Incorporating time and income constraints in dynamic agent-based models of activity generation and time use: approach and illustration

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ABSTRACT

Existing theories and models in economics and transportation treat households' decisions regarding allocation of time and income to activities as a resource-allocation optimization problem. Arguably, this stands in contrast with the dynamic nature of day-by-day activity-travel choices. Therefore, in the present paper we propose a different approach to model activity generation and allocation decisions of individuals and households that acknowledges the dynamic nature of the behavior. We propose an agent-based model where agents, rather than acting on the basis of a resource allocation solution for a given time period, make resource allocation decisions on a day by day basis taking into account day-varying conditions and at the same time respecting available budgets over a longer time horizon. Agents that share a household interact and allocate household tasks and budgets among each other. We introduce the agent-based model and formally discuss the properties of the model. The approach is illustrated on the basis of simulation of behavior in time and space.

General Terms

Human Factors, Theory.

Keywords

Travel demand modeling, agent-based modeling, activity generation, time use, income constraints.

1. INTRODUCTION

The importance of financial constraints on individuals' time-use and activity choice has long been recognized particularly in the context of households' long-term mobility decisions (e.g., [1], [2], [3], [4], [5]). Long-term decisions such a residential location, job location, working hours, car possession and so on, may have significant implications for the amounts of time and money available for daily activities such as shopping, recreation and social activities. For example, a decrease of working hours increases available time but decreases income that can be spent in daily activities. As another example, a change of residential location to a place farther away from work increases commuting times and, hence, reduces available time budgets for activities. Because of such implications, long-term mobility decisions generally require trading-off utility derived from activities against utility of spending time and money in living, traveling or luxury goods.

Since the seminal work of Becker [6], households' decisions regarding the allocation of time and income to activities have been conceptualized and modeled as a resource-allocation optimization problem. In this approach, the allocation of time and income to activities of a household in a given time period is determined based on an objective to maximize a total household utility [8], [9]. Although later studies have accomplished important refinements and elaborations [7], the basic assumption of framing resource allocation behavior as a global optimization problem has not been questioned. Arguably, this stands in contrast with the dynamic nature of day-by-day activity choices. The physical and social environment in which activities are implemented, and the needs, desires and constraints for these activities are to an important extent stochastic and non-stationary. This dynamics imply that objectives and conditions are never exactly the same and decisions to implement and spend a certain amount of money and time in activities often need to be adapted to current circumstances.

Therefore, in the present paper we propose a different approach to model activity-resource allocation decisions of individuals and households that acknowledges the dynamics of the behavior. We propose an agent-based model where agents, rather than acting on the basis of a resource allocation solution for a certain time period, make resource allocation decisions on a day by day basis taking into account the specific conditions of the moment and at the same time respect available budgets over a longer time horizon. We show that by using a local decision rule the agents are able to act flexibly and at the same time maximize a utility they derive from activities over a longer term, given existing budget constraints. To accomplish this, the rule uses for each resource a threshold parameter representing the scarcity of the resource. The appropriate value of each threshold is not known a-priori. Through a process of learning based on experience, the agents gradually find the threshold values that optimize their behavior globally.

The proposed model will be incorporated in an integrated land-use, transportation system called PUMA [5], [10]. The model fits in current activity-based approaches to travel demand modeling. In existing conceptual frameworks, the programming and scheduling of activities are considered different, successive phases in a decision process for generating an activity schedule for a given day [15]. Programming decisions determine which activities are conducted for how long and possibly also (tentatively) the locations where the activities are conducted. Activity scheduling decisions then determine the sequence of the activities, the exact timing of each activity, trip-chaining characteristics (e.g., insert yes or no a return home trip between two consecutive out-of-home activities) and transport modes used for the resulting tours. In this same scheduling phase, location choices for activities may be reconsidered, for example, to utilize opportunities for saving travel time, given trip-chains. The model we propose in the present study deals with activity programming decisions. This means that it needs to be complemented with an activity scheduling model, before it can be used for predicting individuals' activity-travel patterns. Furthermore, we note that, in contrast to existing approaches, our model is dynamic in the sense that the activity needs of an individual are considered to be dependent on the activity history of the individual. Rather than predicting an activity program for an average or typical day, the proposed model, as a consequence, generates activity programs that fit in a longitudinal activity pattern of an individual (of arbitrary length).

The paper is structured as follows. In Section 2, we first introduce the basic concepts of the approach. Then, in Section 3, we propose specifications of the components of the framework. Next, in Section 4, we describe results of simulations that we conducted to illustrate the system. Finally, we conclude the paper by discussing major conclusions and avenues for future research.

2. THE AGENT-BASED APPROACH

In this section, we describe the basic framework. We first consider the utility functions and a decision rule for a single agent and next discuss how this can be extended to take within household interactions into account.

2.1 Utility functions

Assume the activity repertoire of an agent is given by a list of activities $A = \{A_1, A_2, \ldots, A_n\}$. On each day of a given time period, the agent decides which activities it will conduct for how long and how much money it will spent (possibly zero). Mandatory activities, such as, for example, a work or school activity, may be scheduled for the current day as well. These activities are considered as given and fixed and reduce the available time for other activities. When mandatory activities and activities selected from the list have been programmed there may be time left on the day. Our model assumes that, by definition, this time is used for leisure-at-home purpose and as such generates utility as well. To put this in another way, the model assumes that time allocated to leisure (at the end of the day at home) is not a separate decision, but a result of all other activity decisions. We use the term slack time and slack activity to refer to the remaining time and use of remaining time on a day.

An activity produces utility and requires time and possibly other resources as inputs. If time is a scarce resource, then utility of time, defined as utility per unit time spent (denoted as UoT), is a useful concept. If time is scarce, then an optimality condition for the allocation of time to activities is that UoT is as much as possible equal across activities conducted (including the slack activity). This is easy to see: if the condition does not hold then it is possible to increase the utility by transferring time from an activity where it is less productive (in terms of utility) to an activity where it is more productive (in terms of utility). Time is merely one resource that is constrained by a budget. In addition, at least some activities also require monetary expenses. In full analogy, if money is a scarce resource, then utility of money, defined as the utility per monetary unit spent (denoted as UoM) is a key issue. If money is scarce then, for the same reason, it should be allocated to activities such that the UoM is the same across implemented activities.

A core assumption of the framework that we propose is that the utility of an activity is dependent on the activity history of the agent. Generally, the longer ago the last time an activity A_i has been conducted, the larger its current utility will be. When (positive or negative) substitution relationships exist between activities, the history of other activities should be taken into account as well. Although such interactions can be readily incorporated in the present framework, for clarity of presentation we leave them out of consideration here. Utility is furthermore dependent on travel demands involved, if any, the location where the activity is conducted and possibly chosen levels of time efficiency and quality. The following utility function captures these notions:

$$U_{di}(m,l,b,q) = V_d^{\mathrm{M}}(m,l) + V_{di}(t_i,l,b,q) + \varepsilon_{si} \quad (1)$$

where d is the current day, t_i is elapsed time since the last time an activity A_i was conducted, s denotes the day this happened ($s = d - t_i$), l is the chosen location for the activity, m is the chosen transport mode ($m = 0$ if no trip is involved), V_d^{M} is the travel-related utility, V_{di} is the activity-related utility, b is a chosen level of time efficiency, q is a chosen level of quality and ε_{si} is an error term. The d subscript of the activity-related component indicates that utility may be dependent on the day when the activity is conducted. This is the case for example when an agent has a specific intrinsic preference for a day of the week to conduct a certain activity (e.g., going out on Saturday). Time efficiency b is a relevant parameter if the agent can choose between conducting the activity in a hurry or at one's leisure or between a slow (and cheap) service and a fast (and expensive) service. This concept is comparable to the concept of activity intensity coined by Ashiru *et al.* [11]. In addition, quality q is a relevant parameter when the activity and location involve goods or services at different consumer price levels. An increase of time efficiency, when it implies an increase of effort rather than a faster service, reduces utility, whereas an increase of quality increases utility.

Besides generating utilities, activities and travel also use time. We model the time spent as follows:

$$T_{di}(m,l,b) = T_d^{\mathrm{M}}(m,l) + T_{di}(t_i,l,b) \quad (2)$$

where, as before, m and l represent transport mode and location choices, b represents choice of time efficiency for the activity, T_d^{M} represents travel time as a function of mode and location and possibly dependent on day (e.g., day-varying congestion levels), and T_{di} is time used for the activity as a function of elapsed time, location and chosen time efficiency. Since the need an activity intends to satisfy increases with elapsed time, the time needed (at the chosen efficiency level) is an increasing function of elapsed time (e.g., a longer shopping list). Furthermore, given the time elapsed, T is a decreasing function of time efficiency b. Finally, the function depends on the day when the activity is conducted (e.g., shorter queues on Monday).

Apart from time, activities and travel may also involve monetary expenses. We model the money spent as:

$$E_i(m,l,q,b) = E_i^{\mathrm{M}}(m,l) + E_i(t_i,l,b,q) \qquad (3)$$

where E_i^{M} is costs of traveling to the chosen location with the chosen mode and E_i is the amount spent for the activity at the location. Expenditure for the activity, the latter component, is an increasing function of size of the need when the activity is conducted and, hence, of elapsed time. Furthermore, expenditure is an increasing function of quality level and it is an increasing function of time-efficiency in as far efficiency is a characteristic of a service that needs to be paid for.

Given the above definitions, the utility of time (UoT) and utility of money (UoM) can now be defined in a straight-forward way as:

$$u_{di}^{\mathrm{T}} = \frac{U_{di}(m,l,b,q)}{T_{di}(m,l,b)}, \quad u_{di}^{\mathrm{E}} = \frac{U_{di}(m,l,b,q)}{E_i(m,l,b,q)} \qquad (4)$$

where u_{di}^{T} and u_{di}^{E} are the UoT and UoM an activity i could generate when conducted on day d conditional upon the choices of mode, location, quality and efficiency. Note that by choosing an efficiency and quality level (and location and mode) an agent is able to adapt the time and money spent. Duration and expenditure are not fully symmetric in that respect. An increase of time efficiency may come at the cost of paying a higher price for a service and, then, increases expenditure (money can buy time). On the other hand, the model assumes that quality cannot be increased by spending more time. Furthermore, the concept of efficiency needs some clarification. In the model, efficiency is increased either by investing more effort (doing things in a hurry) or by paying more for a faster service. One could argue that service and effort refer to different dimensions. Although it is possible to treat the dimensions as separate variables in the model, we assume that within activities either one of the two dimensions is relevant, so that a single variable, with an activity-context dependent meaning, suffices.

To elaborate and extend the latter issue, we distinguish the following three activity types, which we denote as Type I, II and III activities:

1. Type I: Neither time-efficiency nor quality can be increased by spending more money.
2. Type II: time-efficiency can be increased by spending more money.
3. Type III: quality can be increased by spending more money.

Obviously, these categories are not mutually exclusive: an activity can be of Type II and Type III at the same time. In case of a Type-I activity, no resource allocation choice is left when location and transport mode have been chosen: the amount of time and money spent are determined by elapsed time. In case of a Type-II activity, time and money are to some extent compensatory in the sense that a lack of time can be compensated by spending more money (e.g., choosing a more expensive service that is faster). In case of a Type-III activity, the individual can spend more money (e.g., pay a higher price for a higher-quality service) and increase the utility derived from the activity without time consequences.

2.2 A local decision rule

The activity utility function given by Equation (1) describes the utility of a particular activity on the current day as a function of time efficiency, quality, location and mode decisions. The function is however dynamic as it takes into account current needs (elapsed time) and intrinsic preferences for a day. The agent-based model we propose assumes that agents use a local decision rule in the sense that they make the decisions on a day-by-day basis. Although this is plausible in terms of what individuals do in reality, it seems to be in conflict with the fact that time and money budgets are defined for a longer time frame than a day. As we argued in previous work [12], however, time budget constraints can be adequately dealt with by a local decision rule of the following form:

R_1: Implement an activity on the earliest day when the UoT of the activity under optimal time efficiency, quality, mode and location choice exceeds a threshold value for that day of the week.

A threshold value is included for each day of the week to account for possible day-by-day variation on time spent on mandatory activities (e.g., more time available in weekend). If the threshold value for each day of the week is appropriately chosen, this rule makes sure that 1) each implemented activity produces approximately an equal UoT and 2) available time is fully used in the sense that utility of slack time equals the utility of activity time. Note that the utility as well as the required duration of an activity increases over (elapsed) time. If utility increases with a faster rate than required duration, then UoT increases over time and a moment will come that it exceeds the threshold. The day-of-the-week threshold values that produce this result are, however, not a-priori known. We also showed how the threshold values can be found through an iterative adjustment procedure based on trial and error. Starting with an arbitrary initial value (for each day of the week), an activity plan for a sufficiently long time period is generated using R_1. Next, utility of slack time is compared to utility of activity time for each day of the week:

R_2: If the utility of slack time is higher than the utility of activity time, then adjust the threshold upwards. If the utility of slack time is lower than the utility of activity time, then adjust the threshold downwards.

where, as before, slack time is time left on a day after having conducted mandatory and selected activities from list A. If the threshold for one or more days is adjusted, then an activity plan is re-generated for the same period and R_2 is applied again. This cycle is repeated until convergence. In equilibrium, the utility of slack time is equal to the utility of activity time and the utility of time of each activity is at or just above the threshold and, hence, approximately the same.

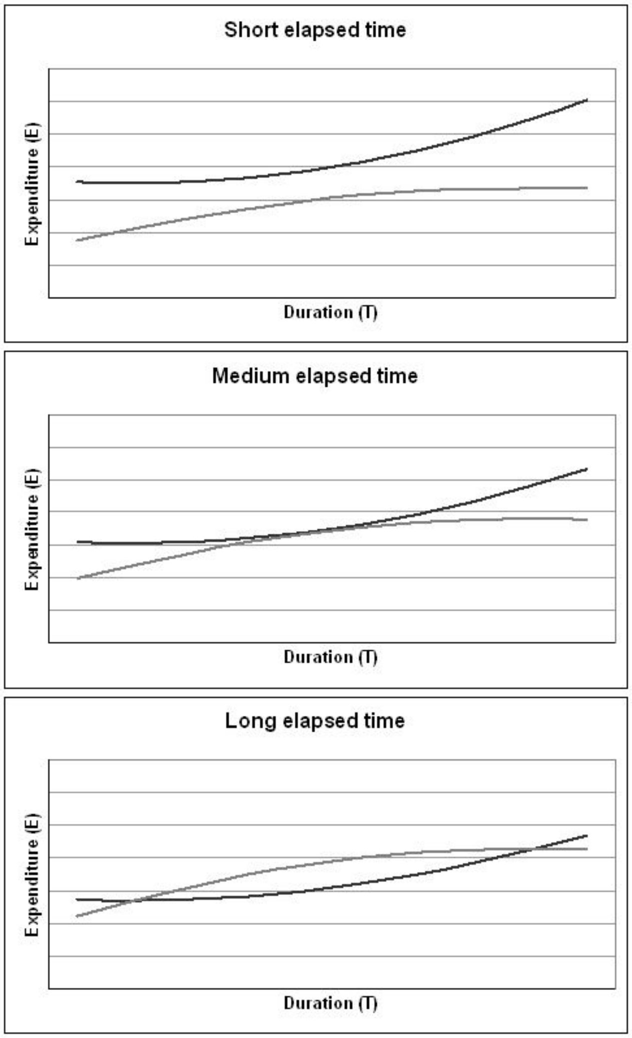

Figure 1. Utility of time (black line) and utility of money (gray line) Influence of elapsed time on for a Type-III in three stages of need development

The activity-day selection rule R_1 and threshold adjustment rule R_2 focus on the time-budget constraint and do not take expenditure into account. Generalization of the rules is straight-forward. The extended activity-day selection rule can be written as follows:

R_1' Implement an activity on the earliest day when the UoT and UoM of the activity under optimal time efficiency, quality, mode and location choices both exceed their threshold value for that day of the week.

Note that for UoM a single threshold value for each day of the week suffices, as financial budgets do not vary on a daily basis. The appropriate threshold value for UoM can be found by a similar threshold adjustment rule as in the case of time. In full analogy, the complementary rule comes down to:

R_3: If total expenditure exceeds the money budget, then adjust the threshold upwards. If not all available money is used, then adjust the threshold downwards.

We illustrate the behavior of the system based on three graphs shown in Figure 1. As an example, the graphs relate to a Type-III activity and depict three moments in the cycle of an activity, i.e. where the need is low (top graph), a later moment where the need is medium (middle graph) and a still later moment where the need is high (bottom graph). In each graph, the black curve represents the combinations of duration and expenditure where UoT equals its threshold value and the gray curve represents the resource allocations where the UoM equals its threshold value. Thus, above the black curve are resource allocations allowed by the time-budget constraint and below the gray curve are the resource allocations allowed by the money-budget constraint. From early to the late stage, the UoT threshold curve (black line) shifts downwards indicating that, as the need increases, increasingly lower levels of expenditure suffice to meet the threshold. At the same time, the UoM threshold curve (gray line) moves upward indicating that, as the need increases, increasingly higher levels of expenditure are allowed given this threshold. In the second stage (the middle graph), the need has reached a level where the two threshold curves start to overlap. Hence, this is the first moment when implementing the activity is feasible. In the late stage, multiple resource allocations are feasible, namely all allocations falling in the area enclosed by the two graphs.

Given the rule that an activity is conducted at the earliest moment when the thresholds conditions are met, the threshold condition leaves no choice as to how much time and money to spend for the activity when it is implemented. Thus, a ready conclusion that can be drawn from the illustration is that in a system where all or at least some activities are of Type III, individuals always use their time and money budgets completely. This conclusion holds if the money curve is convex and moves down and the time curve is concave and moves up, as the need for the activity increases. Then, the first moment when the activity is feasible is always the moment when the curves intersect in a single point. Because the activity will be selected at that moment, there is no time and expenditure choice left. In reality, of course, day is a discrete variable and, hence, time does not pass in a continuous fashion. In case of Type-III activities, however, even if a choice is left, money will be spent exactly up to the point where UoM meets its threshold value. For example, if more money were spent utility would rise but too little to prevent the UoM from dropping below its threshold.

For Type-II activities the same mechanism applies. For these activities there is even another level of dynamics that makes sure that budgets are fully used. Assume for example that an agent would consistently choose to spend more money to save time. Then, not all time is used and by the working of the threshold adjustment procedure the UoT threshold would be adjusted downwards. This would continue till the moment when the UoT threshold line would intersect the UoM threshold line in a single point. At that moment the activity will be implemented without leaving a choice regarding the quantities of time and money. This self-organizing behavior makes sure that the system indeed exhausts its budgets.

For Type-I activities, however, the outcome may be different. For these activities there is a single point in time where the UoM-threshold line meets the line that represents the fixed quantity ratio between the resources. This point does not necessarily coincide with the point where the UoT equals its threshold. Thus, there are two possibilities with different outcomes. If time is the limiting factor, the UoT threshold determines when the activity is conducted and how much money is spent. On the other hand, if money is the limiting factor, the UoM threshold determines when the activity is conducted and how much time is spent. In the first case, money is left and in the second case time is left. Furthermore, we note that also under Type-II and Type-III conditions circumstances are conceivable where not all resources are used. The utility and resource functions impose limitations on the extent to which time can be exchanged by money (Type-II) or more money can be spent to increase utility (Type-III). If the money budget is large, this may mean that money is not a limiting factor for utility and may not be fully used. In such a case, the UoM threshold would drop to zero.

2.3 Multi-person households

The household context is relevant when at least some activity needs are shared by the individual agents sharing a household. If multiple agents are able to conduct such household activities, then time can be re-allocated between agents. Furthermore, an important implication is that agents may derive utility from an activity even if it is conducted by someone else. The proposed system assumes that agents have their own perception about needs and activities and interact pair-wise with each other to consider re-allocations of (household) activities using the following rule:

R_4: If $dU_{di}^{g}(h, g)$ is the change in utility for agent g when g would take over a (household) activity i from agent h on day d and $dU_{di}^{h}(h, g)$ is the change in utility for agent h of the same re-allocation, then implement the re-allocation only if $dU_{di}^{g}(h, g) + dU_{di}^{h}(h, g) > 0$. If g takes over an activity from h then g re-considers the duration of the activity based on his own perceptions.

This rule is applied iteratively to all pairs of agents and all household activities. Since all agents in the household apply R_1', this means that each household activity is always conducted on the earliest day when it meets the lowest threshold value across the agents that can conduct the activity. By using R_4 an activity then possibly may be re-allocated among the individuals.

Finally, in cases where multiple individuals share a household, multiple money budgets are relevant. If there are n agents, then there are n + 1 sets of needs, namely n sets of personal needs and a set of shared needs. A money budget needs to be defined for each set of needs implying that n + 1 UoM threshold values are required to represent existing money-budget constraints. In everyday terms, this means that individuals sharing a household should decide on how much of the household income they wish to use for shared needs and how much they wish to use for the personal needs of each individual. Note that this is another asymmetry between the two resources: for the time resource there exists no rationale for adopting a shared budget.

2.4 Concluding remark

The dynamic-process approach makes it possible to account for many irregularities that exist in the real world. Specifically, the proposed system takes the following conditions into account:

1. Mandatory activity time may vary from day to day.
2. Intrinsic preferences for certain activities may vary by day of the week.
3. Physical conditions (e.g. traffic) and, thus, time demands may vary from day to day
4. Preferences and perceptions may differ between individuals sharing the same household.

The activity-day selection rule R_1', the threshold adjustment rules R_2 and R_3 and the allocation rule R_4 are all sensitive to day-varying and person-varying conditions and perceptions and at the same time consistent with an objective of maximizing utility within resource constraints. However, it should be noted that, because of the irregularities and discrete character of activity-day selection decisions, temporal patterns where all activities generate equal UoT and equal UoM may not emerge in the system (and neither in reality). For example, it may not be possible to (further) re-allocate time between individuals or between days of the week to (further) solve existing differences in UoT between days of the week. In that sense, adjusted UoT thresholds accurately represent day-varying time pressures on an individual's agenda.

3. POSSIBLE SPECIFICATIONS

In this section, we propose further specifications of the functions involved in the above framework that suite the purposes of transportation modeling. First, regarding the costs of traveling we propose the following simple function:

$$E_i^{\mathrm{M}}(m,l) = P_m^{\mathrm{M}} + p_m^{\mathrm{M}} D(m,l) \tag{5}$$

where $D(m, l)$ is traveled distance given mode choice m and location choice l, P_m^{M} is a constant costs for using mode m and p_m^{M} is a costs per unit travel distance for mode m. Not all terms may be relevant. For private-vehicle modes the constant costs component normally is equal to zero or used to represent parking costs. For public transport tariff structures of transport modes may be more complex. Ticket prices may not be a linear function of distance, and so on. Even in those cases, however, the above linear function may suffice for a reasonable approximation of actual costs. Furthermore, we note that in case of multi-activity tours it is not always straight-forward which part of traveling should be attributed to which activities. However, we leave this issue out-of-consideration here.

We assume that activities that are relevant for transportation modeling may be of Type I or III, but are never of Type II. That is, we assume that for none of the activities time can be saved by spending more money. This means that the time efficiency parameter, b, refers exclusively to an effort of the agent and can be dropped as argument from the expenditure function (cf. Eq. 3). Furthermore, we operationally define quality parameter q and efficiency parameter b on a zero-one scale, where zero means lowest level and one means highest level of quality and efficiency respectively.

Given these assumptions, we propose the following simple linear function to define amount of expenditure for an activity of Type I or Type III in general, as follows:

$$E_i(t_i,l,q) = (1-q)E_i^{\min}(t_i,l) + qE_i^{\max} \tag{6}$$

$$E_i^{\min}(t_i,l) = P_{li}^{\min} + p_{li}^{\min}t_i \tag{7}$$

$$E_i^{\max}(t_i,l) = P_{li}^{\max} + p_{li}^{\max}t_i \tag{8}$$

where, as before, t_i is elapsed time, $P_{li}^{\min}$ is a constant price and $p_{li}^{\min}$ a price per unit of the need for the activity (as measured by elapsed time) at a lowest quality level and $P_{li}^{\max}$ and $p_{li}^{\max}$ are the constant and variable prices at a highest quality level. As implied by Equation (6), the choice of quality level determines the actual amount spent, given the size of the need on the day the activity is conducted and the location. Note that Type I is a special case of Equation (6) where $P_{li}^{\min} = P_{li}^{\max} = P_{li}$ and $p_{li}^{\min} = p_{li}^{\max} = p_{li}$ and, where, as a consequence, parameter q is redundant.

The proposed function for time spent on an activity can be defined in a fully analogues way as:

$$T_{di}(t_i,l,b) = bT_{di}^{\min}(t_i,l) + (1-b)T_{di}^{\max}(t_i,l) \tag{9}$$

$$T_{di}^{\min}(t_i,l) = \alpha_{li}^{\min} + \delta_{li}^{\min}t_i \tag{10}$$

$$T_{di}^{\max}(t_i,l) = \alpha_{li}^{\max} + \delta_{li}^{\max}t_i \tag{11}$$

where $\alpha_{li}^{\min}$ is a constant time investment and $\delta_{li}^{\min}$ a time demand per unit of size of the need (as measured by elapsed time) at the highest level of time efficiency and $\alpha_{li}^{\max}$ and $\delta_{li}^{\max}$ are the corresponding figures at the lowest level of time efficiency. The travel-time component T_d^M (Eq. 2) is a more complex function of the transportation system which can be modeled as usual and which we will leave out of consideration here.

A possible specification of the utility function which captures the notions discussed in the previous section is as follows:

$$V_{di}(t_i,l,b,q) = V_{di}^0 + (1+q)^{\gamma_i}(1+b)^{\chi_i}\ f_i(t_i) \tag{12}$$

where V_{di}^0 represents a constant component, which may vary between days, f_i is a need-related component that varies as a function of time elapsed and γ_I and χ_i are activity-dependent parameters. Parameter $\gamma_I \geq 0$ defines a weight of quality and parameter $\chi_i \leq 0$ a weight of efficiency in utility. Note that the multiplicative form makes sure that quality and efficiency act so as to rescale the utility derived from need satisfaction. Several functional forms for the latter need-size function f could be considered. In earlier studies ([12], [13]), we proposed a logistic function. Arguably, an essential characteristic of this function is that a subjectively felt need grows with declining rate over time. A simpler function that also displays this property and has been proposed in several empirical studies on time-use modeling (Kitamura 1984) is the following logarithmic function:

$$f_i(t_i) = \beta_i \ln(t_i + 1) \tag{13}$$

where β_i is a scaling factor representing the growth rate of the need for the activity. For example, high frequency activities are characterized by a large value for beta, and vice versa. Unity is added to elapsed time in the argument of the logarithm to make sure that the need is larger than zero after an elapsed time of one day.

In terms of UoM and UoT, the system has the following properties. Equation (6) implies that expenditure increases linearly with quality level (given the scale on which we measure quality). Equation (12) implies that utility increases with decreasing marginal utility if $0 < \gamma_I < 1$. Under that setting, therefore, utility of money decreases with increasing expenditure. In the special case where $\gamma_I = 1$, utility increases linearly with expenditure and, hence, utility of money will be independent of the amount spent. We consider the decreasing UoM behavior to be more realistic meaning that generally a setting of $0 < \gamma_I < 1$ is appropriate. As for the time resource, Equation (9) implies that time spent decreases linearly with efficiency level (again, given the scale we use to measure efficiency). Equation (12) implies that utility decreases with a decreasing rate when efficiency increases for all settings of $\chi_i < 0$. As a consequence, UoT increases with increasing time efficiency, as we would expect.

Cross-elasticities are also evident in the system. Keeping the time spent constant, spending more money for an activity means that the utility increases and, hence, also UoT increases. Vice versa, keeping expenditure constant, spending less time for an activity leads to an increase of utility and, with that, an increase of UoM. Combined with the threshold adjustment rule, these relationships give rise to the following self-organizing behavior. Spending more money for activities means that activities exceed UoT thresholds earlier in terms of elapsed time and, thus, lead to increase of time expenditure. To prevent time shortage, the UoT threshold is adjusted upward and the activity frequency will be restored. Through this mechanism, an increase of available money (for activities) drives the UoT threshold up if the change is not accompanied by an equivalent increase of time budget. Or to put it another way, the system predicts that income correlates positively with utility-of-time demands. On the other hand, spending more time on activities (doing things in a less efficient way) means that activities exceed the UoM threshold earlier and to prevent shortage of money the threshold for UoM of money is adjusted upward if the money budget does not increase. Thus, the model predicts that utility-of-money demands increase with increasing time budgets.

4. ILLUSTRATION

In this section, we describe some results of a simulation to illustrate the model system. The simulation focuses on day-to-day activity choices for a multi-week period of two hypothetic persons sharing a household.

4.1 The simulation system

The simulation was conducted using an existing agent-based system that we developed in earlier work [14]. The system is based on a needs-based model of activity generation, which assumes that activities are driven by a set of needs which grow over time. In this system, there is not necessarily a one-to-one relationship between needs and activities: a single activity may have a (positive or negative) influence on multiple need dimensions at the same time. The model proposed here is implemented as a special case where one activity acts on one need. The system assumes a logistic (S-shaped) function to describe need-growth.

As for the resource functions, the system assumes that time spent on an activity is a function of the size of the need at time of implementation. However, time efficiency is not a parameter in this framework and, hence, this choice facet cannot be modeled. As for monetary expenditure, the system assumes as parameters of each activity and location combination a constant price (P), a price per unit duration (p) and a maximum amount of expenditure. The constant and price per unit define a minimum amount of expenditure given an activity duration. The minimum and maximum defines a range within which agents can choose the actual amount spent at the moment an activity is implemented. Utility is an increasing function of expenditure with decreasing marginal utilities in line with the specifications we proposed in this study. Furthermore, the agents use rules R_1-R_4 for their daily activity decisions. In sum, the system allows us to run the model proposed here and simulate the behavior under Type-III activities with fixed time efficiency.

Table 1 represents the activity settings assumed in the case. Shopping (daily and non-daily), service-related activities, medical activities, fitness and going-out (eating/drinking and cultural) need particular facilities in the spatial environment. In addition, the activity list includes several in-home activities including, jobs in or around the house, housekeeping, leisure passive (e.g., reading, watching TV etc.) and sleeping. Daily shopping, service-related activities and housekeeping are considered household activities, i.e. activities that can be conducted by both agents and satisfy a shared need by both agents. Leisure passive is considered a slack activity, i.e. the activity an agent is engaged in during time on a day not occupied by the activities in the list. Finally, the list specifies a work activity for each person.

The residence of the agents is explicitly situated in space somewhere in the Netherlands. For each facility-based activity, a location choice set for each transport mode is defined for each agent. Facilities for the activity are available at these locations. Travel distances by mode are calculated based on shortest paths across the Dutch road network. Fast and slow modes are distinguished as possible transport modes. Activities are consistently evaluated under best location and mode choices. For fast modes no direct implications for utility are assumed (only indirect namely through saving time). A slow mode on the other hand produces a (positive) utility depending on an existing need for physical exercise. The latter is also the need involved in the fitness activity meaning that fitness and slow mode are partly substitutable.

A beta parameter for each activity describes how fast the need for the activity grows over time (in the context of a logistic growth function). Leisure passive is considered the slack activity. Furthermore, it is a special activity in the sense that the need for the activity is supposed to grow within a day rather than across days, as the other activities do. As reflected by the scale of the beta parameter, the unit of time is a minute rather than a day. The asymptotic maximum, which is an additional parameter of a logistic function, was not differentiated and set to 100 units for each activity. As an exception, the maximum for the leisure activity is set to 300 units. Activity duration parameters (not shown) were set based on assessments of typical time requirements for activities.

Table 1. Assumed activity settings

Activity	Need (beta)	Expenditure (P, p, Emax)
Daily goods (H)	0.700	(10, 0.333, 100)
Non-daily good	0.350	(0, 0.667, 200)
Services (H)	0.250	(10, 0.333, 100)
Medical	0.080	(20, 0.5, 200)
Go-out (drink-eat)	0.500	(0, 0.2, 100)
Go-out (cultural)	0.080	(30, 0, 200)
Fitness	0.250	(5, 0.667, 100)
Social	0.600	(0, 0, 0)
House keeping (H)	0.800	(0, 0, 0)
House jobs	0.350	(0, 0, 0)
Leisure passive	0.008	(0, 0, 0)
Sleep		(0, 0, 0)
Work		(0, 0, 0)
Travel by fast mode		(0, 0.17, -)
Travel by slow mode	0.250	(0, 0, 0)

In-home activities (Jobs, Housekeeping, Leisure, Sleeping) do not involve expenditure and neither do social and work activities (except that traveling may incur costs). Activities that do involve expenditures were all considered Type-III activities, with a gamma value of 0.5. Work is considered a mandatory activity, with fixed times and durations. Since it is a fixed activity no utility function is specified for work. The weekly work schedule of each agent is predefined and determines the time budget for the flexible activities on each day for each agent. P1 and P2 differ regarding this schedule. Being a fulltime worker, P1 has a work activity of 8 hours on each weekday. P2 has a part-time job which involves four workdays (Wednesday off) of 6 hours a day.

We simulated the day-by-day activity choices of the agents arbitrarily for a period of 7 weeks; the initial sizes of activity needs (i.e., elapsed times) are randomly chosen (assuming that the agents have the same perceptions of household needs). On each day, each agent goes through its list of activities and determines for each activity the best choices for choice facets and travel time and evaluates the utility given the best choices and elapsed time for the activity. The choice facets include location, transport mode, duration and expenditure. Best choices are choices that meet the existing UoT and UoM threshold requirements and maximize utility within that constraint. Activities that meet the threshold constraints (under best choices) are put on the activity agenda for the day and person concerned.

Household activities are also included in the activity list of each person. Which person, P1 or P2, conducts the activity is considered an additional choice facet of household activities. Each person puts household activities on an own agenda making a best person choice considering the appropriate thresholds, but without consulting the other person. This means, for example, that P1 may put a housekeeping activity to be performed by P2 on its agenda when P1 considers this feasible given (its knowledge of) P2's threshold constraints and based on its own perception of the need for the activity. Having determined their activity agendas independently of each other, the two agents start a negotiation process. In this process they apply rule R_4 to each household activity, to see if a re-allocation is desired. A change of an initial allocation may occur if opportunity costs or perceptions differ. Opportunity costs are defined as the utility loss associated with sacrificing leisure time. After completing the negotiations the agents agree with each other on who does which activity. Finally, they implement their activity agendas and update their needs depending on the activities implemented. They repeat the same process for the next day, and so on.

Available time on a day is the time not occupied by the mandatory activities working and sleeping. Expenditures are charged at a personal money budget if they serve personal needs and at a shared household budget if they serve a household need (irrespective who conducts the activity). The threshold adjustment procedure uses rules R_2 and R_3. This involves recursively generating activity agenda's for a full 7-week period under currently assumed threshold values and evaluating the budget constraint. Since available time may vary by day of the week, each agent uses a threshold value by day of the week for time use. Since threshold adjustments of one person may affect utility of time of the other person, the two agents perform the adjustment procedure simultaneously. As for expenditure, a threshold value is related to each of the three budgets. A threshold is decreased if not all money is used and increased if too much money has been spent.

Because adjustment of a money threshold may have an influence on the UoT and, vice versa, an adjustment of a time threshold may have an influence on UoM, the adjustment procedure is run for one resource nested within the adjustment for the other resource. Arbitrarily, we chose to run time-threshold adjustment within money-threshold adjustment. This means that for each implemented adjustment of a money threshold the time thresholds are re-adjusted. A linear approximation method is used to determine best guess threshold adjustments in each step of the procedure. Considering the fact that (a multi-week) activity generation is an embedded processes, the routine is very efficient and takes only several seconds to complete on a standard PC.

4.2 Some results

As an example, we consider the results of a simulation where the total household budget was (arbitrarily) set to 1800 Euros per month. As it appears, allocating this budget as 658 Euro, 702 Euro and 433 Euro to the personal budget of P1, the personal budget of P2 and the shared budget, respectively, yields an approximately equal utility of money of 1.92 (P1), 1.83 (P2) and 1.81 (shared) across budgets. This means that, if the interests of P1, P2 and Shared have equal weight, this allocation maximizes the overall household utility (given the activity settings). The UoT of each person differs between days of the week. On average, they are 0.38 (P1) and 0.31 (P2). Tables 2-4 portray results per activity based on activity patterns for a 7 week period after adjustment of thresholds.

Table 2 represents activity frequencies (working and sleeping not included). On average, P1 and P2 perform 3.8 and 5.2 activities per day, respectively. The larger activity frequency for P2 eventually is due to the fact that P2 works less hours a week and, therefore, has a larger time budget resulting in a lower time threshold for activities. Also note that P2 conducts considerably more household activities (daily goods and housekeeping). This reflects a task allocation effect. Fitness is conducted by none of the two persons. As it appears, both persons prefer to use the slow mode every now and then to satisfy a need for physical exercise.

Table 2. Activity frequency by activity and agent (average number per day)

	P1	P2
Daily goods	0.07	0.21
Non-daily good	0.14	0.21
Services	0.04	0.04
Medical	0.04	0.04
Go-out (drink-eat)	0.25	0.36
Go-out (cultural)	0.04	0.04
Fitness	0	0
Social	0.36	0.57
House keeping	0.04	0.68
House jobs	0.14	0.43
Total	3.83	5.15

Table 3 shows the monthly expenditure per activity related to each budget (P1, P2 and Shared). Expenditures for social and work activities relate only to travel costs (by fast mode). In sum, P2 gets a larger budget for its (personal) activities since the shorter work hours for this person means that more time can be spent and, thus, more value can be generated per unit expenditure on activities.

Table 3. Expenditures by activity and budget (Euro / month)

Activity	P1	P2	Shared
Daily goods	0	0	350
Non-daily good	165	209	0
Services	0	0	83
Medical	41	40	0
Go-out (drink-eat)	277	294	0
Go-out (cultural)	31	31	0
Fitness	0	0	0
Social	48	51	0
Work	95	76	0
Total	658	702	433

Table 4. Utility of money by activity and budget

Activity	P1	P2	Shared
Daily goods	0	0	1.81
Non-daily good	1.67	1.52	0
Services	0	0	1.81
Medical	1.69	1.54	0
Go-out (drink-eat)	1.68	1.52	0
Go-out (cultural)	1.86	1.54	0
Fitness	0	0	0
Social	8.29	7.97	0
Total	1.92	1.83	1.81

Finally, Table 4 shows the UoM per activity and budget (P1, P2 and shared). Expenditures for social and work activities relate only to travel costs (by fast mode). The high UoM for social activities follows from the fact that these activities generate utility against only travel costs. In sum, P2 gets a larger budget for its (personal) activities since the shorter work hours for this person means that more time can be spent and, thus, more value can be generated per unit expenditure on (non-work) activities.

5. CONCLUSION AND DISCUSSION

In this paper, we showed how time and money constraints can be incorporated in a dynamic agent-based model of activity-travel choice. The standard economic approach assumes that activity generation and time use behavior is based on global solutions for an entire time period. In contrast, the model we proposed shows that by using a local decision rule an equivalent result can be obtained provided that agents are given time to learn based on experience. The dynamic agent-based approach makes it possible to describe behavior under day by day variation in budgets, physical conditions and preferences for activity choices. Furthermore, the model accounts for interactions between agents within households in terms of task allocation. In stark contrast to existing approaches, the model imposes virtually no restrictions on the level of detail of the used activity classification. For example, individuals' activity repertoires may include a large set of mandatory, discretionary in-home and out-of-home activities. The model simultaneously deals with choice facets of activities such as location and transport mode. Finally, we mention, that unlike global optimization approaches, the agent-based system is computationally very efficient. Agents have only limited memory requirements. All they need to remember is their current needs and dynamic utility thresholds regarding the use of time and money. The activity generation and negotiation process only requires linear list processing, which requires only a minimum of computation. Given good initial threshold settings, the threshold adjustment process is very efficient as well. This means that the model can be used in large-scale micro-simulation systems without causing excessive computation times.

Several problems and ways to extend the model could be considered in future research. A first issue relates to the estimation of parameters of activity utility functions. As the model is dynamic, existing one-day or two-day activity-travel diary data, which are collected in standard surveys in many countries, may not suffice. At least the surveys should be extended to reveal for the day observed the activity-history in terms of elapsed time for each activity that can be conducted (not just the activities that are conducted) on the observed day. Longitudinal activity diary data would offer more information but clearly also incur higher costs of data collection. Furthermore, data on the amount of money spent in the context of activities is needed to estimate quality choice parameters in the present framework. This would require an extension of existing survey instruments too, as this data is generally not covered in existing activity diary data collections in transportation research.

Second, our model focuses on the activity programming process and does not consider scheduling behavior. In a scheduling phase agents may be able to economize traveling by using opportunities for trip-chaining and adapt location, mode and possibly activity choices to utilize such opportunities. Furthermore, the timing of activities within a day is not considered in the present model. Opening hours (e.g., of stores) or commitments (e.g., joint activity participation) generally restrict choice opportunities for the timing of activities. Consequences of such restrictions are not limited to the activities for which they hold but also impact the time windows for preceding and succeeding activities and so on. In exceptional cases, timing conflicts may render an activity program infeasible and necessitate a subject to cancel an activity (e.g., postpone it to the next day). A complementary scheduling model is needed to cover these aspects.

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