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Multi-Day Activity Scheduling Reactions to Planned Activities and Future Events in a Dynamic Agent-Based Model of Activity-Travel Behavior

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ABSTRACT

Modeling multi-day planning has received scarce attention today in activity-based transport demand modeling. Elaborating and combining previous work on event-driven activity generation, the aim of this paper is to develop and illustrate an extension of a need-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 conducted for six different activities and parameter values. The results show that the model works well and that the influences of the parameters are consistent, logical and have clear interpretations. These findings offer further evidence of face and construct validity to the suggested modeling approach.

INTRODUCTION

Behavioral processes underlying the (re-)planning and (re-)scheduling of activities have been studied in a relatively small but accumulative stream of research. Most of this research has been conducted in the context of computer-assisted data collection instruments. Perhaps the first of these has been MAGIC (*1*) which has been used to record travelers response to external scenarios as reflected in changes in a planned single-day activity schedule. Chase (*2*) developed a similar data collection instrument but added the important feature that the planning and rescheduling of activities across a much longer time horizon could be traced, offering very important and unique opportunities to analyze and better understand the underlying dynamics. Later, similar data collection tools with similar functionalities were developed.

Chase and similar instruments led to behaviorally very interesting research on the re-planning and rescheduling of activities. For example, Doherty (*3,4*) and Doherty and Mohammadian (*5*) found that the distinction between fixed and flexible activities, which is often made in activity-based modeling, is not necessarily reflected in the activity scheduling process. Similarly, evidence for priority-based scheduling is limited (*6,7*).

This work is related to explicit attempts of modeling short term dynamics. In an attempt to elaborate seminal work of Garling and co-workers, Timmermans et al. (*8*) and Joh et al. (*9*) developed Aurora (see Joh et al. for an overview). This model assumes an S-shaped utility function for activity duration. Dynamics (rescheduling) are modeled by allowing travelers to adjust one or more facets of their activity-travel schedule. Although the model is based on utility functions and a utility maximization objective, it is not based on exhaustive evaluation of solutions but rather various decision operations are assumed. The first estimates of the model were based on aggregate data. More recently, stated adaptation experiments were used to validate the assumptions underlying the model (*10,11,12*). These results suggest that individuals first tend to adjust those aspects that require least effort (e.g., duration), and if this is insufficient, change other facets of their schedule. Similar results were reported by Roorda and Andre (*13*).

Although this research offers highly relevant food for thought and is particularly relevant for modeling rescheduling decisions, research on modeling the dynamic generation of activity agendas, to the best of our knowledge, is even scarcer. Mohammedian and Doherty (*14*) used neural networks and logit models to analyze the time horizons between planned and executed activities. This work offers a more rigorous and integral approach to the problem at hand, but still these statistical models primarily serve for analysis; it is not readily evident how these can be used in the context of a dynamic activity-based model of transport demand. Habib and Miller (*15,16*) suggested a model for activity generation. They assumed that the utility of an activity is split into two parts: the goal utility (gained by the end state accomplished by the activity) and the process utility (gained by the execution process of the activity). They argue that the goal utility of activity episode is important for modeling activity program generation, while the process utility component may primarily influence activity scheduling and rescheduling trade-offs.

To contribute to this emerging line of research, this paper reports the findings of the next step of developing a dynamic activity agenda generator. It integrates two lines of previous research. First, it is based on the need-based theory to the problem of dynamic activity generation, suggested by Arentze and Timmermans (*17,18*). This 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.

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. Such activities will occur frequently as individuals will participate in many socially and culturally induced events, such as Christmas, birthdays etc. 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. (*10*) 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. Similarly, Chen and Kitamura (*19*) found that 30% to 45% of the executed activities were scheduled a day before or earlier. 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 (*11*). 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 thus to bring these lines of research together and address the question how rhythms in needs-driving activities are blended with pre-planned activities and events. The structure of the remainder of this paper is as follows. Section 2 describes the theory and models first in terms of the existing need-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.

THEORY AND MODELS

Before describing the proposed extension, we first briefly summarize the basic need-based model for activity generation that was proposed in Arentze et al. (*20*).

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 optimization 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). To simplify notation, we leave an individual specific subscript out of consideration in the equations below.

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

$$U_{sdi} = V_i + V_{sdi} + V_{di} + \varepsilon_{sdi} \qquad (1)$$

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_{sdi} 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 modeled as activities with zero need growth ($V_{sdi} = 0$) and a relatively high utility for the day ($V_{di} \gg 0$) 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. Although a logistic growth function may describe this, a logarithmic form has more favorable properties for estimation and has therefore been typically applied in time use (*21*). It can be expressed as:

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

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 behavior 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):

$$\frac{U_{sdi}}{D_{di}} > u_d^* \tag{3}$$

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 ensures that every activity generates approximately an equal utility per unit of time when it is conducted. 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, we 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:

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

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:

$$D_{di} = D_{di}^0 + \varepsilon_{di} \tag{5}$$

Anticipation of the Future

A shortcoming of the existing decision heuristic (Eq. 3) is that it does not anticipate 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.

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. On the one hand, postponement means a gain, because the time left can be used for other activities. On the other hand, it is a loss in that the utility gained by the activity will not be available until at a later point in time. If the circumstances are more favorable at the later moment (e.g., in terms of time pressure and day preferences), the profit possibly may be higher than the loss. The (net) utility of conducting the activity on current day d can be written as:

$$U_{sdi} - c_d D_{di} = Z_d \tag{6}$$

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 the next period and should be discounted. Postponement is rational only if there is an $m > 0$ such that:

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

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:

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

and this reduces to:

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

This derivation shows that error terms do not play a role in decisions to postpone an activity. Furthermore, it is noted that 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 will be considered only in cases where gains in terms of day preferences or opportunity costs possibly can be achieved.

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 $m \geq 1$.

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 increased by one day in this waiting scenario.

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

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

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 behavior 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:

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

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:

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

This reduces to:

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

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 than 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 straightforward function:

$$c_d = \tau \times u_d^* \tag{22}$$

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 spend his or her time just as well 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 well 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). Opportunity costs also include e.g. location, travel time and transport mode variables. If, for instance, the travel time is shorter or the location is better accessible, the opportunity costs are lower and this influences the utility of conducting an activity.

In summary, 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 of how close a future event satisfying the same need is. If opportunity costs are equal to utility-of-time ($\tau = 1$), an activity will always be postponed until the event, irrespective of how far away the event is in the future. Although both extremes are not realistic, we have no ways of defining the τ parameter a priori. This means that the parameter should be estimated empirically.

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 behavior of the basic model for a range of activities.

Basic model
The following activities were included in the simulation:
- Shopping – one store
- Shopping – multiple stores
- Service related activities
- Social activities
- Leisure activities (other than touring)
- Touring (by car, bike or foot)

For the simulation the values for the parameters per activity were used as shown in Table 1. Those parameters are consistent with results of estimations on a national trip diary data set (the MON 2004 survey) (*20*). This dataset includes one-day diary observations of 46,877 individuals in total. The β 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 Assumed values of the parameters in the simulation

	Shopping- one store	Shopping- multiple stores	Service related activities	Social activities	Leisure activities	Touring (by car, bike or foot)
β	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. As a simplification, we used error terms of the form ε_{si} instead of ε_{sdi}. We assumed a normal distribution for the error term with average of zero and a standard deviation of 0.25 (the latter standard deviation was taken from an earlier empirical estimation study (20)). The results of the simulations are shown in Table 2 for three different hypothetical individuals having different work hours: 0 hours work a week, 40 hours work a week and 24 hours work a week. 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 $u_d^* = 1 + \delta \times W_d$ (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 the table shows the total number of times the column activities were conducted and the next rows the numbers of times per day of the week. The second individual considered in Table 2 works 40 hours a week distributed equally across five weekdays (i.e., 8 hours each workday) and the third individual works 24 hours a week: 8 hours on Monday, Tuesday and Thursday. 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.

TABLE 2 Simulation results

	Shopping-one store	Shopping-multiple stores	Service related activities	Social activities	Leisure activities	Touring (car, bike or foot)
0 hours work a week						
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
40 hours work a week						
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
24 hours work a week						
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

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 also shows realistic results. Table 3 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 hours a week. The τ parameter 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 behavior. The third example however shows unexpected behavior. 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 behavior that was explicitly modeled, 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 favorable to an extent that it is not beneficial to wait until the event. Thus, this example shows 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 behavior of the model.

TABLE 3 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 τ and frequency of events. Table 4 and Figure 1 indicate the influence of the τ 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 τ is smaller than 0.4, there hardly is a difference between the event and the basic model. If τ increases, the average number of days an individual waits until the event increases. Thus, the value of τ 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 τ can be estimated based on an event's temporal influence on activity patterns.

TABLE 4 Influence of τ: n wait / n events

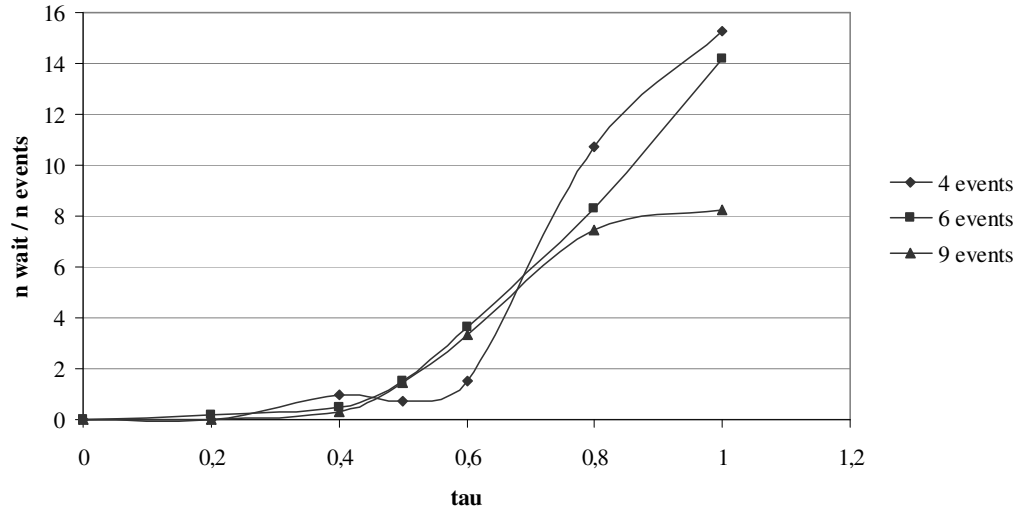| τ	4 events (1 every 40 days)	6 events (1 every 30 days)	9 events (1 every 20 days)
0.2	0	0.17	0
0.4	1	0.50	0.33
0.5	0.75	1.50	1.44
0.6	1.50	3.67	3.33
0.8	10.75	8.33	7.44
1	15.25	14.17	8.22

FIGURE 1 Influence of τ: n wait / n events.

In Table 5 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 behavior). 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 5 Influence of τ: 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

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. In this way, the influence of pre-planned activities and events on activity scheduling can be included in the need-based model of activity generation.

Using estimates derived from a national travel survey, the results of the simulation indicate that the model has face validity and that the outcomes are consistent with theoretical expectations. It would suggest that we can use the theory of needs-driven rhythms and regimes in activity generation, and take into account influences of anticipated future events on scheduling decisions as stepping stones to develop an operational model of dynamic activity agendas. This can be used to simulate how these regimes are blended with events and pre-planned activities. At the same time, this approach could also be used fruitfully in the discussion about activity planning and scheduling along a longer time horizon.

The precise value of the suggested approach should however be further explored and proven in future research. As for our immediate research agenda, we plan to design experiments and a survey to collect data for validating and estimating the model (i.e., the τ 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 (*22*). This would mean that we have the same set of equations describing the timing of activities and events. We plan to report on these further elaborations and tests in future papers and publications.

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