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MEASURING AND PREDICTING ADAPTATION BEHAVIOR IN MULTI-DIMENSIONAL ACTIVITY-TRAVEL PATTERNS

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This article reports the results of research on modeling activity pattern measurement and prediction. The theoretical background of the proposed model is the time-geographic notion of interdependency and sequential connectivity that reflects the choreography of everyday life. The model employs and extends biological sequential alignment methods to address the multidimensional nature of activity patterns. The model predicts activity patterns as a result of a set of decision heuristics and activity utility functions. The measurement and prediction models are complementary: the measurement model can be used to identify segments of homogeneous activity patterns so that the prediction model can be estimated for each segment separately. The measurement model could possibly also be used to measure the goodness-of-fit between predicted and observed activity patterns in a parameter estimation process. The face validity of the proposed models was assessed using activity diary data, the results of which support the suggested approach.

KEYWORDS: Activity-travel patterns, rescheduling behavior, activity utility function, search tree, multi-dimensional sequence alignment

1. INTRODUCTION

Following the seminal work of Pas (1982), Jones et al. (1983) and Recker and McNally (1985), the transportation research community has gradually become interested in activity-based analysis of transport demand. Progress in this area of research has been reported in a series of progressive resource papers (e.g., Recker and Kitamura, 1985; Kitamura, 1988; Axhausen and Gärling, 1992; Jones et al., 1993; Bhat, 1997; Ettema and Timmermans, 1997; Pas, 1998; Timmermans, 2000; Timmermans et al., 2002). These resource papers witness the substantial progress that has been made in developing complex models of transport demand.

From a policy perspective, however, in many countries transportation policy is no longer concerned only with the physical planning of the transportation network and land use, but also with transportation demand management (Watterson, 1993). These policies, which focus on the optimal use of the existing infrastructure, primarily have an impact on the *implementation* of activity agendas on a short-term basis. To predict the impact of such policies on activity travel patterns, comprehensive models of activity scheduling and rescheduling behavior are required. Such models will augment the network models of traffic flows, which are often based on rigorous assumptions about activity patterns. An examination of the relevant literature indicates that such dynamic models do not truly exist yet.

This paper reports the results of a PhD project that set out to explore the possibilities of developing a comprehensive model of activity rescheduling behavior. The aim of the model is to predict activity schedule adaptations in response to changes in the transportation environment. When faced with a changing transportation environment, time pressure or unexpected events, individuals may decide to adjust any facet of their activity-travel schedule (timing, duration, sequence, destination, mode, etc.) or any

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combination of these facets. The envisioned model should allow the prediction of adaptation in any combination of these choice facets. Especially, the model should be sensitive to the sequencing of activities. This requires a measure that can (i) capture the similarity in the sequences of activities (and other facets) between activity-travel patterns, which can be used to classify activity-travel patterns, and (ii) serve as a goodness-of-fit measure in parameter estimation. Because such a measure was not readily available, except perhaps the measure suggested by Recker and McNally (1985), the formulation of such a measure was a sub-goal of the project.

Thus, the following research questions were formulated to guide the project.

- How can activity-(re)scheduling behavior be conceptualized, taking into account variability in behavior and different decision styles?
- How can this conceptual framework be represented in terms of a mathematical model?
- Knowing that any model of (re)scheduling behavior would necessarily be complex, how can the parameters of the model be estimated?
- What is the best way of representing the multidimensional nature of activity-travel patterns, taking into account the embedded sequence of activities?

2. LITERATURE REVIEW

Most travel behavior is the result of an implementation of a particular set of activities. The activity-based approach was advocated to analyze and predict travel behavior, resulting from such interrelated activity decisions. It implies an understanding of the holistic and dynamic nature of the interrelated activity decisions. Decisions related to the implementation of a particular activity are often hard to understand without information about the other activities included in the schedule for a day, a week or a month. To position the current research in this regard, this section discusses the recent studies on decision process of activity travel behavior.

2.1 Activity measurement studies

Because activity-travel patterns imply by definition a sequence of activities, any valid measure should allow one to quantify, in addition to the composition of attribute elements, the sequential information of activity-travel patterns (Kitamura, 1984; Hatcher and Mahmassani, 1992; Arentze et al., 1993; Kitamura et al., 1996a; Timmermans, 1996; McNally, 1997). Moreover, because the choices of destination, travel mode, activity type, etc. are likely interrelated (Gärling et al., 1997; Arentze et al., 2001), any valid measure should also incorporate such interdependencies.

A critical review of the literature indicates that the existing methods measuring similarity between activity-travel patterns do not capture cross-sectional, sequential or interdependency relations between scheduling decisions embedded in the multidimensional, multivariate activity-travel patterns simultaneously. The Euclidean measure (Burnett and Hanson, 1982; Koppelman and Pas, 1985) involving the concept of primary and secondary attributes focuses on the interdependencies across choice facets, but is incapable of capturing the sequential relations between activities implemented in the pattern. The signal process measure (Recker and McNally, 1985) explicitly takes into account the sequence of a particular activity attribute but does not incorporate the possibility of collective decision-making across choice facets.

2.2 Decision process studies

Gärling et al. (1998) suggested a simulation model of household activity scheduling and rescheduling behavior. His model is based on a theory entailing behavioral principles of how persons acquire, represent, and use information from and about the environment. Simulation results from his proposed model tell that the model is sensitive both to agenda and to environmental differences.

In subsequent work on the role of anticipated time pressure in activity scheduling, Gärling et al. (1999) argued that the major problem in individuals' scheduling is that people frequently want to do more than they are able to. To solve conflicts in a short-term, individuals may consider several strategies such as re-sequencing activities, compressing activity durations and changing priority (or postponement).

Doherty and Axhausen (1999) suggested another, similar conceptual model of scheduling behavior. Scheduling is assumed a multi-stage process, which distinguishes between routine scheduling decisions and short-term, impulsive, opportunistic decisions. Routine planning is approached with optimization models, whereas a more sub-optimal, rule-based simulation model replicates the decision process during the week within the constructs of the optimized routine plan. An overall modeling work therefore consists of first taking individuals' household agenda, then optimizing a weekly skeleton schedule based on a set of identified routine activities, and finally implementing a weekly scheduling process model that replicates scheduling decisions including addition, deletion and modification made by individuals during the execution of the weekly schedule. An activity priority function plays a key role in combination with decision rules.

The importance of studying scheduling process in implementation situation is further discussed in the literature (Timmermans et al., 2000; Joh et al., 2005a; Ruiz et al., 2005; Joh and Huh, 2005). This overview of the relevant literature shows that operational models of (re-)scheduling decisions are still virtually lacking.

3. PREDICTING ACTIVITY BEHAVIOR – AURORA

In order to fill this gap, we developed a comprehensive theory and model of activity rescheduling decisions as a function of time pressure. Two distinguishing components of the modeling approach should be stressed here. The *first* component defines the (anticipated) utility of rescheduling options depending on duration, travel mode, location, sequence and time-of-day of scheduled activities and (dis)utility of non-scheduled activities. Thus, this set of equations defines a utility space of all feasible rescheduling operations that the individual could possibly consider. Obviously, this search space is extremely large and bounded rationality of individuals prohibits an exhaustive search strategy. The *second* component, therefore, is complementary and defines heuristics for a partial search. The search tree repeatedly makes decisions on schedule adjustments on the basis of the expected schedule utility in an attempt to best improve the schedule utility at each time of adjustment until no more improvement is available. In particular, the search tree mimics human search behavior to find a (sub)optimal solution by efficiently reducing the vastly wide solution space of alternative adjustments. The utility function and decision tree both assume a continuous time representation of the schedule. We develop in this section such a model, named Aurora (Agent for Utility-driven Rescheduling Of Routinized Activities).

3.1 Utility function

Individuals derive a certain level of utility directly or indirectly from participating in activities. Existing theories on time allocation in transportation and economics generally assume that activity utility is a monotonically increasing function of duration (Becker, 1965; Kitamura et al., 1996b). Although this assumption is computationally convenient, theoretically it is rather rigorous. In contrast, we assume that marginal utilities are initially small and increase as time is extending up to some point. This might be interpreted as negative saturation or a 'warming up' period. More specifically, our activity utility function including duration and other key choice facets is defined as follows.

$$U = \sum_{a=1}^{A} U_a \,, \tag{1}$$

with

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

and

$$\sum_{a=1}^{A} v_a = B \,, \tag{3}$$

where a is an index of activities, v is the duration of the activity, Λ is the time required to travel from the previous to the current location, which implies that $(v - \Lambda)$ gives the net duration of the activity, $U^{\min}$ and $U^{\max}$ are coefficients that asymptotically determine the minimum and maximum utility of the activity, respectively, α, β and γ are additional coefficients of the activity utility, U is the total utility of a schedule, B is the total duration ($B > 0$), representing the budget constraint that limits the total amount of time that can be assigned to activities at the moment of scheduling, $U^{\max}$ is in turn a function of many key choice facets such as time of day, location attractiveness, accompanying person, activity performance history, travel time, mode preference and activity sequence.

It is to note that travel is included as part of the activity. The travel plays an important role of reducing the net activity duration and thus the utility of the activity. The general form of the activity utility function of equation (2) is an *asymmetric* S-shaped curve with an inflection point. The maximum utility ($U^{\max}$) represents the (anticipated) utility derived from the activity if the time available is unlimited. The minimum utility ($U^{\min}$) represents an individual's evaluation of the situation if activity duration is zero.

The α coefficient determines the duration at which the marginal utility reaches its maximum value (inflection point). The β coefficient determines the slope of the curve, a larger β-value meaning that the activity is more sensitive to duration and hence less flexible in terms of adaptation. The γ coefficient determines the relative position of the inflection point. If the value is close to 1, the curve approximates a symmetric curve, and the inflection point is in the middle between the maximum and minimum utilities. When the value approximates 0, the utility at the inflection level is also close to the minimum utility, implying that marginal utility is diminishing at virtually all levels of duration. These α, β and γ parameters represent technical aspects of the activity related to the *productivity of time units (indirect utility) or strength of the saturation effect (direct utility)*. The impacts of utility parameters are illustrated in Figure 1.

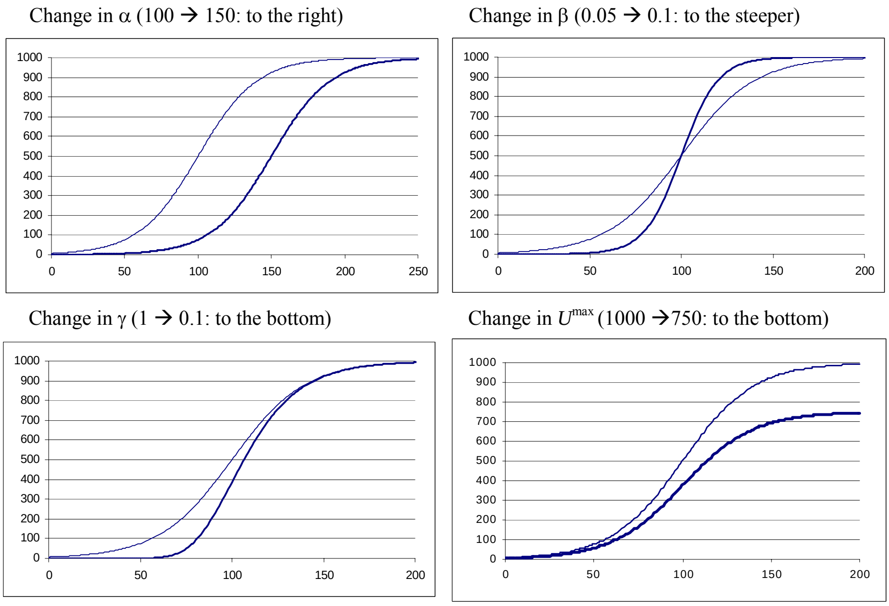


FIGURE 1: Impacts of utility parameters

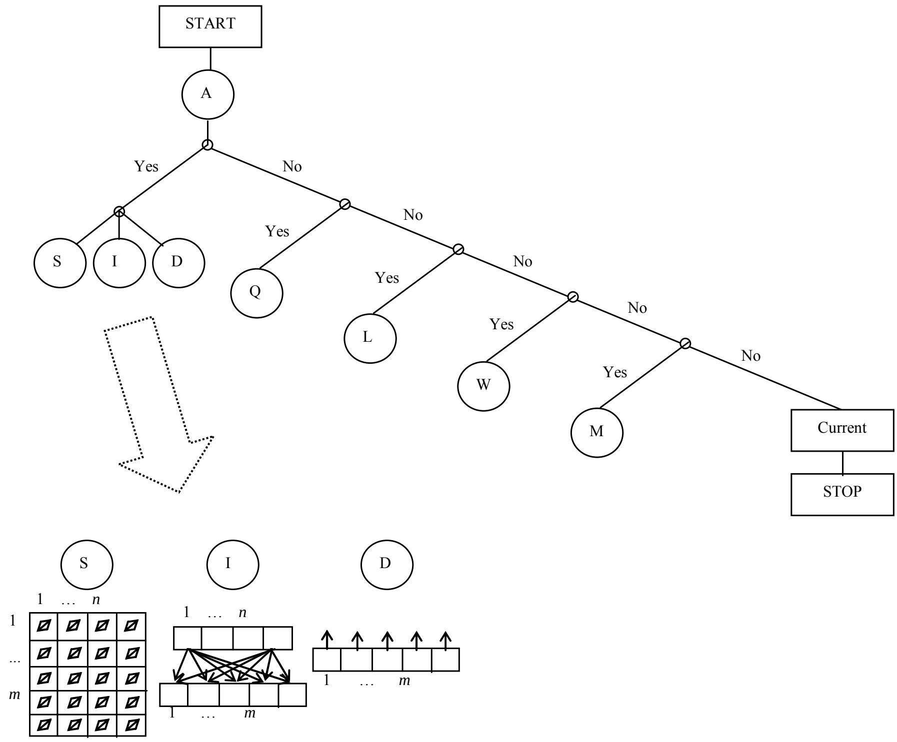
3.2 Search tree

During the execution of the schedule, the individual may consider to for example add one or more activities if time becomes available, due to shorter travel or activity duration than was anticipated in the planned schedule.

The schedule adjustment model is a complementary component to the model of activity utility. The model provides heuristics for schedule adjustment decisions by means of a partial search that is a reduction of the entire search space of utility defined by all feasible rescheduling operations. The heuristics of the search-space reduction mimic human search behavior of bounded rationality. The proposed heuristic search model is based on the following assumptions:

1) Individuals evaluate elementary operations on an initial schedule one at a time and implement the operation that offers the maximum increase in perceived utility.
2) Consequently, the overall rescheduling heuristic describes an iterative process that stops when the best possible operation does not increase utility.
3) The mental effort involved in searching and the resistance to change the current schedule impose a threshold for considering and implementing additional operations.
4) The total amount of mental effort invested is an individual-specific function of the number of changes that have been implemented.
5) Resistance to change is an individual-specific function of the type of change implied by an operator.

We assume a set of operators that individuals may consider to adjust schedules. The operators refer to a variety of choice facets such as list of activities, location, transport mode, accompanying person, etc. The operators include the duration, substitution, insertion, deletion, sequencing, location, accompanying-person and transport-mode operators. The proposed model (Figure 2) uses a tree structure to arrange options for rescheduling and control the search process.



Note: A = duration adjustment; S = substitution; I = insertion; D = deletion; Q = sequence change; L = location change; W = accompanying-person change; M = transport-mode change; *m* = the number of activities that are currently scheduled; *n* = the number of activities that are currently not scheduled yet; Each of operators denoted by corresponding symbols contains the level of resistance to change.

FIGURE 2: Search tree

In the figure,

1) START with a schedule given as the current schedule.
2) Evaluate the utility of rescheduling through each operation, respectively.
3) Evaluate the utility of the current schedule, denoted by 'Current', assuming no adjustments in any choice facet by any operator.
4) If any of the possible adjustments leads to an increase of utility compared to the current schedule, implement rescheduling through the operator that offers the highest increase in the utility, and recursively go back to START and set the adjusted schedule as the current schedule. Otherwise, Stop the process and implement the current schedule as it is. Each 'Going-back to START' procedure also increases the mental fatigue index by one unit.
5) The duration operator is applied at START (initial and going-back after each operator). It is repeated after each adjustment because a change through all other operators still requires a set of incremental fine-tunings of the activity duration such that the schedule comes to an equilibrium state.
6) Each parent node in the tree includes a parameter representing the resistance to change, defined as a reduction of the utility of rescheduling using the concerned operator.

The suggested search structure has several notable characteristics. First, the search is conducted *choice facet by choice facet* as opposed to a structure that searches an exhaustive set of combinations of adjustments across choice facets.

The best adjustment alternative is determined for each choice facet, and then, the best of the best ones across choice facets is chosen. This process is repeated until no further improvement is possible. As such, the number of computations required for a solution is additive, instead of multiplicative.

Secondly, the search is repetitive and *recursive*. Obviously, a single adjustment improves only a single choice. The suggested search structure allows the mental process to go back again to the very first step that checks if there is any further adjustment to be made again on the schedule.

Finally, we emphasize that the search does not rely on any a-priori hierarchy of decisions but allows any order of operator applications. This *non-hierarchical* search structure overcomes the possible limitation of a predetermined order of search processes and offers much more flexibility. The implementation algorithms were further sophisticated and a variety of numerical simulation was conducted to examine the face validity of the suggested models (Timmermans et al., 2001; Joh et al., 2002a, 2002b, 2003a, 2003b, 2005b).

4. MEASURING ACTIVITY BEHAVIOR – MDSAM

In order for measuring activity-travel behavior, the analysis should consider the difference between activity patterns with regard not only of activity composition but also of activity sequence and interdependency between activity attributes. We develop such a model, named MDSAM (Multi-Dimensional Sequence Alignment Method), an extension of molecular biology-originated sequence alignment method.

Consider the problem of comparing two multidimensional activity patterns, called a source and target pattern, respectively, in terms of K qualitative attributes. These attributes may refer to activity type, location, transport mode, accompanying person, etc. Each activity pattern then consists of K attribute sequences, and each attribute sequence consists of a set respectively of m and n elements for source and target pattern. The source and target patterns to be compared can then be represented by $K \times m$ and $K \times n$ matrices, respectively, as *source pattern* $\boldsymbol{s} = [\boldsymbol{s}_{1\bullet} \dots \boldsymbol{s}_{k\bullet} \dots \boldsymbol{s}_{K\bullet}]'$ with $\boldsymbol{s}_{k\bullet} = [s_{k0} \dots s_{ki} \dots s_{km}]$, and *target pattern* $\boldsymbol{g} = [\boldsymbol{g}_{1\bullet} \dots \boldsymbol{g}_{k\bullet} \dots \boldsymbol{g}_{K\bullet}]'$ with $\boldsymbol{g}_{k\bullet} = [g_{k0} \dots g_{kj} \dots g_{kn}]$, where, $\boldsymbol{s}_{k\bullet}$ and $\boldsymbol{g}_{k\bullet}$ are the vectors of the kth attribute sequences of the source and target pattern, respectively; s_{ki} and g_{kj} are the ith and jth element of the kth attribute sequence of the source and target pattern, respectively ($i = 0, \dots, m$; $j = 0, \dots, n$; $k = 1, \dots, K$); $s_{ki} \in A_k$, and $g_{kj} \in A_k$.

Consequently, row vectors $\boldsymbol{s}_{k\bullet}=[s_{k0} \dots s_{ki} \dots s_{km}]$ and $\boldsymbol{g}_{k\bullet}=[g_{k0} \dots g_{kj} \dots g_{kn}]$ represent the sequential order of elements of the kth attribute of the source and target pattern, respectively, while column vectors $\boldsymbol{s}_{\bullet i}=[s_{1i} \dots s_{ki} \dots s_{Ki}]'$ and $\boldsymbol{g}_{\bullet j}=[g_{1j} \dots g_{kj} \dots g_{Kj}]'$ potentially represent the interdependency between the dimensions of the ith and jth activity of the source and target pattern, respectively. The problem of multidimensional activity-pattern comparison then is to find the minimum amount of effort required to change $\boldsymbol{s}=[\boldsymbol{s}_{1\bullet} \dots \boldsymbol{s}_{K\bullet}]'$ into $\boldsymbol{g}=[\boldsymbol{g}_{1\bullet} \dots \boldsymbol{g}_{K\bullet}]'$ as a measure of similarity.

The minimum-cost trajectories of the uni-dimensional alignment allow one to capture the sequential relationships within activity-travel patterns. They, however, do not capture any *interdependencies* between attributes. Simply summing the uni-dimensional optimum alignment costs across dimensions would not solve this problem because activity type, location, transport mode, etc. would be aligned independently of other attributes' elements. To solve this problem, we propose the set of deletions, insertions and substitutions that are applied to the elements belonging to the same activity to be treated as a single deletion, insertion and substitution, respectively. This integrated operation combines a set of elements that can be aligned simultaneously as if it were one element. We call such a set of elements a segment. If there were no interdependencies, the resulting alignment costs would be identical to the simple sum of uni-dimensional optimum alignment costs. Any costs-savings are indicative of interdependencies across the dimensions underlying the activity-travel patterns.

If this reasoning is accepted, the problem then is how to determine the aggregate alignment costs. Unless the weights attached to attributes are all the same, the alignment costs depend on the method of aggregation that is used. In general, several methods for aggregating a set of values may be used, such as, for example, determining the average, median, maximum, etc. We argue that the maximum weight across attributes of the segment is the most appropriate method of aggregation. It reflects the notion that people's decisions in activity scheduling may be dominated by the most important attribute. The stronger the interdependency between attributes, the higher the cost reduction.

The problem of multidimensional pattern comparison then is to find the set of segments that minimizes alignment costs. Unfortunately, this is not an easy problem as the only known way to guarantee the optimality of the multidimensional comparison is to try all possible alignments of each attribute, generate all possible combinations of the alignments across attributes and then find the minimum costs among all possible alignment combinations. It will be evident that enumerating all alignments of even a single attribute may already require an enormous amount of computing time. We therefore suggest employing a heuristic method. This will become a guiding principle later on for developing the implementation algorithms that effectively reduce the search space. Such a method is developed below.

The proposed multidimensional alignment method proposed first finds the uni-dimensional least-cost alignments, then integrates the alignments across attributes and, finally, computes the costs for the integrated alignments. More specifically, given a pair of K-dimensional activity patterns, the proposed method first obtains K sets of operations used for the uni-dimensional optimum alignments, then identify the sets of elements to which the same operations are applied and next integrates K sets of operations applied to elements into a single set of operations applied to segments, and finally, computes the costs of the operations for segments. The rationale underlying this heuristic lies in the expectation that the combination of the uni-dimensional least-cost alignments likely generates a result that is nearer to the multidimensional optimum than any other approach within acceptable computing time.

To formally specify the proposed segment-based alignment method, we first introduce a set representation of the alignments of uni-dimensional sequences by using the 'trajectory' information from the comparison table. A trajectory is a set of operations used for equalizing or aligning two sequences. Alignments can therefore be summarized by recording the operations, the positions to which these operations are applied, and the attributes on which the operations are applied, translating each trajectory into a set of operations. Note that the identity operation is not recorded because it is cost-free. We shall call this a uni-dimensional operation set and define it as:

$$O_{k,l} = \{p \mid p=\mathtt{d}(i,k) \vee p=\mathtt{i}(j,k) \vee p=\mathtt{s}(i,j,k)\}, \qquad (4)$$

with $i \in \{1, .., m\}$, $j \in \{1, .., n\}$, $1 \leq k \leq K$, where, $O_{k,l}$ is the lth uni-dimensional operation set of the kth attribute sequence, containing the deletions, insertions and substitutions; $\mathtt{d}(i,k)$ is the deletion of the ith element of the kth source sequence; $\mathtt{i}(j,k)$ is the insertion of the jth element of the kth target sequence into the jth position of the kth source sequence; $\mathtt{s}(i,j,k)$ is the substitution applied to both the ith and jth elements of the kth source and target sequences, respectively; m and n are the number of elements of the source and target sequences, respectively.

For example, assume that Figure 3 represents the 2nd attribute of an arbitrary activity pattern. The alignment represented by the trajectory in that figure is summarized as $O_{2,1} = \{\mathtt{i}(1,2), \mathtt{d}(3,2)\}$. The set representation facilitates the identification of segments. By comparing the K sets relating to K tables, we can easily identify the operations that can be linked into a segment.

pos	j	0	1	2	3	(=n)
i		null	A	B	C	g
0	null	①				
1	A		②	③		
2	C				④	
3	B					
(=m)	s					

FIGURE 3: Comparison table (an example)

In general, there are multiple least-cost trajectories for each attribute. Many of these least-cost trajectories, however, often result in identical operation sets. An illustration of this many-to-one relationship between trajectories and operation sets is given in Figure 4. The uni-dimensional operation sets corresponding to the trajectories are:

$$O_{2,1} = \{\mathtt{i}(1,2), \mathtt{i}(\underline{3,2}), \mathtt{d}(\underline{2,2}), \mathtt{d}(3,2), \mathtt{i}(5,2)\},$$

and

$$O_{2,2} = \{\mathtt{i}(1,2), \mathtt{d}(\underline{2,2}), \mathtt{i}(\underline{3,2}), \mathtt{d}(3,2), \mathtt{i}(5,2)\}.$$

pos	J	0	1	2	3	4	5	(=n)
i		null	A	B	C	D	E	g
0	null	0	1	2	3	4	5	
1	B	1	2	1	2	3	4	
2	E	2	3	2	3	4	3	
3	A	3	2	3	4	5	4	
4	D	4	3	4	5	4	5	
(=m)	s							

FIGURE 4: Two different trajectories of the same operation set

While these trajectories are different in terms of the order of the underlined operations, the operation sets are identical. In other words, the order of operations included in a set is arbitrary, and it does not make a difference in which alignment step an element is aligned. The proposed method therefore develops an efficient algorithm that ignores the order of operations, applied when tracing the optimum trajectories. This results in the following method of identifying the multidimensional operation set. The proposed method integrates K sets of operations applied to elements into a single set of operations applied to segments. Because there are multiple uni-dimensional operation sets for each attribute, multiple combinations of K uni-dimensional sets for operation integration exist to be tested.

Let T_k be the number of uni-dimensional operation sets of the kth attribute sequence. The number of combinations of uni-dimensional operation sets, T, is given by:

$$T = \prod_{k=1}^{K} T_k \, . \tag{5}$$

For each combination, t (t = 1, …, T), we have K operation sets, $O^t_{1,l'}$, …, $O^t_{k,l}$, …, $O^t_{K,l''}$, where $O^t_{k,l}$ is the lth uni-dimensional operation set of the kth attribute sequence included in the tth combination. We shall call such a combination of uni-dimensional operation sets a *multidimensional operation set*. Let O^t be the tth multidimensional operation set. Then:

$$O^t \;=\; \{p | p=\mathtt{d}(i,\boldsymbol{k}) \vee p=\mathtt{i}(j,\boldsymbol{k}) \vee p=\mathtt{s}(i,j,\boldsymbol{k})\}, \tag{6}$$

where $\boldsymbol{k}$ identifies the set of attributes to which the concerned operation was applied.

Thus, the set $\boldsymbol{k}$ defines a segment and represents interdependency between the concerned attributes. For example, if the uni-dimensional operation sets of three attribute sequences (a three-dimensional case) included in the tth combination are:

$$O^t_{1,l'} = \{\mathtt{d}(2,1),\ \mathtt{i}(4,1),\ \mathtt{s}(5,6,1)\},$$

$$O^t_{2,l} = \{\mathtt{d}(3,2),\ \mathtt{i}(4,2),\ \mathtt{s}(5,5,2)\},$$

$$O^t_{3,l''} = \{\mathtt{d}(2,3),\ \mathtt{i}(4,3),\ \mathtt{s}(5,5,3)\},$$

then the tth multidimensional operation set is:

$$O^t = \{\mathtt{d}(2,\{1,3\}),\ \mathtt{d}(3,\{2\}),\ \mathtt{i}(4,\{1,2,3\}),\ \mathtt{s}(5,5,\{2,3\}),\ \mathtt{s}(5,6,\{1\})\},$$

implying that the 2nd elements of 1st and 3rd source attribute sequences are deleted, the 3rd element of 2nd source attribute sequence is deleted, the 4th element of 1st, 2nd and 3rd target attribute sequences are inserted, the 5th elements of source and target attribute sequences are substituted, and the 5th element of source attribute sequence and the 6th element of target attribute sequences are substituted. The multidimensional operation set, O^t, represents the overall trajectory in multidimensional space.

Given the multidimensional operation sets, computing the multidimensional similarity is straightforward. The weighting value of each operation is determined as its own weighting value multiplied by the maximum attribute weight across the attributes to which the operation is applied. This set is represented by k. Hence, the alignment cost calculated from the tth multidimensional operation set, C^t, is:

$$C^t = \sum_{p \in O_t} c_p \, , \tag{7}$$

with

$$c_p = \begin{cases} w_d \beta^{\max}_{\boldsymbol{k}} & \text{if } \; p = \mathtt{d}(i,\boldsymbol{k}) \\ w_i \beta^{\max}_{\boldsymbol{k}} & \text{if } \; p = \mathtt{i}(j,\boldsymbol{k}) \\ w_s \beta^{\max}_{\boldsymbol{k}} & \text{if } \; p = \mathtt{s}(i,j,\boldsymbol{k}) \end{cases} \, ,$$

where, w_d, w_i and w_s are the weighting value attached to the deletion, insertion and substitution operation, respectively (w_d = w_i, and w_s = w_d+w_i); $\beta_{\boldsymbol{k}}^{\max}$ is the maximum weight across attributes in the set ***k***, which takes in effect the interdependency relationships that was addressed in the section of the multidimensional operation set.

Finally, the minimum alignment cost, C^*, is:

$$C^* = \min [C^1, \ldots, C^t, \ldots, C^T]. \quad (8)$$

That is, the minimum cost across trajectory combinations is taken as a measure of multidimensional similarity. The implementation algorithms were subsequently developed and applied (Arentze et al., 1998; Bargeman et al., 1999; Joh et al., 2001a, 2001b, 2001c, 2002c, 2003c, 2005c; Bargeman et al., 2002; Kemperman et al., 2004).

5. EMPIRICAL ANALYSIS

5.1 Activity-travel diary data

The data used to estimate Aurora was collected in the Amsterdam-Utrecht corridor, The Netherlands, in the context of the Amadeus research program. The survey was conducted in April and September 2000. The study area is shown in Figure 5. Within this study area, a number of neighborhoods were chosen for the sample selection. (The 'neighborhood' is the spatial unit defined by the Central Bureau of Statistics (CBS) of The Netherlands.) The selection was based on a neighborhood classification scheme, to balance the sample on a number of relevant spatial and non-spatial characteristics.. Figure 6 shows the resulting spatial distribution of the selected neighborhoods. A total of 50,000 questionnaires were distributed to randomly selected households in the selected neighborhoods. Of the 50,000 households, 7488 (15.0 %) returned the questionnaires. Of these 7488, 4800 (64.1 %) were willing to participate in the main survey.

In the main survey, respondents were asked to complete an activity-travel diary for two designated consecutive days. The diary contained activity-pattern information such as the list of activities, duration, location, transport mode if traveled, accompanying person, etc. Of the 4800 households who were willing to participate in the main survey, 1966 (41.0 %) returned the questionnaires.

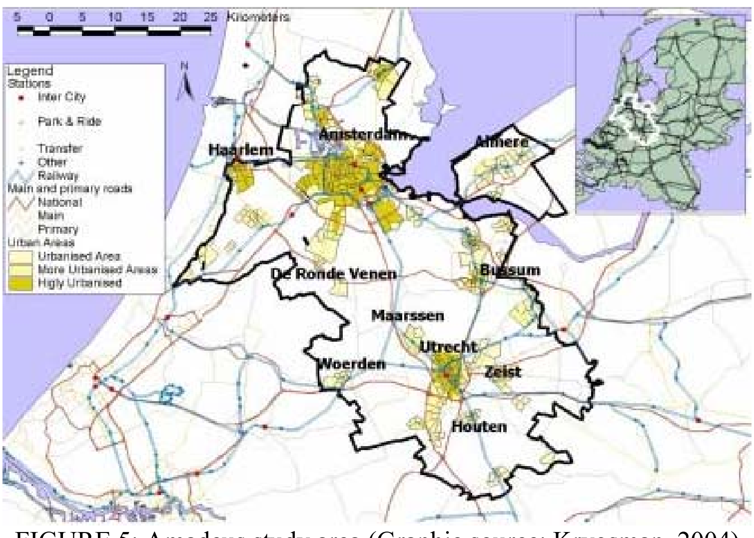


FIGURE 5: Amadeus study area (Graphic source: Krygsman, 2004)

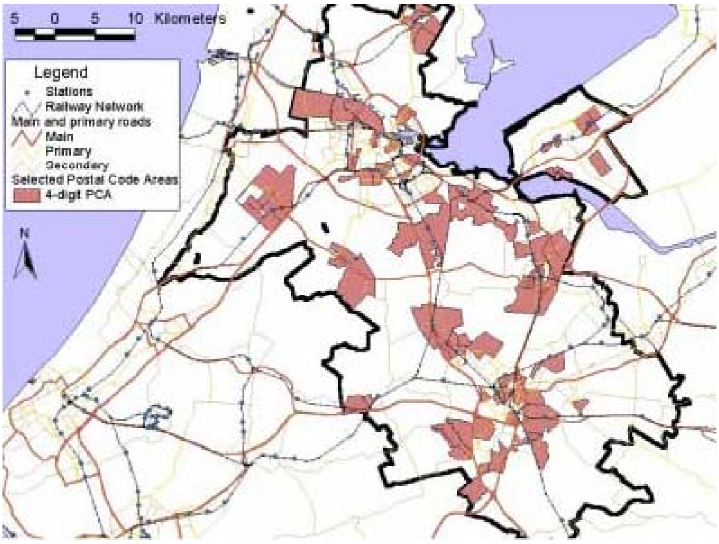


FIGURE 6: Selected neighborhoods (Graphic source: Krygsman, 2004)

The data of 6950 activity patterns of 3575 individuals, belonging to these 1966 households, were identified available. After screening the cases with missing information of activity history, a total of 5904 activity patterns were employed for the analysis. The number of activity patterns is yet too large to compute pairwise similarities, and the current study randomly selected 1000 activity patterns. The attributes included in the analysis were activity type, location and transportation mode.

5.2 Analysis scheme

The estimation of activity utility functions is based on the observed activity durations and histories in the reported activity patterns. In order to estimate segment-level utility functions, the activity-travel patterns were first clustered using pairwise similarities. These pairwise similarities between patterns were computed with regard to the compositional, sequential and interdependency information of the attributes of the activity-travel patterns. The multidimensional sequence alignment method was used for this purpose. Next, the resulting similarities between activity patterns were used as input to a cluster analysis. Ward clustering algorithm was employed for a hierarchical cluster analysis, which explicitly attempts to minimize the within-segment distance and maximize the between-segment distance.

The activity utility functions for each segment were then estimated using a genetic algorithm. The proposed estimation method is based on the assumptions that the marginal utility is the same across activities, and that the level of equal marginal utility can be predicted by a set of cross-sectional characteristics of the activity patterns. The essential equation for the estimation for each of the activity in the schedule is:

$$(MU_a)_s = TP_s \,, \tag{9}$$

where $(MU_a)_s$ is the marginal utility of activity a of activity pattern s, which is a marginal function of equation (2) regarding activity duration; TP_s is the time pressure with activity pattern s. The equation implies that the equal marginal utility reflects the level of time pressure of the activity schedule.

For the simplicity of the estimation, we assume that $U^{\min}$ is zero, while $U^{\max}$ is a function of activity history since the last engagement of the activity, which can be expressed as follows.

$$U^{\max} = \frac{U_x}{1 + \exp[\beta_x(\alpha_x - T)]}, \tag{10}$$

where T is activity history; α_x, β_x and U_x are activity-specific parameters of $U^{\max}$. Time pressure can be formulated as follows.

$$TP_s = \delta_1 (X_1)_s + \delta_2 (X_2)_s, \tag{11}$$

where, $(X_1)_s$ and $(X_2)_s$ are the duration of fixed activities and the number of flexible activities of activity pattern s, included as indicators of time pressure. Equation (11) is consistent with our theory. Given the number of flexible activities chosen to implement, a longer total duration of fixed activities implies a shorter disposable time budget and hence a higher time pressure. Given the disposable time budget, more flexible activities to implement would increase the time pressure. In both cases, the increase in time pressure raises the level of equal marginal utility across activities of the activity pattern.

Overall, the equation for the activity utility parameter estimation is expressed as follows.

$$\left(\left(\frac{\beta U^{\max} \exp[\beta(\alpha - v)]}{\left(1 + \gamma \exp[\beta(\alpha - v)]\right)^{1/\gamma + 1}} \right)_a \right)_s = \delta_1 (X_1)_s + \delta_2 (X_2)_s, \ \forall a \in s. \tag{12}$$

A tailored genetic algorithm simulates the set of parameter estimates at each genetic population and repeatedly improves the estimates on the basis of the simulated solutions' computed feedback that is defined as the gap between the observed duration and the duration predicted by the simulated parameter estimates.

5.3 Estimation results

5.3.1 Cluster analysis

A set of randomly selected 1000 activity patterns requires 499,500 pairwise comparisons of three-dimensional activity-travel patterns. Similarity was measured in terms of MDSAM. The weights of 2, 1 and 1 units were assigned to activity type, location and transport mode attributes, respectively. The relative sizes of the weights are based on some preliminary studies (Joh et al., 2001c) to best distinguish among different activity pattern groups. Ward method was used for iterative hierarchical clustering, using the multidimensional sequence alignment scores as input. The analysis resulted in seven distinctive groups of activity patterns.

Tables 1, 2 and 3 summarize the cross-sectional characteristics of the activity patterns and the socioeconomic/situational characteristics associated with the activity patterns for each segment. Table 1 describes the average relative frequency of each activity per activity pattern, whereas Table 2 reports the average number of episodes associated with each location and transport mode.

Based on the characteristics of activity patterns and the socioeconomic/situational characteristics of seven clusters as shown in these tables, we can label each segment's profile as follows. Segment 2 can be labeled 'work-home only activity patterns' and Segment 4 'activity patterns of work and out-home activities', whereas Segment 3 'work-free old people's busy activity patterns'. Segment 5 can be labeled 'work-oriented, sportive activity patterns'. Segment 6 and 7 can be labeled 'activity patterns of both work and childcare-oriented busy young people' and 'work-free, childcare and entertaining-oriented young females', respectively. Finally, Segment 1 can be labeled 'Weekend-social activity patterns'.

TABLE 1: % frequency of activity occurrences per pattern and segment

Activity	Segment1 (160)	Segment2 (301)	Segment3 (114)	Gsegment4 (149)	Segment5 (90)	Segment6 (111)	Segment7 (75)
Dshop	31.9	13.6	37.7	16.8	14.4	16.2	30.7
nDshop	13.8	8.0	28.9	8.7	13.3	12.6	20.0
Pbiz	6.3	2.3	12.3	4.0	7.8	3.6	8.0
social	48.8	17.9	41.2	23.5	21.1	18.9	42.7
entertain	11.9	7.3	6.1	20.1	3.3	4.5	4.0
recreat	7.5	0.3	1.8	6.0	2.2	7.2	5.3
task	92.5	65.8	100.0	69.8	86.7	82.9	100.0
leis	98.1	96.3	97.4	75.2	97.8	90.1	98.7
pickup	3.1	2.0	3.5	2.7	2.2	10.8	5.3
work/edu	36.3	95.3	42.1	79.2	95.6	84.7	50.7
medical	4.4	2.3	6.1	2.0	8.9	10.8	5.3
sport	12.5	8.0	7.9	9.4	16.7	8.1	4.0
church	2.5	1.0	5.3	0.0	0.0	1.8	4.0
union	1.9	4.0	2.6	4.7	1.1	1.8	1.3
Cultural	5.0	2.3	5.3	5.4	1.1	0.0	0.0
other out	10.0	9.6	22.8	24.8	27.8	24.3	22.7
Childcare	10.6	8.0	20.2	6.7	20.0	97.3	92.0
Illness	0.0	0.3	0.0	0.7	0.0	0.0	0.0
# episodes/pattern	13.88	11.55	20.41	9.68	16.61	14.23	24.93

Note: Dshop means grocery shopping, nDshop non-grocery shopping, Pbiz personal business, recreat recreation, task in-home task, leis leisure, and pickup picking up goods or persons.

TABLE 2: Number of activity episodes with particular locations and modes per pattern and segment

Attribute	Level	Segment1	Segment2	Segment3	Segment4	Segment5	Segment6	Segment7
Location	home	11.69	9.27	18.22	5.75	14.01	11.96	22.99
	work	0.28	1.14	0.19	0.88	0.72	0.70	0.25
	other	1.91	1.15	2.00	3.02	1.88	1.56	1.69
Mode	no	10.04	8.00	16.74	5.88	12.54	10.27	20.65
	slow	2.14	1.61	2.28	1.29	2.16	1.99	3.11
	public	0.09	0.54	0.24	0.47	0.39	0.36	0.01
	auto	1.34	1.18	1.00	1.56	1.27	1.45	1.05

Note: public indicates such modes as bus, tram and metro, while slow modes include walk, bike, scooter, etc.

TABLE 3: Socioeconomic/situational characteristics

	Variable	Segment1	Segment2	Segment3	Segment4	Segment5	Segment6	Segment7
Category (%)	male	46.5	54.5	34.5	61.2	61.8	43.7	21.3
	car avail	62.6	47.5	48.4	64.4	40.0	61.3	42.3
	child yes	40.8	51.6	39.8	41.1	59.1	97.2	91.7
	weekend	55.0	24.0	37.8	36.4	12.6	28.2	34.7
Metric	age	46.4	39.4	51.0	41.7	40.0	38.1	38.4
	income	5.5	5.6	4.2	6.2	5.5	5.7	4.2
	work hr	17.52	27.67	12.17	29.91	22.01	29.11	17.8

5.3.2. Segment-level estimation

Given the segments of more homogeneous activity-travel patterns, our problem is to estimate for each segment the activity-specific parameters, α, β, γ, α_x, β_x and U_x on the data of duration v and history T. The estimation includes flexible activities but not fixed activities such as work/education. Given the number of parameters of six to be estimated for each activity, we further decided not to estimate parameters for the three activities with the smaller number of observations such as personal business, outside-entertainment and recreation and merge some of the seven segments into bigger segments, considering the dendrogram obtained in the cluster analysis.

The result is three super-segments, which now provide at least the minimum number of observations for the five main activities including grocery and non-grocery shopping activities, social activity, and in-home task and in-home leisure activities. Segment group 1 (SG1) consists of small Segments 1, 5 and 6. SG2 consists of Segments 2 and 4. SG3 consists of Segments 3 and 7. Table 4 provides the number of observations of grocery shopping, non-grocery shopping and social activities before and after the merging. Segment Group 2 can be labeled as 'young people's work-oriented simple activity patterns', whereas Segment Group 3 can be labeled as 'older people and females' busy activity patterns of non-work activities'. Segment Group 1 is labeled as 'a work-plus-other activities oriented patterns of young people or weekend-social activity patterns of older people.'

TABLE 4: The number of observations of activities in each activity-pattern segment

Big G	SG1 (361)				SG2 (450)			SG3 (189)		
Small G	G1	G5	G6		G2	G4		G3	G7	
Dshop	16	5	2	23	11	9	20	17	8	25
nDshop	7	5	5	17	12	2	14	11	6	17
Social	17	1	3	21	8	5	13	7	9	16

The proposed estimation method uses a heuristic search algorithm. It was decided to apply a sequential estimation process. After examining different orders of parameters in a sequential estimation in terms of stability of the parameter estimates across runs and goodness-of-fit, it was decided to estimate parameters in the following order: α, β, γ, α_x, β_x and U_x.

That is, in the initial run when all parameters are simultaneously estimated, α was the best parameter and decided to be estimated. Given all other parameters' average values across 30 initial runs, α was estimated 30 times. The average across these 30 runs was taken as the estimate of α. Then, β was chosen to estimate as it showed the most stable estimates in the next initial 30 runs given the α estimate. In this way, γ, α_x, β_x and U_x were also estimated in turn.

The sizes of parameter estimates for the different activities were examined to assess the face validity regarding the profiles of the segments (Table 5). The α parameter size is in the order of [in-home leisure > social > task > non-grocery > grocery shopping activities] for Segment Group 1, [social > in-home leisure > in-home task > non-grocery > grocery shopping activities] for Segment Group 2 and [in-home leisure > in-home task > social > non-grocery > grocery shopping activities] for Segment Group 3, respectively. A sharp contrast is that SG2's α of social activity is very big while SG3's α of in-home task is very large. The α of SG1 show approximately average trends between SG2 and SG3 across activities.

TABLE 5: Parameter estimates of Segment Group

Activity	α	β	γ	α_x	β_x	U_x
Parameter estimates of Segment Group 1 (SG1)						
Dshop	19.02	0.414	0.527	3.697	0.577	1848
nDshop	39.95	0.167	0.105	0.022	8.804	5118
social	154.49	0.038	0.554	0.006	9.771	1348
task	124.79	0.033	0.525			1466
leis	213.98	0.032	0.522			1279
Parameter estimates of Segment Group 2 (SG2)						
Dshop	17.32	0.646	0.639	5.861	0.014	1343
nDshop	41.45	0.136	0.345	0.016	0.674	3241
social	228	0.069	0.601	0.008	7.359	9942
task	85.72	0.047	0.483			1486
leis	163.77	0.025	0.563			1368
Parameter estimates of Segment Group 3 (SG3)						
Dshop	26.04	0.205	0.570	2.777	0.874	1306
nDshop	49.68	0.210	0.596	0.048	8.341	2297
social	96.47	0.068	0.229	0.006	1.652	4400
task	202.17	0.036	0.582			1303
leis	249.88	0.027	0.687			1241

The β parameter size is very small for social, in-home task and in-home leisure activities across segments. The β for non-grocery shopping is also very small in SG1 and SG2, while it is rather big in SG3. The biggest difference in β size between segments can be found in grocery shopping activity. The β of SG2 is very large, whereas SG3's is very small that is almost the same as the β of non-grocery shopping. SG1 shows again an in-between figure.

The overall level of the γ parameter value is higher in SG3 than in SG2, but one cannot say that there is a significant difference. The lowest γ value activity is social activity in SG3, whereas this parameter is lowest for non-grocery shopping in SG1 and in SG2. The difference between SG1 and SG3 is bigger than that between SG2 and SG3 in this parameter.

The α_x parameter level shows almost no difference between segments for non-grocery shopping and social activities, except the grocery shopping activity.

Non-grocery shopping and social activities' α_x values are very close to zero, implying that there is no increasing marginal utility period for the U^{max} level in these activities with regard to activity history. The α_x parameter value in SG2 is about six days while that in SG3 is three days. SG1 again shows an in-between figure.

The β_x parameter estimates is extraordinarily high for the social activity in SG2 and for non-grocery shopping in SG3. Moreover, SG1 has the highest β_x estimates for both non-grocery and social activities. The reason for these extraordinarily high, and unreliable results is partly the limitation of the influence of this parameter's size on the activity utility, which requires more observations to identify. At the same time, if the value of this parameter is bigger than 1, the utility curve is extremely steep and effectively suggests a constant function determined directly by U_x instead of a function of activity history. The stable parameter value of grocery shopping activity suggests that the increase of U^{max} level is steeper in SG3 than in SG2.

The U_x estimates are also less consistent than others in that the values jump around, but this is perhaps due to the bigger range of possible values for estimates. The grocery shopping, in-home task and in-home leisure activities are almost the same in U_x, having values ranging from 1000 to 2000. It is difficult to interpret the social activity's U_x estimates because they are not very stable and are extraordinarily high. Except this, it can be said that the U_x of non-grocery shopping is in general rather higher (highest in SG1) than other activities', and social activity's U_x is highest in SG3. Grocery shopping activity's U_x is highest in SG1. Statistical tests indicated that the estimation results do differ between classified segments and are largely interpretable and consistent with the activity-pattern and socioeconomic/situational profiles of the segments.

6. CONCLUSION AND DISCUSSION

The aim of this research project has been to explore the possibilities of developing a model of activity rescheduling behavior. The model that was developed was given the acronym Aurora (Agent for Utility-driven Rescheduling Of Routinized Activities). Similar to the utility-maximizing models of transport demand, the model is based on the concept of utility, but it differs in a number of important respects from these models. First, the shape of the utility different differs. The Aurora model assumes that utility is also a function of the duration of activities. The marginal utility function for the duration of activities is assumed to be asymmetric S-shaped. This has the theoretical advantage that one can differentiate between a "warming up" period, which will typically differ between activities, and the remaining duration. The maximum utility is assumed to be a function of history, state, time of day, etc, allowing the model to simulate context-dependent behavior. This is a second major difference between Aurora and the existing utility-maximizing models of transport demand. Thirdly, although individuals are assumed to try and increase their utility, concepts such as resistance to change and limited mental effort are incorporated in the modeling process.

In addition, Aurora allows for different decision styles in the sense that some travelers may be taking risk, when faced with time pressure and delays in the implementation of their activity schedule, while others may be risk-avoiders. For these reasons, the model is likely more in tune with the process of activity rescheduling behavior compared with the existing utility-maximizing models, which tend to focus on the output patterns. An example of the most likely extension of the current model in the context of regional demand forecasting and management will be using the microsimulation of multi-agent system to suggest collective behaviors to the changes in transportation environments and policy measures.

Regardless of one's view about the current evidence on the face and predictive validity of Aurora, the use of empirical rescheduling data and the use of the model in a simulation context, implies the need to develop an operationalization of concepts such as mental effort, resistance to change etc. One approach again would be a more or less straightforward approach in which one derives values for the operators that drive this process, and that potentially make the rescheduling process differentiate from an equilibrium state. Alternatively, and theoretically appealing, the multidimensional sequence alignment method that was developed in this study can also be viewed as the effort that is involved in changing the current activity-travel patterns into another pattern, a lower distance representing less effort. Hence, the measure that was suggested may also be used as an operationalization of the concept of resistance to change. It seems worthwhile to explore this possible link both theoretically and in empirical research.

These reflections on the limitations of the current project and interesting future research issues indicate that the work on developing Aurora certainly is not yet completed. This project has made several contributions to the literature. The conceptual framework includes several new concepts and represents a view of linking traditional utility theory to more process-oriented view of complex decision-making. The estimation method that was developed can also be used in other context to estimate asymmetric, S-shaped utility functions. The experiences with alternative specifications and alternative genetic algorithms may be relevant to other applications as well. Certainly, any genetic algorithm should be tailored, and one should be very cautious about any straightforward, brute force applications of a genetic algorithm. The newly developed generalizations of uni-dimensional sequence alignment methods have opened up new possibilities for analysis. Hopefully, the research community in activity-based analysis will find these elements useful in their research endeavors.

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