show that the model works well and the influences of the parameters are clear and seem logical.

1. INTRODUCTION

There has been considerable progress in the development and application of activity-based models over the last decade. Examples of fully operational models are CEMDAP (Bhat and Singh, 2000), Famos (Pendyala et al, 2005) and Albatross (Arentze and Timmermans, 2000). Currently, these models are making the transition to practice where they find application as instruments for planning support and policy evaluation. However, there is still ample room for improvement. High on the research agenda are the generation of activities based on the needs they satisfy or induce, interactions between activities and scheduling at the household level.

Arentze and Timmermans (2006, 2008) developed a needs-based theory to the problem of dynamic activity generation. The new theoretical framework is based on the assumption that activities are driven by a limited and universal set of subjective needs at the person and household level. The needs grow autonomously over time according to a logistic curve with parameters depending on the nature of the need and characteristics of the individual and the household. In the model, the utility of conducting an activity is equal to the sum of satisfied needs minus the sum of induced needs. The theory also takes into account interactions between activities and the allocation of household tasks. Arentze (2008) derived from this theory an operational model to generate longitudinal activity patterns and showed how this model can be estimated on one-day observations of activities of individuals.

This theory provides an explanation for drives of regularly recurring activities such as shopping, social visits, recreation etc. It does not take into account, however, that planned future activities may influence the activity scheduling decisions of individuals. For example, if a person has planned to go to a birthday party next day, the person may postpone the satisfaction of the social need. In the survey described in Nijland et al (2006) the respondents were asked, for eight flexible activities that are conducted out-of-home, when they usually plan the concerned activity. The results show that especially in cases of a sports activity, visiting relatives/friends, visiting a café, bar or discotheque and buying clothes, the activity is often planned earlier than a day before. This has consequences for the scheduling of other activities that satisfy or induce the same needs. Furthermore, planned activities seem to be less flexible for adjustment in case of delay (Nijland et al, 2007). They are less often skipped or postponed when there is less time available to conduct the activity. In most of the cases, planned activities are performed together with other persons (friends/relatives) and are therefore more difficult to adapt.

The purpose of the present paper is to develop and illustrate an extension of the needs-based model of activity generation, to take into account possible influences of pre-planned activities and events. The framework that we take as a starting point is the operational model developed by Arentze (2008). The structure of the remainder of this paper is as follows. Section 2 describes the theory and models first in terms of the existing needs-based framework and next regarding the extension proposed here. The extended model is implemented in an agent-based system for simulating activity patterns of individuals for a multi-day period. Section 3 describes results of simulations carried out to test the face-validity of and illustrate the model. Finally, the last section discusses the major conclusions and implications of the new model for planning and policy support in areas of transportation and urban planning, and identifies remaining problems for future research.

2. THEORY AND MODELS

In this section, we introduce the theory and models for activity generation taking future events into account. Before describing the proposed extension, we first briefly summarize the basic need-based model for activity generation that was proposed in Arentze (2008).

2.1 The basic model of dynamic activity generation

The model predicts a multi-day activity pattern for a given person for a period of arbitrary length. Rather than solving some resource allocation optimisation problem, the model assumes that individuals make activity-selection decisions on a daily basis. Although the model is able to take into account interactions between activities and between persons (in a household context), we will consider here a more limited situation where an individual is faced with a decision to conduct an activity i on a current day d given that the last time the activity was conducted was on day $s < d$ (this means that the time elapsed equals $d - s$ days).

In the basic model, the utility of conducting an activity of type i on a given day d is defined as:

$$U_{sdi} = V_i + V_{sdi} + V_{di} + \varepsilon_{si} \tag{1}$$

where d is the current day, s is the day activity i was conducted the last time before d, V_i is a utility constant of implementing activity i, V_{sdi} is the utility of satisfying the need for activity i built-up between s and d, V_{di} is a (positive or negative) preference for conducting activity i on day and ε_{si} is an error term.

The utility components can be interpreted as follows. V_i represents the utility that is always attained independent of the length of elapsed time (i.e., the time between s and d). If this component is large relative to the need growth rate, then the activity does not depend on dynamic needs, but will always be conducted on the preferred day (V_{di}) provided that it generates sufficient utility given a utility-of-time requirement on that day. The second term (V_{sdi}) represents the amount of the need that has been built up across the elapsed time and that will be satisfied if the activity is implemented. The fourth term (V_{di}) represents a correction of utility related to day of implementation (e.g., going out on Saturday). Note that events that are not driven by needs, but rather take place on a certain fixed day can be modelled as activities with zero need growth (V_{sdi} = 0) and a relatively high utility for the day (V_{di} >> 0) when the event is to take place.

The need for an activity grows over time. There are several functional forms conceivable for a need's growth curve. A linear function is not a suitable form since we have reasons to assume that growth is decreasing over time. Although a logistic growth function may describe this, a logarithmic form has more favourable properties for estimation and has therefore been typically applied in time use (Kitamura, 1984). It can be expressed as:

$$V_{sdi} = \beta_i \ln(t_i + 1) \qquad (2)$$

where β_i is a growth rate and t_i is the need growth period between s and d. (Unity is added to t to make sure that calculated need after one day growth is non-zero).

A decision heuristic that appears to generate rational behaviour states that the activity should be conducted on day d if d is the earliest moment when the following condition holds (again, s is the day the activity was conducted the last time):

$$\frac{U_{sdi}}{D_{di}} > u_d^* \qquad (3)$$

where D_{di} is a normal duration of activity i on day d, u_d^* is a utility-of-time requirement imposed by the individual for day d. The utility-of-time threshold imposes a constraint on activity generation and represents an individual's scarcity of time. The smaller a time budget for activities the larger the threshold needs to be. When the threshold is well adjusted, the rule leads to fully use of available time (i.e., the budget is exhausted). At the same time, the rule makes sure that every activity when it is conducted generates approximately an equal utility per unit of time. In that sense, the heuristic, even though it is very simple, is consistent with an objective to maximize the utility of activities across a longitudinal period.

As for activity duration, assume that the time spent on an activity when it is implemented is an increasing function of the current size of the need and a decreasing function of time pressure on the day concerned (i.e., doing the activity in a more efficient way when time pressure is higher). Formally, this can be represented as follows:

$$D_{di} = D_{di}^0 + f(V_{sdi}) + g(u_d^*) + \varepsilon_i \qquad (4)$$

where D_{di}^0 is a constant, f is an increasing function, g is a decreasing function and ε is an error term. In the present study, we conveniently assume that duration depends on day only, so that (4) reduces to:

$$D_{di} = D_{di}^0 + \varepsilon_i \quad (5)$$

2.2 Anticipation of the future

A shortcoming of the existing decision heuristic (Eq. 3) is that it does not anticipate on the future. There are two ways in which this could lead to a suboptimal result: 1) a future day is more attractive in terms of an intrinsic preference and/or available time, such that it would be rational to postpone the activity, and 2) an event in the near future would be able to satisfy the same or similar needs, so that costs of conducting the activity can be saved. In this section, we extend the basic heuristic (Eq. 3) to take future conditions into account in terms of these two cases. First, we consider postponement decisions and next the influence of future events. Methods proposed in both sections rely on a concept of opportunity costs. In the last section, we propose a possible operationalization of this concept.

2.2.1 Case 1: activity postponement

In this section, we consider the question: under which circumstances is it rational to postpone an activity one or more days? The general answer to this question is: postponing one or more days is rational when this increases the pattern utility of an activity and is allowed by the utility-of-time requirement. Pattern utility is the long-term utility of an activity, i.e. the utility over a (long enough) multi-day period. The (net) utility of conducting the activity on current day d can be written as:

$$U_{sdi} - c_d D_{di} = Z_d \quad (6)$$

where c_d is the utility of a unit of time when spent in another way than on activity i on day d. Thus, the second term on the left-hand-side of the equation represents opportunity costs, which occur because conducting the activity takes D_{di} units of time which then cannot be spent in another way. On the other hand, the utility of conducting the activity on some later day $d + m$ is given by (for any $m > 0$):

$$U_{s,d+m,i} - c_{d+m} D_{d+m,i} - V_{d,d+m,i} = Z_{d+m} \tag{7}$$

This equation has the same structure except for an additional term – the last term on the left-hand-side of the equation. This additional term is included for the sake of pattern utility: by postponing the activity *m* days a need growth of *m* days is lost for a next period and should be discounted. Postponement is rational only if there is an $m > 0$ such that:

$$Z_{d+m} > Z_d \text{ and } \frac{U_{s,d+m,i}}{D_{d+m,i}} > u^*_{d+m} \tag{8}$$

The first condition, $Z_{d+m} > Z_m$, of this proposition comes down to (substituting (6) and (7) in (8) and rearranging terms):

$$(U_{s,d+m,i} - U_{sdi}) + (c_d D_{di} - c_{d+m} D_{d+m,i}) - V_{d,d+m,i} > 0 \tag{9}$$

Replacing the utility variables by their definition (Eq. 1) gives:

$$\begin{aligned}&(V_i + V_{s,d+m,i} + V_{d+m,i} + \varepsilon_{si} - V_i - V_{s,d,i} - V_{d,i} - \varepsilon_{si}) + \\ &+ (c_d D_{di} - c_{d+m} D_{d+m,i}) - V_{d,d+m,i} > 0\end{aligned} \tag{10}$$

and this reduces to:

$$\begin{aligned}&(V_{s,d+m,i} - V_{s,d,i}) + (V_{d+m,i} - V_{d,i}) + \\ &+ (c_d D_{di} - c_{d+m} D_{d+m,i}) - V_{d,d+m,i} > 0\end{aligned} \tag{11}$$

This derivation shows that error terms do not play a role in decisions to postpone an activity. Furthermore, it is noted that that the last term ($V_{d,d+m,i}$) is always larger than the first term between brackets ($V_{s,d+m,i} - V_{sdi}$) because growth rate is ever decreasing in a logarithmic growth curve. This means that, if time is homogeneous in terms of day preferences and opportunity costs, then postponing is never rational or, to put it another way, then it is rational to conduct the activity always at the earliest moment when it exceeds the threshold. Thus, postponing needs to be considered only in cases where gains in terms of day preferences or opportunity costs possibly can be achieved.

2.2.2 Case 2: future event

Now consider the case where there is some event on day $d + m$ that is able to satisfy the same need as an activity considered for a present day d. An example is a birthday party (event) that could satisfy the same (social) need as a certain social activity. The event is fixed and given. The question is: under which conditions would it be rational to abstain from conducting the activity and wait until the event? We will first consider the case where the event is scheduled for the next day, i.e. where $m = 1$ and then focus on the general case where $m > 0$.

The event takes place the next day (m = 1)

The utility of not waiting and conducting the activity now equals:

$$U_{s,d,i} + U_{d,d+1,i} = Z_{not-wait} \tag{12}$$

The first term indicates the utility derived from the activity on day d and the second term indicates the utility derived from the event on day $d + 1$ (with respect to the need addressed by the activity) given the activity was lastly conducted on day d. Note that at the time of the event the need satisfied is as small as the grown need over one day. On the other hand, when the agent would wait until the event, the total utility becomes:

$$c_d D_{di} + U_{s,d+1,i} = Z_{wait} \tag{13}$$

where c_d is the utility per unit time spent on other activities on day d and other terms are defined as before. The first term represents opportunity gains on day d, i.e. the utility of an alternative way of spending the time freed by not conducting the activity and the second term indicates the utility at the time of the event (regarding the need related to the activity concerned). Note that the size of the need at the time of the event has grown one day longer in this waiting scenario.

Clearly, it is rational to wait if $Z_{\text{wait}} > Z_{\text{not-wait}}$. This means that waiting until the event is rational if:

$$c_d D_{di} + U_{s,d+1,i} > U_{s,d,i} + U_{d,d+1,i} \tag{14}$$

Rewriting and rearranging terms gives:

$$(c_d D_{di} - U_{s.d,i}) + (U_{s,d+1,i} - U_{d,d+1,i}) > 0 \qquad (15)$$

The two terms between brackets indicate utility gains of waiting measured on two moments in time: on day *d* and at the time of the event, respectively. For day *d*, the gain equals the utility of spending freed time in an alternative way minus the utility of spending time on activity *i*. At the moment of the event, the gain equals the difference between utility growth over a prolonged period by one day (from *s* to *d*+1) and the utility growth of just one day (because it was conducted on the day before the event in case of not waiting). Note that, whereas the second gain is always positive (growth is positive), the first gain will become negative when *s* is far enough in the past. So, in the relevant range of elapsed time, a decision to wait involves a trade-off between, on the one hand, a loss of not conducting the activity on day *d* (there are no better ways of spending time) and, on the other, a gain of increased need at the time of the event (and, hence, a higher utility).

The general case (m > 1)

The above equations assume a case where $m = 1$, i.e. where the event takes place one day later in time. In general, an event may take place *m* days later. To generalize the above decision rule, we should take into account that an activity could be conducted multiple times in the period between now and the event. We therefore compare a scenario of waiting until the event with a scenario where the individual does not wait and conducts the activity on day *d* as well as every next time $d - s$ days have elapsed before the event. In other words, we assume that if it is rational to conduct the activity on this day *d*, then it will also be rational to conduct the activity every other moment when the same amount of time has elapsed. Although this assumption may not be valid in cases where time is heterogeneous (e.g., in terms of day preferences and opportunity costs), it serves our purpose here to formulate a heuristic which is simple and generates rational behaviour by approximation.

To describe a scenario of not-waiting, therefore, we define the whole number of times the activity would fit in the period from now to the day of the event as follows:

$$n = \text{int}\left(\frac{m}{d-s}\right) \qquad (16)$$

where int(x) is the floor of x (i.e., the result of rounding x down to the nearest integer). Now the rule given by Equation (15) can be easily extended to cover the general case as:

$$\sum_{j=0}^{n}(c_{d+j(d-s)} D_{d+j(d-s),i} - U_{d+(j-1)(d-s),d+j(d-s),i}) + \\ + (U_{s,d+m,i} - U_{d+n(d-s),d+m,i}) > 0 \tag{17}$$

The first term indicates the sum of utility gains across all times of not conducting the activity in a wait scenario, which is on day d and each time after elapsed time $d - s$. The second term indicates the gain at the day of the event, which now is the difference between the utility grown over the full length of the period between days s and $d + m$ and the utility grown over a much smaller period between the last time the activity was conducted and the time of the event.

Given our purpose to formulate a simple decision heuristic, we propose to simplify this rule as follows:

$$(n+1)(c_d D_d - U_{s,d,i}) + (U_{s,d+m,i} - U_{d+n(d-s),d+m,i}) > 0 \tag{18}$$

Note that this rule reduces to a similar form as the rule derived for the $m = 1$ case if n is zero, since then we get:

$$(c_d D_d - U_{s,d,i}) + (U_{s,d+m,i} - U_{d,d+m,i}) > 0 \qquad \text{if} \quad n = 0 \tag{19}$$

Finally, to formulate a more operational version of this rule, we replace the utility variables (Eq. 19) by their definition (Eq. 1). This results in:

$$(n+1)(c_d D_{di} - V_i - V_{s,d,i} - V_{d,i} - \varepsilon_{s,i}) + \\ + (V_i + V_{s,d+m,i} + V_{d+m,i} + \varepsilon_{s,i} - V_i - V_{d+n(d-s),d+m,i} - \varepsilon_{d+n(d-s),i}) > 0 \tag{20}$$

This reduces to:

$$(n+1)(c_d D_{di} - V_i - V_{s,d,i} - V_{d,i} - \varepsilon_{s,i}) + \\ + (V_{s,d+m,i} + V_{d+m,i} + \varepsilon_{s,i} - V_{d+n(d-s),d+m,i} - \varepsilon_{d+n(d-s),i}) > 0 \tag{21}$$

2.2.3 Opportunity costs

The specification of opportunity costs in the models described above requires additional theory and model development. In this section, we discuss this issue and propose such a model.

Clearly, the utility of spending time in an alternative way on a day *d* (rather tan on activity *i*) is closely related to the utility-of-time on day *d* and, hence, also to the threshold requirement u_d^*. To capture, this notion we propose the following straight-forward function:

$$c_d = \tau \times u_d^* \qquad (22)$$

where tau is a system parameter to be set ($0 \leq \tau \leq 1$). To explain the impact of this parameter, consider an extreme case where we set $\tau = 1$. This setting implies the assumption that at the moment an activity is due in the sense of the threshold utility, the individual can always spent his or her time just as good in another way than on activity *i*. Assume for the sake of argument that day *d* corresponds exactly to the moment when the activity first exceeds the threshold utility. This means that the activity will not be conducted before day *d*, given the basic rule (Eq. 3). If $\tau = 1$ an individual will always decide to wait, at least if time is homogeneous (no preference or time pressure differences), since the gain of conducting the activity will be approximately zero (time can be spent just as good in another way) and the gain of additional need growth is always positive. If the individual decides to wait on day *d*, he/she will also decide to wait on $d + 1$, because the growth until the event will be larger than the increment since the day before, and so on. Thus, if $\tau = 1$ (and time is homogeneous), the individual will always wait until the event no matter how far away the event is located in the future. Now, consider the other extreme where $\tau = 0$. In that case there are no opportunity costs and it is easily seen that the individual will always decide to conduct the activity on day *d* (when it exceeds the threshold) given the fact that need grows with declining rate (which is what we assume).

In sum, the model realistically predicts that if opportunity costs are zero ($\tau = 0$) an activity will always be conducted when it is due (i.e., exceeds the threshold) irrespective how close a future event satisfying the same need is, and if opportunity costs are equal to utility-of-time ($\tau = 1$) an activity will always be postponed until the event irrespective how far away the event is in the future. Although both extremes are not realistic, we have no ways of defining the tau parameter a-priori. This means that the parameter should be estimated empirically.

3. SIMULATION

In this section, we discuss some results of simulations that were carried out to test and illustrate the model. Before considering the extended model, we will first look at the behaviour of the basic model for a range of activities.

3.1 Basic model

Table 1 lists the activities that were included in the simulation. For the simulation the values for the parameters per activity were used as shown in Table 2. Those parameters are consistent with results of estimations on a national trip diary data set (the MON 2004 survey) (Arentze 2008). This dataset includes one-day diary observations of 46,877 individuals in total. The Beta parameter indicates the growth rate of the need for the activity, the D-parameters relate to the duration function and the V parameters indicate preferences (positive or negative) for conducting the activity on a particular day of the week.

Table 1. Activity classification used

Label	Description
Shop1	Shopping – one store
Shopn	Shopping – multiple stores
Serv	Service related activities
Social	Social activities
Leisure	Leisure activities (other than touring)
Touring	Touring (by car, bike or foot)

Table 2. Assumed values of the parameters in the simulation

	Shop1	Shopn	Serv	Social	Leisure	Touring
Beta	30	32	14	77	45	28
D	45.90	71.49	42.94	136.76	120.91	60
D sat	5.00	-2.07	-2.66	39.21	18.51	0.00
D sun	0.76	-0.78	-2.97	33.65	6.57	-0.20
V Mon	-2.38	-0.26	-0.52	-5.58	1.13	0.65
V Tue	-2.19	-0.22	-0.29	-3.98	-1.11	0.40
V Wed	0.00	0.00	0.00	0.00	0.00	0.00
V Thu	0.15	-0.47	0.79	-9.20	-3.01	0.26
V Fri	3.17	0.07	1.27	-15.83	-8.98	-1.10
V Sat	13.66	0.80	-2.10	27.22	13.68	-1.59
V Sun	-1.15	-0.46	-3.89	29.96	11.08	0.82

The period considered in the simulations is 14 weeks. The results of the simulations are shown in Tables 3, 4 and 5 for three different hypothetical individuals having different work hours: 0 hours work a week (Table 3), 40 hours work a week (Table 4) and 24 hours work a week (Table 5). In the simulation the utility-of-time requirement imposed by the individual for day *d* (u_d^*) was set to a base level of 1 for every day. Increases due to time pressure were captured as an additive effect using the equation $u_d^*=1+\delta \times W_\mathrm{d}$ (where W_d is work hours on day *d*). For parameter δ we used the value 0.02, so that u_d^* varied between 1 (0 hours) and 1.2 (10 hours). The simulation starts with conducting the activity on Saturday. The first row in each table shows the total number of times the column activities are conducted and the next rows the numbers of times per day of the week.

Table 3. Simulation results (0 hours work a week)

	Shop1	Shopn	Serv	Social	Leisure	Touring
Freq	35	9	6	16	7	12
n Mon	5	2	2	3	0	4
n Tue	4	0	0	1	0	0
n Wed	5	2	0	4	0	3
n Thu	6	0	2	1	0	1
n Fri	6	2	1	1	0	0
n Sat	8	3	1	4	5	1
n Sun	1	0	0	2	2	3

Table 4. Simulation results (40 hours work a week)

	Shop1	Shopn	Serv	Social	Leisure	Touring
Freq	28	8	4	11	7	10
n Mon	2	0	0	0	0	0
n Tue	3	0	0	0	0	0
n Wed	7	0	0	2	0	0
n Thu	2	0	0	0	0	1
n Fri	5	2	0	0	0	2
n Sat	8	5	4	7	5	3
n Sun	1	1	0	2	2	4

Table 5. Simulation results (24 hours work a week)

	Shop1	Shopn	Serv	Social	Leisure	Touring
Freq	34	12	5	14	7	12
n Mon	3	0	0	0	0	0
n Tue	4	0	0	0	0	0
n Wed	8	4	2	6	0	4
n Thu	1	0	0	0	0	0
n Fri	11	4	2	1	0	3
n Sat	6	3	1	5	5	1
n Sun	1	1	0	2	2	4

The individual considered in Table 4 works 40 hours a week distributed equally across five weekdays (i.e., 8 hours each workday). In table 5 the results of the simulations were based on an individual with 24 hours work a week: Monday 8, Tuesday 8 and Thursday 8. The influences of working hours and day preferences are clear and seem logical. For example, in case of 24 hours work a week, the activity was conducted more often on Wednesdays and Fridays and the fulltime worker conducts the activities during the weekends.

3.2 Anticipation of the future

As expected, postponement of the activity as a result of a higher utility on the next day did not occur very often. This implies that the basic model works well. Only in case of 'Shopping – one store' for an individual with 40 working hours a week, the activity was postponed three times. This happened on Fridays and is caused by both the relatively high preference for the Saturday and the time pressure due to work on Fridays.

The simulation of the extended model with anticipation of future events shows realistic results too. Table 6 shows three different cross-sections of the multi-day activity pattern as examples of the influence of the event-based model. All cross-sections relate to a period of 14 days before an event occurs and the activity considered is shopping – one store for the individual working 40 working hours a week. Tau was set equal to 0.5. In the first example the Basic model wants to conduct the activity four days before the event, but the Event model waits until the event. In the second example, the Basic model conducts the activity one day before the event, but the Event model waits. These cases refer to rather straightforward behaviour. The third example however shows unexpected behaviour. Here the Basic model wants to go shopping seven days before the event (Friday), but the Event model waits. However, rather than waiting until the event, on the next day, a Saturday, it decides not to wait and to conduct the activity. This means that in effect the model postponed the activity one day. Although postponing is not behaviour that was explicitly modelled, it does make sense. If all next days until the event were like Friday, then indeed it is rational to wait until the event. However, on Saturday conditions are more favourable to an extent that it is not beneficial to wait until the event. Thus, what this example shows is that the presence of an event may lead to postponing even if postponing is not rational if the event does not take place. This is unexpected but sensible behaviour of the model.

Table 6. Examples of differences between Basic model and Event model

1.	14	13	12	11	10	9	8	7	6	5	4	3	2	1	event
basic															
event															

2.	14	13	12	11	10	9	8	7	6	5	4	3	2	1	event
basic															
event															

3.	14	13	12	11	10	9	8	7	6	5	4	3	2	1	event
basic															
event															

Conduct activity
Basic model wants to conduct, Event model waits
Not conduct activity

In a next series of experiments we (arbitrarily) focused on the shopping-one-store activity and varied the value of tau and frequency of events. Table 7 and Figure 1 indicate the influence of the tau parameter on the tendency of waiting for different occurrence frequencies of an event. They show for four, six and nine events within a time frame of six months, the number of days the model wants to wait divided by the number of events. If tau is smaller than 0.4, there hardly is a difference between the Event and the Basic model. If tau increases, the average number of days an individual waits until the event increases. Thus, the value of tau determines to a large extent the size of the influence of an event on an activity pattern. As Figure 1 indicates, the relationship is non-linear and irregular (with a tendency of an S-shaped form). This result indicates that the value of tau can be estimated based on an event's temporal influence on activity patterns.

Table 7. Influence of τ (tau): n wait / n events

τ	4 events (1 every 40 days)	6 events (1 every 30 days)	9 events (1 every 20 days)
0.2	0	0.17	0
0.4	1	0.50	0.33
0.5	0.75	1.50	1.44
0.6	1.50	3.67	3.33
0.8	10.75	8.33	7.44
1	15.25	14.17	8.22

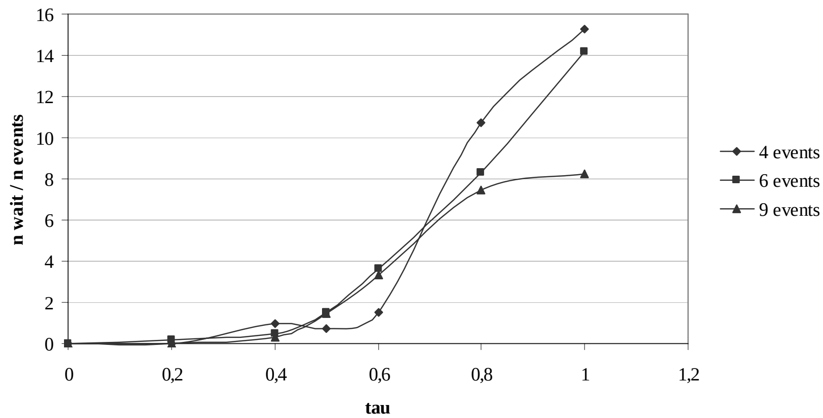

Figure 1. Influence of τ (tau): n wait / n events

In Table 8 we compare, for different values of τ, the differences in total utility of a longitudinal activity pattern between the Basic and the Event model. The results show higher utilities for the Event model, even though the frequency of conducting the activity is lower. If τ is raised, there is a considerable increase in the difference between the total utilities of the models. This results show that the heuristic, even though it is very simple, is consistent with an objective of utility maximization (i.e., rational behaviour). The negative result in only one case is explained by the fact that, indeed, it is a heuristic which does not guarantee optimal solutions.

Table 8. Influence of τ (tau): comparison utilities

	Number of events	Days between events	Utility basic model	Utility event model	% difference
$\tau = 1$	9	20	24.41	465.53	95
	6	30	38.53	421.50	91
	4	40	85.61	420.53	80
$\tau = 0.8$	9	20	462.85	668.39	31
	6	30	476.49	632.41	25
	4	40	451.77	534.57	15
$\tau = 0.6$	9	20	901.28	879.60	-2
	6	30	923.04	922.96	-0.01
	4	40	868.64	874.19	0.63
$\tau = 0.4$	9	20	1339.71	1347.86	0.60
	6	30	1352.42	1354.01	0.12
	4	40	1266.82	1269.48	0.21

4. DISCUSSION AND CONCLUSIONS

In this study, we extended the dynamic need-based model of activity generation to account for future events and conditions. The model employs a simple decision heuristic to determine when to postpone an activity to benefit from better conditions or to save opportunity costs. The model is able to deal with non-homogeneous time in terms of day-varying preferences and time budgets.

For future research, we plan to set-up experiments and a survey to collect data for validating and estimating the model (i.e., the tau parameter). Furthermore, an interesting question is whether we can also use this (simplified) framework to predict occurrences of events in time and estimate the parameters on the event data that were collected in an earlier study (Arentze et al., 2006). This would mean that we have the same set of equations describing the timing of activities and events.

5. REFERENCES

Arentze, T.A., 2008, Estimating method to estimate a dynamic activity-based model on one-day activity-pattern data, Working paper, Urban Planning Group, Eindhoven Univeristy of Technology.

Arentze, T.A., A.W.J. Borgers, M. Ponje and H.J.P. Timmermans, 2006, "From activity-based modeling to social event-based modeling: Conceptual framework and empirical results", in: *Proceedings of the IATBR Conference, Kyoto* (CD-ROM, 17 pp.)

Arentze, T.A. and H.J.P. Timmermans, 2000, *Albatross: A Learning-Based Transportation Oriented Simulation System,* EIRASS, Eindhoven.

Arentze, T.A. and H.J.P. Timmermans, 2006, "A new theory of dynamic activity generation", in: *Proceedings 85th TRB Annual Meeting, Washington, D.C.*, (CD-ROM: 20 pp.)

Arentze, T.A. and H.J.P. Timmermans, 2008, A need-based model of multi-day, multi-person activity generation, Submitted for publication.

Bhat, C.R., and S.K. Singh, 2000, "A comprehensive daily activity-travel generation model system for workers", *Transportation Research Part A*, 34, 1-22.

Kitamura, R., 1984, "A model for daily time allocation to discretionary out-of-home activities and trips", *Transportation Research B*, 18, 255-266.

Nijland, E.W.L., T.A. Arentze, A.W.J. Borgers and H.J.P. Timmermans, 2006, "Modelling complex activity-travel scheduling decisions: Procedure for the simultaneous estimation of activity generation and duration functions", in: *Proceedings of the 11th Conference on Travel Behaviour Research, Kyoto Japan* (CD-ROM)

Nijland, E.W.L., T.A. Arentze, A.W.J. Borgers en H.J.P. Timmermans, 2007, "Activity-travel rescheduling decisions: Estimating parameters of response patterns", in: *Proceedings 86th TRB Annual Meeting, January 2007, Washington, D.C.* (CD-ROM)

Pendyala, R.M., R. Kitamura, A. Kikuchi, T. Yamamoto and S. Fujii, 2005, "Famos, The Florida activity mobility simulator", in: *Proceedings 84th TRB Annual Meeting, Washington, D.C.*