Measuring and predicting adaptation in multidimensional activity-travel patterns

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MEASURING AND PREDICTING ADAPTATION IN

MULTIDIMENSIONAL ACTIVITY-TRAVEL PATTERNS

PROEFSCHRIFT

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Preface

This book describes the results of my research on activity analysis over the last eight years. The content covers the issues of modeling activity pattern measurement and prediction. The theoretical background of the proposed model for activity pattern measurement 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 character of activity patterns. The theoretical background of the prediction model stems from micro-economic utility theory, time-geographic theory on possibility and constraints, and psychological decision making theory. The model predicts activity patterns as a result of a set of decision heuristics and activity utility functions.

The measurement and prediction model are complementary in the sense that 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 research was conducted in the context of the *Amadeus* project that seeks insight into how various characteristics of multi-modal transport systems. I hope that the result reported in this book attracts a wide attention of academic groups and other interested readers.

In order to finish what is written here and to become what I am now, many people helped me so much, which I never forget, and I would like to explicitly express my thanks to only some of them here. According to the theory of Buddhism, I am sure that I was a great person to these people in the lives before this life. Professor Harry Timmermans, my first promoter, is the very first person whom I truly want to thank. He simply made my Ph.D. research and life possible by his boundless intelligence and patience. Many thanks also go to Professor Wilfred Recker, my second promoter, for his willingness to review the entire thesis. I thank Associate Professor Theo Arentze, my co-promoter, not just for having helped my research activity a lot, but also for having been the best friend to me and sometimes an elder brother to me.

I appreciate very much Benedict Dellaert who helped me to start my study here and ever since has been encouraging me all the time. Thanks also go to Professor Woo-Kung Huh who guided me to the start of my academic career and Professor John Polak who guided me to another challenge after the Ph.D. Special thanks go to my highschool teacher Rah, Young-Joon.

Perhaps I would miss the following four people most, however: Ria Timmermans, Mandy van de Sande-van Kastern, Peter van der Waerden and Leo van Veghel. I have never seen such beautiful people before and perhaps no one else again. Especially, Leo, I would miss the Parliament with you so much, as the life there was sometimes painful but after all turned out to be glorious. My regards also go to our friend Harry.

My Korean friends at the Eindhoven University of other departments envied me very much because of the friendly, family-like, and best research atmosphere that the Urban Planning Group created, which is mostly initiated via Thursday Coffee Time. I enjoyed

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1 Introduction

Following the seminal work of Pas (1982), Jones, *et al.* (1983) and Recker, *et al.* (1986a; 1986b), the transportation research community has gradually become interested in activity-based analysis of transport demand. Especially since the mid-1990's, the number of publications in this area of research has rapidly increased. Two major streams of research can be distinguished. On the one hand, activity-based analysis has led to a large literature on the analysis (of facets) of complex activity-travel patterns, focusing on the classification of such patterns, interdependencies between particular facets, and correlations between activity-travel patterns and selected spatial and socio-demographic variables. On the other hand, it has led to the development of models, which predict which activities are conducted, where, when, where, for how long, with whom, and the transport mode involved. This wider set of choice facets represents an attempt to build more comprehensive models compared to the traditional four-step models, which only consider trip generation, transport mode, destination and route choice. Progress in this area of research is reported in a series of progressive resource papers (e.g., Recker & Kitamura, 1985; Pas, 1985; Kitamura, 1988; Axhausen & Gärling, 1992; Jones, *et al.*, 1993; Fox, 1995; Kitamura, *et al.*, 1997; Bhat, 1997; Ettema & Timmermans, 1997; Pas, 1998; Bhat & Koppelman, 1999; Timmermans, 2000; Timmermans, *et al.*, 2002a).

These resource papers witness the substantial progress that has been made in developing complex models of transport demand. Activity-based models provide more detail than the four-step approach and capture many interdependencies in activity-travel behavior. Nevertheless, because these models typically are based on cross-sectional data, they still are primarily suited to predict the effects of infrastructure and land use planning on transport demand and traffic flows. They try to capture the structural relationships between the urban and transport environment, the institutional context, socio-demographics and particular facets of activity-travel patterns.

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, including congestion pricing, road guidance and other ITS technologies, 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.

An examination of the relevant literature indicates that such *dynamic* models do not yet exist. Transportation demand management has led to a new model development, but such models typically focus on isolated facets of the dynamics of activity-travel behavior. For example, several models of departure time dynamics have been developed (e.g., Mannering, 1989; Mannering & Hamed, 1990; Caplice & Mahmassani, 1992; Mannering, *et al.*, 1994; Chin, 1990; Mahmassani & co-workers, 1990, 1991, 1998), but these models do not trace the impact of departure time dynamics on the timing and duration of activity schedules. Similarly, several studies have examined route switching behavior (e.g., Nakayama, *et al.*, 2001; Srinivasan & Mahmassani, 2002), but again implications on other facets of activity-

travel patterns were typically not incorporated in the modeling attempt. There have been some empirical studies on scheduling and rescheduling behavior (Doherty & Miller, 2000; Chen & Kitamura, 2000), and even some proposals for conceptualization (Gärling, *et al.*, 1998; Doherty & Axhausen, 1999), but to date this has not (yet) led to comprehensive, operational models of activity-rescheduling behavior.

Given this state of the art, this PhD project sets 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 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. A study of adaptation behavior requires a measure that can capture the similarity in the sequences of activities (and other facets) between activity-travel patterns and that can be used to classify activity-travel patterns. Because such a measure was not readily available, except perhaps the measure suggested by Recker, *et al.* (1985, 1986a, 1986b), a second goal of this thesis was to formulate and test such a measure.

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 measuring the multidimensional nature of activity-travel patterns, taking into account the embedded sequence of activities?

This thesis reports the analyses that were conducted to provide an answer to these research questions and the results that were obtained. The thesis is organized into two parts and nine chapters. Part I deals with the measurement of similarity of activity-travel patterns, while Part II is concerned with a model of activity (re)scheduling behavior. Following this introductory chapter, Chapter 2 provides a brief review of the relevant literature. It should be emphasized from the very beginning that this chapter is not meant to be a comprehensive, in-detail review of activity-based analyses in general. Rather, this chapter will discuss in some detail previous research that has some direct relevance to the problems that are addressed in this thesis. In particular, we will discuss previous proposals of measuring activity-travel patterns. The review serves to better understand the part of this thesis that is concerned with the measurement of similarity of activity-travel patterns, capturing cross-sectional, sequential and interdependency relations between individual events and between facets embedded in the activity-travel behaviors. In addition, we will focus on previous work on conceptualizing, modeling and predicting activity-travel dynamics in response to changes in

the transportation environment. This review serves to position our conceptualization and modeling of activity (re)scheduling behavior. The studies on respectively the measurement and prediction of adaptation in activity-travel patterns are complementary.

Based on this general review, Chapter 3 then discusses the fundamentals of the sequential alignment and illustrates one of possible ways to modify the original method to deal with a particular problem of analyzing activity-travel patterns. Chapter 4 then develops an extension of the sequence alignment methods, originally proposed in molecular biology. This is followed by an empirical analysis to examine the validity of the proposed theory and method. In particular, the analysis is concerned with a comparison of the performance of the proposed method with other existing methods in terms of the appropriateness of the information presented and computing time. The latter is highly relevant when the proposed similarity measure is to be used for larger samples. Therefore, considerable effort was made in developing heuristic methods to reduce the required computing time.

Having developed an appropriate multidimensional similarity measure and the corresponding algorithms, Part II then reports on the development of the model of rescheduling behavior, which was given the acronym Aurora (Agent for Utility-driven Rescheduling Of Routinized Activities). First, Chapter 5 discusses the development of a comprehensive theory, model and implementation algorithm of activity-travel scheduling and rescheduling behavior. The model is meant to simulate how travelers react to time pressure and unexpected events by dynamically adjusting an existing schedule. An illustrative example is presented using a simulated transportation environment to examine the face validity of the model.

Having provided evidence of the face validity, the next step is to apply the model to empirical data. This requires a method to estimate the model, which is far from a straightforward task given the combinatorial nature and complexity of the proposed model. In Chapter 6, we report on the development of an estimation method. The suggested estimation method is first tested on simulated activity schedule data, examining whether the estimation method can reproduce a 'known' set of parameters used to generate the simulated data. The test is conducted first for deterministic schedule data and then for data incorporating simulated noise of different magnitude to examine the extent to which the suggested estimation method is robust for noisy data.

Explorations of several alternatives led to the identification of a sequential estimation method that worked well for the simulated noisy data. This method was applied to activity-travel data that were collected in the Amsterdam-Utrecht corridor in The Netherlands. The results are presented in Chapter 7. First, method was applied to estimate a single set of parameter values for the complete sample. Secondly, in addressing the problem of heterogeneity, the proposed method was applied to estimate different sets of parameter values for segments of more homogeneous activity patterns. The multidimensional similarity measure that was developed in Part I was used to identify homogeneous groups of activity-travel patterns. The estimation results are examined with regard to the profiles that define each group and are compared between groups.

Chapter 8 then concludes the thesis. The chapter summarizes the modeling efforts and analyses. This is followed by a discussion of the interpretation and implication of the results. The chapter ends with some discussion of the future research agenda and a plan of implementation of the developed models.

2 Measuring and Predicting Activity-Travel Behavior: A Literature Review

2.1 Introduction

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.

Of central interest therefore are previous attempts to classify comprehensive activity-travel patterns and describe the resulting segments in terms of some key underlying attributes. In addition to being a relevant research stream in its own right, the various approaches towards classifying activity patterns is of central interest in the context of identifying prototypical patterns that may be used in subsequent modeling efforts (e.g., Recker, *et al.*, 1985, 1986a, 1986b). In this chapter, we will therefore first summarize the existing literature on the measurement of the similarity of activity-travel patterns and evaluate this literature for the purpose of segmentation.

As indicated in the introduction, the second primary goal of this thesis is the formulation and test of a model of activity (re)scheduling behavior. To position this model in the literature, we will also briefly review existing models and modeling approaches, which aim at predicting activity-travel patterns. First, we will consider cross-sectional approaches. Because the ultimate goal of our efforts is concerned with choice dynamics, we will continue discussing dynamic models. In particular, we will first discuss some of the models that have been suggested to predict the dynamics of single facets of activity-travel patterns such as route choice and departure time choice. Then, we will discuss some relevant conceptualizations and models that have been suggested to simulate the dynamics of comprehensive activity travel patterns.

It should be emphasized from the very beginning that this chapter is not meant to be a comprehensive, in-detail review of activity-based analyses in general. Rather, this chapter will discuss in some detail previous research that has some direct relevance to the problems that are addressed in this thesis. This chapter is organized as follows. First, Section 2.2 provides a literature review of alternative ways of measuring the similarity between activity-travel patterns. The review will focus on particular measures that cover particular aspects of information embedded in activity-travel patterns. Section 2.3 then provides a review of the literature on predicting activity-travel behavior. The review will focus on the research that has attempted to to develop a truly activity-based approach that captures interrelated, dynamic choices of activity-travel behavior.

2.2   Measuring activity-travel behavior

2.2.1   Measurement purposes

The measurement of activity-travel patterns has raised significant interest in geography, regional science and transportation research in the past. Multidimensional or multivariate activity-travel patterns have been measured in terms of such crucial attributes as activity type, activity location, start and end time, duration, transport mode, etc. In this line of research, the measurement typically served two different purposes. First, a fundamental assumption of activity-travel analysis is that particular characteristics of individuals and households and contextual situations are systematically related to their activity-travel patterns (Hanson, 1982; Pas, 1984; Golledge & Stimson, 1987; Hanson & Hanson, 1993; Strathman, *et al*., 1994). To explore this assumed relationship, the similarity between observed activity-travel patterns has formed the basis for classifying and identifying homogeneous activity-travel patterns. A matrix of similarities between observed activity-travel patterns is used as input for a subsequent cluster analysis. The resulting cluster memberships or representative activity patterns were then typically correlated with individuals' locational and/or sociodemographic characteristics. Examples include Hanson & Burnett (1981), Pas (1983, 1984), Koppelman & Pas (1985), Golob & Recker (1987), Hanson & Hanson (1993) and Cha, *et al*. (1995). Another example is the work on space-time prisms, which have been suggested to identify and explain interactions between individuals' behavior and social-institutional settings (Hägerstrand, 1970; Lenntorp, 1978; Pred, 1977, 1981a, 1981b; Thrift, 1983). Yet another example is the analysis of intrapersonal variability in activity-travel patterns across the days of the week (Hanson & Huff, 1986, 1988; Pas & Koppelman, 1986; Pas, 1988).

Secondly, the measures have been used to quantify the goodness-of-fit in assessing how well observed activity-travel patterns are predicted by some activity-based model of travel demand. Examples include Kitamura, *et al*. (1995) and Arentze, *et al*. (2001c). Because activity-based models aim at predicting which activities are conducted where, when, for how long, and the transport mode involved (Ettema & Timmermans, 1997), the measurement of activity-travel patterns typically involve multiple variables, constituting the multidimensional nature of activity-travel patterns.

2.2.2   Key measurement facets

In general, the formal properties of the measurement of activity-travel patterns should capture the specific needs underlying the goals and objectives of the analysis. Many applications require some representation of nominal and interval information. As argued in Chapter 1 for the contextual approach, it is critical to realize that in addition to such nominal and interval information, sequential information and information about interdependencies in

activity-travel patterns are also crucial in these applications. 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. Sequential relationships are in particular a primary concern in research on trip chains, activity sequencing, and sequential choice of activities and locations, acknowledging that consecutive activities likely affect one another (Kitamura, 1984a; Hatcher & 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*., 2001c), any valid measure should also incorporate such *interdependencies* in the quantification of the measurement. Three existing representative groups of measures of activity-travel patterns will be evaluated along these lines in the following section.

2.2.3 Measurement methods

Euclidean measures

The first group considers the element composition of activity-travel patterns and compares the corresponding elements of two activity-travel patterns to quantify their difference. Some scholars have suggested distance measures, using metric information, to quantify the difference between activity-travel patterns (e.g., Cha, *et al*., 1995; Ma & Goulias, 1997). Others have explored the problem of incorporating qualitative information of activity-travel patterns (e.g., Burnett & Hanson, 1982; Pas, 1983; Golob, 1985). Differences in attributes are summed across attributes to produce an overall measure of difference between the activity-travel patterns.

Perhaps the best known of these measures is Pas' (1983) similarity index, originally developed in botanical taxonomy (Gower, 1971). Pas identified differences in the attributes of activity-travel patterns using a generalized distance measure, and the sum of such differences across choice dimensions was taken as a measure of difference between activity-travel patterns. A hierarchical pattern description first identifies whether a stop (primary attribute) is made at a particular moment and then describes the details (secondary attributes such as activity type, timing, etc.). In equation:

$$\cos \phi_{sg} = \frac{\alpha l + \beta \sum_h \sum_k W_k S_{khsg}}{\sqrt{L \cdot l}} \tag{2.1}$$

with

$$S_{khsg} = \begin{cases} 1 & \text{if } s_{kh} = g_{kh} \\ 0 & \text{otherwise} \end{cases} \qquad \text{for qualitative attributes} \tag{2.2}$$

where,

$\cos\phi_{sg}$ is a measure of similarity between activity-travel patterns s and g;
α is a relative weight assigned to the primary attribute;
β is a relative weight assigned to the group of secondary attributes ($\alpha + \beta = 1$);
W_k is a normalized weight assigned to the kth secondary attribute, relative to other secondary attributes;
L and l are respectively $\max[m,n]$ and $\min[m,n]$, where m and n are the number of stops in s and g;
S_{khsg} is a similarity measure on the kth secondary attribute of the hth stop ($h = 1, \ldots, H$ where $H = l = \min[m,n]$);
s_{kh} and g_{kh} are observed values for s and g on the kth secondary attribute of the hth stop.

The direction cosine between two H-element vectors $\vec{a}$ and $\vec{b}$ is given by

$$\cos\phi = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|}, \text{ where } \vec{a} \cdot \vec{b} = a_1 b_1 + a_2 b_2 + \ldots + a_H b_H, \text{ and } |\vec{a}| = \sqrt{a_1^2 + a_2^2 + \ldots + a_H^2}.$$ The

numerator in equation (2.1) corresponds to the outer product of this direction cosine and is determined by the weighted sum of similarities across primary attribute and secondary attribute group. If two vectors are completely identical in terms of primary and secondary attributes, then $\cos\phi_{sg} = 1$. If two vectors are completely different, then $\cos\phi_{sg} = 0$. Note that the expression, $H = l = \min[m,n]$ implies that no comparison is made for the $(l+1)^{th}, \ldots, L^{th}$ activities of the longer pattern because the details of the secondary attributes of the shorter pattern are not defined.

The cosine similarities are then transformed into inter-point distances to locate activity-travel patterns in Euclidean space by using Gower's (1966) principal coordinate method:

$$d(s, g) = \sqrt{2(1 - \cos\phi_{sg})} \tag{2.3}$$

Pas (1984, 1988) subsequently used these inter-point distance measures as input for Ward's cluster algorithm.

The measure however does not properly capture the sequential information embedded in each attribute sequence. Consider, for example, activity-travel pattern 1-2-3 and activity-travel pattern 3-1-2. Pas' similarity index would indicate that the distance between the two patterns is equal to 3 units because all corresponding activities differ ($1\neq3$, $2\neq1$, and $3\neq2$), and hence, the two patterns are completely different. The same result would be obtained if pattern 1-2-3 would be compared to its reverse order 3-2-1. The difference in the former comparison is however merely due to the difference in position of activity 3 between the two patterns, and the costs for changing the order of only a single activity might be smaller than the costs for substituting all three activities.

Koppelman & Pas (1985) realized this characteristic of their measure, and therefore suggested to consider a linear assignment programming technique to overcome the problem. The technique measures the extent to which the patterns have elements in common without considering the possible differences in sequence between the patterns. Consider the above

two patterns of 1-2-3 and 3-1-2 again. As their linear assignment pairs the common elements without additional costs for matching the sequential order, these two patterns would then become identical. This approach would provide the same results with comparison of patterns having the elements '1', '2' and '3' of any order, while the result would be different for a comparison with a pattern of for example 4-1-2. Hence, their suggested approach does not solve the problem of sequential information.

Signal processing theoretical measure

The second group of measures is concerned with both element composition and sequential order of activity-travel patterns, but considers each attribute dimension separately. An example is Recker, *et al.*'s (1985, 1986a, 1986b) feature extraction method, based on the Walsh/Hadamard transformation, originally developed in signal processing theory (Young & Calvert, 1974). Each activity-travel pattern is encoded by a pattern matrix consisting of column vectors of attribute elements that respectively denote the temporal variation of the distance from home and binary indices of different activity types and transport modes. Each column vector is then transformed into a column of coefficients, each characterizing the element's sequence in terms of the degree of correspondence against the sequences of various binary Walsh functions. Finally, the column vectors of Walsh/Hadamard-transformed attribute elements are cluster-analyzed to classify the activity-travel patterns. In equation:

$$\underset{H \times N}{\mathbf{Y}} = \underset{H \times H}{\mathbf{H}} \cdot \underset{H \times N}{\mathbf{X}} \tag{2.4}$$

where,

H is the designated number of time slices a day;
N is the total number of levels across attributes (for example, when there are 5 different activity types, 10 locations and 5 travel modes considered, $N = 5+10+5 = 20$);
$\mathbf{X}$ is an original activity-travel pattern matrix that consists of N column vectors, each encoding the presence or absence of the level of a nominal attribute or the distance from home (location attribute) at each time slice;
$\mathbf{H}$ is Walsh/Hadamard transformation matrix consisting of H binary Walsh functions that define specific sequences and are orthogonal to each other;
$\mathbf{Y}$ is the transformed activity-travel pattern matrix that consists of N Walsh/Hadamard feature coefficient vectors, each defining the sequence of the attribute's level in terms of the degree of correspondence against H different binary Walsh functions' sequences.

Their method takes the sum of differences in corresponding coefficients between $\mathbf{Y}$s as a measure of dissimilarity between activity-travel patterns. The distance between s and g is thus defined as:

$$d(\boldsymbol{s}, \boldsymbol{g}) = \sum_{n} \sum_{h} \left| s_{hn} - g_{hn} \right| \tag{2.5}$$

where, s_{hn} and g_{hn} are the nth feature coefficient of the hth time slice of s and g's $\mathbf{Y}$s, respectively ($n = 1, \ldots, N$ where N is the number of columns of $\mathbf{Y}$, and $h = 1, \ldots, H'$ where H' ($\leq H$) is the number of feature coefficients taken from the first in each column of $\mathbf{Y}$).

Because the differences in the coefficients are summed independently, this approach excludes the possibility of collective comparison of multiple elements of different attributes between activity-travel patterns. When the sequences of the presence and absence of elements of different attributes over a time period are interdependent, a distance measure should recognize the collective decisions made for the elements of different attributes instead of measuring them separately. Consider, for example, two two-dimensional patterns 1 and 2, $\begin{smallmatrix} C & A & B \\ c & a & b \end{smallmatrix}$ and $\begin{smallmatrix} A & B & C \\ a & b & c \end{smallmatrix}$. Clearly, the attributes are perfectly correlated, and therefore, a distance should be measured on a collective change of the first activity $\begin{smallmatrix} C \\ c \end{smallmatrix}$ of pattern 1 into the last position. Recker, *et al.*'s measure calculates the costs for changing the orders of C and c independently and produces a sum of these costs without recognizing the interrelated decisions between activity contexts, C and c (as well as A and a, and B and b).

Evaluation

The literature review indicates that the existing methods measuring similarity between activity-travel patterns do capture cross-sectional, sequential *or* interdependency relations between scheduling decisions embedded in the multidimensional, multivariate activity-travel patterns, but not all of them. The Euclidean measure 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 explicitly takes into account the sequence of a particular activity attribute but does not incorporate the possibility of collective decision-making across choice facets. Structural relationships between activities and choice facets may exist (Gärling, *et al.*, 1997), and a measurement method should take both into account to provide an accurate measure of distance in behavioral space.

2.3   Predicting activity-travel behavior

In this section, we will review the literature on predicting activity travel behavior. First, we will consider comprehensive activity-based models of transportation demand forecasting. Next, models of dynamics of activity travel behavior will be discussed.

2.3.1 Comprehensive models of transportation demand forecasting

Comprehensive models of activity-travel patterns focus on multiple, interrelated choice facets that characterize activity-travel patterns. Several modeling approaches have been suggested in the literature. These approaches can be labeled as constraints-based models, utility-maximization models and computational process models. Constraints-based models have their roots in time geography, utility-maximization models stem from microeconomic theory and psychology, while computational process models have been inspired by psychological decision process theories.

Constraints-based models

These models typically examine whether particular activity patterns can be realized within a specified time-space environment. These models require as input activity programs, which describe a set of activities of a certain duration that can be performed at certain times. The space-time environment is defined in terms of locations, their attributes, available transport modes and travel times between locations for various transport modes. One of the attributes of interest is the opening hours of the facilities at that location. To examine the feasibility of a certain activity program, a combinatorial algorithm is typically used to generate all possible activity sequences. The feasibility of each sequence is then tested by checking whether (i) the interval between the end time of the previous activity and the start time of the next activity is sufficient to travel between locations; (ii) the activity can start after the earliest possible start time and be finished before the latest possible end time, (iii) conditions about the sequencing of activities are not violated. The number of feasible activity schedules is often used as a measure of the flexibility that the time-space environment offers.

One of the first models in this tradition is Lenntorp's (1976) PESASP model. A similar model is CARLA, which basically is a combinatorial algorithm for generating feasible activity patterns (Jones, *et al.*, 1983). Huigen (1986) proposed another combinatorial algorithm, BSP. This program is similar to CARLA in that it evaluates the options to maintain the current activity pattern in a changed spatial-temporal setting. However, as PESASP, it does so by exhaustively evaluating all possible sequences of activity/destination combinations. Furthermore, there are minor differences with respect to how constraints are incorporated. It allows that different trips in a chain are made by different modes. Another difference is that it defines available time windows specifically for destinations and not for activities.

Another similar model is MASTIC (Dijst & Vidakovic, 1997). Its goal is to identify the action space of individuals, using the notion of a space-time prism. A potential action space is defined as the area containing all activity locations that are reachable, subject to a set of temporal and spatial constraints, including type and location of activity bases, available time interval, travel speed, and the travel time ratio.

Kwan's (1997) GISICAS can be classified as a constraints-based model as well, although it also makes references to computational process models. Given an activity agenda, this GIS-based system begins scheduling by fitting the activities on the agenda into the free time a person has, and orders them into a sequence. Activities with higher priority are ordered first, and the time constraints for performing certain activities are also taken into account.

Various search heuristics can be specified to identify the locations where the activities can be carried out. The system then reports a preliminary schedule and also lists the activities that cannot be scheduled. The spatial search is based on a dynamic identification of feasible locations.

A limitation of constraints-based models is that they lack the necessary mechanisms to predict adjustment behavior of individuals. When faced with a changed time-space environment, individuals are likely to adjust/reschedule their activity programs. Constraints-based models, however, do not attempt to predict such behavior.

Utility-maximization models

The evolution of utility-maximizing models of activity patterns more or less followed the general progress made in discrete choice modeling. In the beginning, the interest was on applying multinomial logit models to predict the probability that a full activity profile is selected. The seminal work by Adler & Ben-Akiva (1979) and Recker, *et al*. (1986a, 1986b) are examples of this approach. Later, nested logit models of increasing complexity were developed.

Perhaps the most advanced, nested logit model in this tradition is *the daily activity schedule model*, initially proposed by Ben-Akiva, *et al*. (1996). Considerable progress has been made since. A prototype was developed for the Boston area (Bowman & Ben-Akiva, 1995), and later implemented for travel forecasting in Portland (Bowman, *et al.*, 1998). At the core of their model is a daily activity schedule, which represents the individual's demand for activity and travel as a multidimensional choice encompassing all the combinations of activity and travel an individual might choose through the course of a day. A schedule consists of a set of tours, which are organized and tied together by a daily activity pattern. The daily activity pattern is characterized by (a) a primary activity, with one alternative being to remain at home for all the day's activities; (b) the type of tour for the day's primary activity, including the number, purpose and sequence of activity stops; and (c) the number and purpose of secondary tours. For each tour in the daily activity pattern the tour schedule includes the choices of destinations for activities in the tour as well as the mode and timing of the associated travel.

The choice of a daily activity pattern determines the number of secondary tours in the daily activity schedule. The choices of secondary tour time, destination and mode are conditioned upon the choice of a daily activity pattern. For daily activity patterns with two or more secondary tours, the conditional choice probabilities of the secondary tours are mutually independent, calculated from the same models. This approach ignores time and space constraints across secondary tours, but simplifies the model structure. It would be possible to incorporate these constraints using a conditional tertiary tour model, but at a large cost in terms of complexity. The model structure is further simplified by removing secondary destinations from the tour schedules. The destination and mode choice model involves the choice of a mode for the tour, instead of the usual choice of mode for a trip. A rule was selected to assign the sample to one of six modes, including auto drive alone, auto shared ride, transit with auto access, transit with walk access, walk and bicycle. Other examples of nested logit models include Wen & Koppelman (1999) and Fosgerau (1998).

These nested logit models of activity-travel patterns have the advantage of being

founded in a well-established statistical methodology and economic theory. However, there are some theoretical and operational limitations. In order to be consistent with the theory of utility-maximizing behavior, the estimated parameters of the model need to satisfy particular constraints. However, most operational models have resulted in parameter values that do not satisfy these constraints, placing doubt on the theoretical basis of the model and/or the parameter estimation process and/or data quality. Another potential disadvantage is that temporal, spatial and institutional constraints are usually not systematically included in the model, implying that the domain of policy application of this modeling approach is rather limited. Finally, in order to be able to estimate the model, researchers have to dramatically reduce its complexity, limiting the number of activities, tours, etc.

The above models are all based on revealed preference data. In contrast, Cobra (Wang & Timmermans, 2000) has been based on conjoint choice experiments. The complexity of the choice problem required the authors to develop new experimental design strategies (Wang, *et al*., 2000a, 2000b). The model specification however was the same: a nested logit model was used. Although their study demonstrated the potential of the newly developed methodologies, it is doubtful whether conjoint experiments suffice to build a comprehensive activity-based model. As discussed in more detail by the authors, the problem is simply too complex and would require a major data collection effort and substantial finances.

The Prism-Constrained Activity Travel Simulator (*PCATS*) has been developed by Kitamura & Fujii (1998). It is a system that simulates activity-travel behavior while considering prism constraints, availability of travel modes, and recognition of potential activity locations. Unlike the previous models that model the choice of activity pattern as a nested structure, *PCATS* assumes that individuals maximize the utility associated within the open periods, subject to the above constraints. The utility associated with a particular activity-travel pattern is assumed to be the sum of the utility associated with activities and trips.

Bhat (1999) developed a comprehensive framework for activity-travel generation. This framework considers workers only. Their activity-travel pattern is divided into several periods: before morning commute pattern, morning commute, midday patterns, evening commute and post-home arrival pattern. These patterns are described by a series of characteristics, including number of tours, number of stops, mode choice, etc. Bhat suggested a series of models to predict these components. Although these have been largely published as isolated modeling efforts, when used in combination, it will result a comprehensive modeling approach. Misra, *et al.* (2003) extended this modeling effort to handle non-workers' activity schedules.

Computational process models

The assumption of utility-maximizing behavior, characteristic for the models discussed in above, has been criticized by some scholars, arguing that individuals do not necessarily arrive at "optimal" choices, but rather use context-dependent heuristics. Computational process models constitute a powerful theoretical approach that conceptualizes choices as outcomes of such heuristics.

The first model in this line of research is SCHEDULER, developed by Gärling, *et al.*

(1989). It is primarily a conceptual framework for understanding the process by which individuals organize their activities. Individuals and households are assumed to try and attain certain goals. Activities are defined as means, which the environment offers to attain these goals. Choice of participation in activities is determined by preferences in conjunction with prior commitments and constraints. Activity scheduling entails an interrelated set of decisions made by the individual, interactively with other (household) individuals, concerning who will participate in the activities, when, where, for how long, and how to travel between locations where the activities can be performed. SCHEDULER has been operationalized in the form of a production system, which chooses the activities that are subsequently performed at particular locations. The model has been applied to predict the activity patterns of commuters after the introduction of telecommuting (Golledge, *et al.*, 1994). In a series of separate papers, parts of the model were further elaborated. Gärling, *et al.* (1999) for example investigated the role of anticipated time pressure in activity scheduling. Many aspects of the model, however, need further development and operationalization.

Another model system that bears some resemblance with computational process modeling, is AMOS, a dynamic micro-simulator of household activities and travel over time and space (Pendyala, *et al.,* 1998). AMOS is an activity-based model of travel decisions that simulates the scheduling, and adaptation of schedules and resulting travel behavior of individuals and households. The model is a very useful approach for policy impact assessment, but it does not represent a generalized approach. Data needs to be collected specifically for each application.

Certain components of AMOS are very similar to *Smash* (Ettema, *et al*., 2000). This model concentrates on the process of activity scheduling. The scheduling process is assumed to be a sequential process consisting of a number of consecutive steps. In every step the schedule, which is empty at the beginning of the process, can be adjusted by one of the following basic actions: (i) adding an activity from the agenda to the schedule; (ii) deleting an activity from the schedule; (iii) substituting an activity from the schedule with an activity from the agenda; (iv) stopping the scheduling process. By repeatedly applying one of these basic actions, the schedule is constructed and adapted until a satisfactory schedule is created. To identify feasible scheduling decisions at each stage of the scheduling process, scheduling decisions are subject to several constraints. A nested logit model is used to operationalize this notion. The higher nest contains the decision to stop the scheduling process and accept the current schedule, or to add, delete or reschedule an activity. The lower nest describes the choice of the specific add, delete and reschedule options. The model was primarily developed as a process model. It does not have a lot to offer as a planning tool.

The latest, most comprehensive and only operational computational process model is *Albatross* (Arentze & Timmermans, 2000). It can be considered a multi-agent rule-based system that predicts activity patterns. The system consists of a series of agents that together handle (the consistency of) the data, the derivation of choice heuristics from activity diary data, the simulation or prediction of activity patterns, the assessment and reporting of model performance, the calculation of various system performance indicators, and the evaluation of alternative model scenarios.

The core of the system is the scheduling engine. It controls the scheduling processes in terms of a sequence of steps. In each step, the scheduling engine identifies the condition information required for making principal scheduling decisions, sends appropriate calls to

agents for the required analyses, passes the obtained information to the rule-based system and translates returned decisions into appropriate operations on the current schedule. An initial schedule is derived from the given activity program in terms of the activities that need to be performed that day as a consequence of longer-term commitments (i.e., job contract), household constraints (e.g., bringing children to school) and, possibly, other pre-scheduling decisions. Scheduling then involves selecting activities to add to the skeleton formed by these fixed activities and, next, determining the schedule position and profile of each added activity. The sequence of steps intends to simulate the way individuals solve the problem. Several important extensions are realized in the second version of Albatross. The most important extension concerns the generation of schedule skeletons on a continuous time scale, which in the original version was taken as given.

Typical for computational process models, reactions are mixed. Computational process models are based on a large number of rules that represent context-specific behavior. As such, they lack the appeal of a simple algebraic equation and generate the feeling of a black box. Moreover, the derivation of decision rules from empirical data, which serves the same role as parameter estimation in utility-maximizing models, is often seen as lacking statistical, econometric rigor. This is true in the sense that the extracted rules do not have error bounds and that the approach is not founded in statistical error theory. On the other hand, the theoretical premises of this modeling approach and its flexibility in defining complex interdependencies among facets of activity-travel patterns and incorporating more facets, do have appeal in that different kinds of spatial, transport and economic policies can be evaluated. Moreover, there is some evidence of better predictive performance (Arentze, *et al.*, 2001c). Considerable more work however is required to draw more definitive conclusions.

Evaluation

This subsection discussed some key models that try to predict comprehensive activity-travel patterns. The so-called activity-based approach has been an important step forward in the sense that compared to earlier approaches it considers the dependencies between multiple facets of activity-travel patterns. Arguably, there are two important aspects on which existing activity-based models can be compared, namely the treatment of constraints and the treatment of time (continuous or discrete). Although the activity-based approach allows one to incorporate choice constraints in a more integrated fashion and to predict activity and travel on a continuous time scale, not all of existing models fully realize this potential. First, *PCATS* and Albatross are the only operational models to date that realize full-fledged interactions while taking into account a full set of constraints. Secondly, unlike other models, Albatross, *PCATS* and Bhat's model address continuous time allocation, which is more realistic and provides more detailed information. The existing models certainly represent a step forward. However, all comprehensive models still have the cross-sectional property and, therefore, heavily focus on the static correlation between observed behavior and explanatory variables. They are static in the sense that they lack the possibility of adaptation during the implementation of schedules.

2.3.2 Studies on the dynamics of travel behavior and decision making process

The above review of the existing literature indicates that most comprehensive models of activity-travel patterns have focused on structural properties. Very few of these models include principles and mechanism to adapt activity schedules. This is not to say that models of dynamic choice behavior are completely missing. Existing dynamic models however typically are concerned with a single aspect of activity-travel patterns and have often been developed to predict the impact of ITS on a particular aspect of travel behavior.

The dynamics of travel-behavior are driven by learning over time and short-term adaptation based on within-day rescheduling. Both areas of research will be reviewed in this section successively.

Travel-behavior dynamics based on learning

Starting point of many of these models is that transport systems and urban environments are highly dynamic, non-stationary and uncertain. An excellent review about learning can be found in Timmermans, *et al*. (2003). Travelers' information is limited, imperfect and often biased (Arentze & Timmermans, 2003). Their day-to-day decisions in activity-travel choice rely on the experience of previous choices, which facilitates and guides the adaptations in a long-term.

Arentze & Timmermans (2003) developed a model of learning and adaptation in activity choice, where memory and search play an important role. Individuals explore choice opportunities through search and keep a memory of cumulative reward or punishment based on the implementation experience. The choice between exploration and exploitation of current knowledge is reflected in the learning mechanism that they proposed. This includes a reward function that simulates good or bad outcomes of implemented actions, a value function that integrates the rewards received in the past to assess the current value of an action, and a policy that defines a choice of an action given a perceived state of the environment and action values. An event, which is the unit of experience, is stored in a long-term memory defined as:

$$e = (\boldsymbol{x}, \boldsymbol{r}, t, \boldsymbol{w}, \rho) \tag{2.6}$$

where,

$\boldsymbol{x}$ is a vector of values of attributes;
$\boldsymbol{r}$ is a vector of reward values related to particular objectives of the individual;
t is an index of the time moment when the event took place;
$\boldsymbol{w}$ is a vector of weights related to particular objectives;
ρ is the retrievability of the event from the memory.

Equation (2.6) expresses that the memory of the system stores attribute information together with the reward value received for each event. Only the subset of attributes believed relevant or potentially relevant for predicting rewards of events is included. Reward is a numeric value of the intrinsic desirability of an event. Individuals have multiple objectives

and are able to evaluate an event in relation to each objective differently. The reward function can be written as:

$$r_g = f_t(\boldsymbol{x}_g^*) + \varepsilon_{tg} \tag{2.7}$$

where,

f_t is a time-varying and individual-specific function;
$\boldsymbol{x}_g$ is a vector of event attributes relevant for objective g;
ε_{tg} is a stochastic error component for objective g at time t.

The weight vector represents for each objective the perceived strength of the association between event and reward. As the memory of an event may decay over time, a retrievability parameter represents the strength of the memory trace or the ease with which it can be retrieved from the memory. The goal of learning is assumed to maximize aggregate reward as:

$$\max_{\{a_1,\ldots,a_T\}} R_T = \sum_t^T r_t \tag{2.8}$$

where,

T defines a sufficiently long time horizon;
r_t is the aggregate reward value for the tth event;
$\boldsymbol{a}_t$ is the vector of chosen levels for the attributes.

Accordingly, action selection refers to the problem of choosing a certain action in a given state, based on its expected return. The value of an action should reflect the expected return. The suggested specification of the incremental action update value function for a given action facet k is:

$$Q_{t+1,i(t),a} = (1 - w_t \alpha) Q_{t,i(t),a} + w_t \alpha r_t \tag{2.9}$$

where,

$Q_{t+1,i(t),a}$ is the expected reward for choosing action a at time $t+1$ in state i;
α is a step-size parameter;
w_t is the relative weight of the event.

This value function assigns a higher weight to a more recently received reward. Then, a possible action-selection method selects an action a with probability:

$$\Pr(a) = \frac{\exp[Q_{t,a}/\tau]}{\sum_{a'} \exp[Q_{t,a'}/\tau]} \tag{2.10}$$

where, τ is a positive parameter. This selection function is a so-called softmax action-selection rule based on Boltzmann distribution.

Learning and adaptation define dynamics of travel behavior, which is an important area of transport research. Timmermans, *et al.* (2003) showed that much of the literature on dynamic route and departure time choice can be viewed as special cases of this overall framework. Related studies in this line of research have adopted the moving-average or a distributed-lag method as the basic learning mechanism, i.e. Mahmassani & Chang (1986), Ben-Akiva, *et al.* (1991), Iida, *et al.* (1992), Axhausen, *et al.* (1995), Nakayama, *et al.* (1999, 2000a, 2000b), Fujii & Kitamura (2000), Polak & Oladeinde (2000), and Polak & Hazelton (1998). For example, Polak & Hazelton proposed a learning model in which the length of memory is restricted to a certain time period. The value function of equation (2.9) shows that the weight of past experience in the current action value is rapidly decreasing. Polak & Hazelton's weights are parameterized according to geometrically declining model as:

$$Q_{t,a} = \sum_{i=t-\pi}^{t-1} w_i r_i \qquad (2.11)$$

with

$$w_i = \alpha^i \Lambda \qquad (2.12)$$

where,

$0 < \alpha \leq 1$ denotes the rate the discount of the past experience;
Λ is a scaling coefficient to ensure that the weights sum to unity.

By setting parameters, many action-value update functions can be modeled as a special case of this method.

Decision process studies

The above models focus on dynamics based on learning over time often related to a single facet of activity patterns, such as departure time and route choice. The goal of our study, in contrast, is to develop a model of rescheduling comprehensive activity-travel patterns. In that sense, the fundamental limitation of the above dynamic models, which do not try to model the implications of changing a particular facet through the complete activity-travel schedule, are alleviated. To our knowledge, fully operational models of activity rescheduling do not yet exist, although some of the models discussed earlier could potentially be used to that effect. There is a limited literature, however, on relevant conceptualizations, proposals for model development and small-scale simulation. These studies will be summarized now.

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. An important question was whether the different conditions make it possible for the simulated person to perform all activities at preferred times and locations. This criterion is similar to utility maximization. As one should expect, in particular long work hours but also living away from the center and slow travel speed prevented maximization of preferences. Thus in this respect the simulation results appear to be realistic.

In a continuation of his innovative work on the role of anticipated time pressure in activity scheduling, Gärling *et al*. (1999) argues that the major problem in individuals' scheduling is that people frequently want to do more than they are able to. In other words, they committed themselves to perform too many activities in a limited amount of time. 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). The most effective method for reducing the total activity duration is likely to be elimination of activities. He accordingly suggests an activity classification based on these notions that distinguish activities to be deleted, postponed with deletion, and postponed without deletion and generally postponed, which depends on the characteristics of activities.

His study suggests a sequential process of adaptation of a schedule in a way that the system minimizes the difference between total activity duration and time budget. This opposes a full combinatorial optimization process that is unlikely in real life. More specifically, the system (1) computes total duration of all activities in the set, (2) computes difference between total duration and time budget, (3) computes the absolute difference between this difference and the duration of each activity, (4) eliminate the activity with the smallest absolute difference (if multiple such activities exist, eliminate one in random) and (5) repeats the process from (1) if total duration still exceeds time budget. His work stresses that anticipated time pressure is an important factor controlling the frequency of activity scheduling and is an additional factor constraining the feasibility of schedules. He also suggests that a distinction is to be made between planned, habitual and impulsive activities on the basis of the degree of planning and time horizon of planning. Although these studies are theoretically appealing and key concepts are supported by numerical simulations, this line of work has not (yet) resulted in a fully operational model of activity rescheduling behavior.

Doherty & 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. In particular, they suggested the following functional form:

$$\frac{\min d_i}{\max W} \tag{2.13}$$

where, d_i is duration of activity i and W is the size of any feasible time windows. The function therefore determines the flexibility of an activity in terms of duration in relation to the possible time window. A higher value thus gives a higher priority.

The suggested decision rules are rather simple. For example, adding an activity to a schedule is driven by a "highest priority" rule. Likewise, the decision of whether to continue the scheduling is driven by the rule:

$$\text{IF [Highest activity priority]} > \alpha \rightarrow \text{THEN [Continue the scheduling]} \tag{2.14}$$

where, α is a empirically determined threshold value. Although the framework has now been suggested a few years ago, to the best of our knowledge to operational or empirical results have been published since.

Evaluation

In this sub-section, we have discussed the literature on dynamic models of travel behavior. Many of these models have been proposed to predict the impacts of ITS on behavioral change, especially related to route and departure time choice. It concerns an important area of research in the sense that the proposed models attempt to predict a change in the implementation of activity-travel patterns in response to some external source. Nevertheless, the models typically focus on an isolated decision dimension and do not account for the impact on the complete activity-travel pattern. In addition, we have discussed the very limited literature on rescheduling decision processes, which potentially could be used for such purpose. The value of this literature is primarily conceptual. Operational models are still virtually lacking.

2.4   Conclusions and discussion

This chapter reviewed the existing literature on the measurement and prediction of activity-travel patterns. The review has identified a number of issues that are paramount to the approach that will be taken in this thesis and that can also be used to differentiate and position this work against earlier work. First, we have argued that the literature on modeling rescheduling decisions is still very scarce and hence there seem a need to explore the possibility of developed an operational model of rescheduling decisions, with strong theoretical underpinnings and that tries to capture the interdependencies of multi-faceted activity-travel patterns. Secondly, to the extent that such modeling attempts are based on classification or segmentation of activity-travel patterns, existing classification methods should be replaced or elaborated such as to incorporate the sequential information embedded

in activity-travel patterns. In the remainder of this thesis, we set out to make a contribution in these areas of research.

Part I: Measuring Activity Rescheduling Behavior

3 Uni-dimensional Sequence Alignment Methods

3.1 Introduction

In the previous chapter, we have argued that traditionally used Euclidean distance measures are inappropriate to measure the similarity between activity-travel patterns. In particular, these measures are not sensitive to difference in activity *sequences*. Sequence alignment methods, as used in the biological sciences and introduced in the transportation and urban planning literature by Wilson (1998), in principle have been developed for measuring similarity between information sequences.

In this chapter, we therefore explore the potential of applying sequence alignment methods to measure the similarity between activity-travel patterns. We will argue that although sequence alignment methods have some interesting and useable properties, their application to the study of activity-travel patterns is limited. First, positional information in the sequence is not used in measuring similarity. Secondly, conventional sequence alignment methods are essentially uni-dimensional, while the classification of activity-travel patterns should ideally be based on multidimensional attribute profiles. Therefore, two extensions were developed in the context of the present study: a position-sensitive sequence alignment method, discussed in the present chapter, and a multi-dimensional sequence alignment measure, discussed in the next chapter.

This chapter is organized as follows. Section 3.2 provides a formal description of conventional sequence alignment methods as originally developed in biology. . In Section 3.3, the first extension of the original method is discussed. In particular, a position-sensitive measure is developed. To illustrate the application of the conventional method and the extension, examples of applications are given in section 3.4. The chapter ends with some conclusions and a discussion.

3.2 Sequence alignment method

The sequence alignment method can be summarized as follows (Kruskal, 1983). Let two sequences to be compared, s and g, have $m+1$ and $n+1$ *elements*, respectively ($s=[s_0 \ldots s_m]$, and $g=[g_0 \ldots g_n]$; $m \geq 0$, and $n \geq 0$, where s_0 and g_0 are 'null' elements that initialize sequences. s and g are called *source sequence* and *target sequence*, respectively. Each element represents a particular character. A missing character, such as '?', represents unknown elements. Distance or dissimilarity is then defined as the *total amount of effort* required to equalize sequence $s=[s_0 \ldots s_m]$ with sequence $g=[g_0 \ldots g_n]$. In this respect, the

sequence alignment method distinguishes various *operations*. In particular, sequences can be made equal by using '*identity*', '*substitution*', '*insertion*' and '*deletion*' operations.

To understand the nature of these operations, assume a two-dimensional table, called *comparison table* or computational array (Figure 3.1). Let s^i and g^j be initial parts of the source and target sequences, respectively ($s^i=[s_0 \dots s_i]$, and $g^j=[g_0 \dots g_j]$; $0 \le i \le m$, and $0 \le j \le n$). Each cell (i,j) of the comparison table stores the amount of effort required to equalize s^i with g^j. The grayed cell is called the corner and is set to 0, indicating the comparison of two empty sequences. The cells in margin g are filled when s^0 is equalized with the g^j's. Likewise, the cells in margin s are filled when the s^i's are equalized with g^0. The equalization process starts at cell (0,0) and ends at cell (m,n). The operations are represented by step-by-step *moves* (transitions: arrows in the table) from one cell to another, first to equalize each s^i with g^j, and finally to change sequence s^m into sequence g^n.

A set of moves from the first to the last cell composes a *trajectory*, i.e. a path of equalizations. For each (i,j), these moves can be made from one of three cells, ($i-1,j$), ($i-1,j-1$) and ($i,j-1$), called *predecessors*. The cells in the margin s and g, however, have only one predecessor each. The cells (0,j) in margin g have the predecessors (0,$j-1$), while the cells ($i,0$) in margin s have ($i-1,0$). Moves into the opposite direction are never made because they involve additional efforts that are not necessary.

Each of these moves represents an operation. The diagonal move represents '*identity*' if s_i and g_j are the same at cell (i,j), and represents a '*substitution*' otherwise. In both cases, the predecessor of cell (i,j) is cell ($i-1,j-1$). A horizontal move where the predecessor is ($i,j-1$) represents an '*insertion*' in that the move adds g_j to s^i. Finally, a vertical move where the predecessor is ($i-1,j$) represents a '*deletion*' in that the move eliminates s_i from s^i.

At the cell (1,1) in Figure 3.1, for example, the first element 'B' of sequence s is being compared with the first element 'A' of g. The predecessor of the vertical move in Figure 3.1 is (0,1), dictating that the previous initial part $s^0=[s_0]=[\ ]$ was equalized with $g^1=[g_0\ g_1]$ by adding g_1 and became $s^0=s^0[s_0\ g_1]=[A]$, which costs 1 unit of insertion. The vertical move then deletes s_1 from the current initial part $s^1=[s_0\ g_1\ s_1]=[A\ B]$ and equalizes s^1 with $g^1=[g_0\ g_1]$, resulting in $s^1=[s_0\ g_1]=[A]$, which costs additional 1 unit of deletion. Likewise, the predecessor of the horizontal move is (1,0), dictating that the previous initial part $s^1=[s_0\ s_1]=[B]$ was equalized with $g^0=[g_0]$ by deleting s_1 and became $s^1=[s_0]=[\ ]$, which costs 1 unit of deletion.
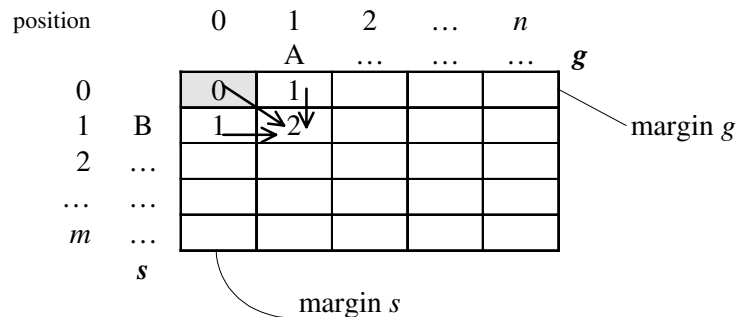
Figure 3.1: Comparison table (An example)

The horizontal move then equalizes $s^1=[s_0]$ with $g^1=[g_0\ g_1]$ by adding g_1 into s^1, resulting in $s^1=[s_0\ g_1]=[A]$, which costs additional 1 unit of insertion. Similarly, the predecessor of the diagonal move is (0,0), where $s^0=g^0$, and the diagonal move equalizes $s^1=[s_0\ s_1]$ with $g^1=[g_0\ g_1]$ by deleting s_1 from s^1 and adding g_1 into s^1, resulting in $s^1=[s_0\ g_1]=[A]$, which costs deletion and insertion of 1 unit each.

Each operation involves a certain amount of effort. The magnitude of these efforts is denoted by weighting values $w_e(s_i,g_j)$, $w_s(s_i,g_j)$, $w_d(s_i,\phi)$ and $w_i(\phi,g_j)$ for respectively identity (**e**quality; $s_i = g_j$), **s**ubstitution ($s_i \neq g_j$), **d**eletion and **i**nsertion operations. In particular, $w_e(s_i,g_j) = 0$. The 'ϕ' symbol implies that no operation is applied to the element denoted by ϕ. When a missing character s_i is to be substituted with a missing character g_j, either the substitution or the identity weighting value is applied, depending on the context of the analysis. The substitution operation may be thought of as the sum of deletion and insertion operations. That is, $w_s(s_i,g_j) = \delta[w_d(s_i,\phi)+w_i(\phi,g_j)]$, where $i,j \geq 1$. If the substitution weighting value is regarded as the simple summation of the weighting values of the two operations, then $\delta = 1$; otherwise, $\delta \neq 1$. Normally, $w_s(s_i,g_j) \geq w_d(s_i,\phi)$, and $w_s(s_i,g_j) \geq w_i(\phi,g_j)$. The computation of dissimilarity proceeds by using these weights. Dissimilarity is then defined as the *sum of operation weighting values* required to change sequence s into sequence g.

Because there are many different possible trajectories, an additional operational decision is required to calculate the dissimilarity measure. The sequence alignment method is based on the calculation of the *Levenshtein distance*, which is defined as the smallest number of substitutions, insertions and deletions required to change sequence s into sequence g. The equations for the 'weighted' Levenshtein distance are:

$$d(s,g) = d(s^m,g^n) \tag{3.1}$$

$$d(s^0,g^0) = 0 \tag{3.2}$$

$$d(s^i,g^0) = d(s^{i-1},g^0)+w_d(s_i,\phi) \tag{3.3}$$

$$d(s^0,g^j) = d(s^0,g^{j-1})+w_i(\phi,g_j) \tag{3.4}$$

$$d(s^i,g^j) = \min\ [d(s^{i-1},g^j)+w_d(s_i,\phi),\ d(s^i,g^{j-1})+w_i(\phi,g_j),\ d(s^{i-1},g^{j-1})+w(s_i,g_j)] \tag{3.5}$$

with

$$w(s_i,g_j) = \begin{cases} w_e(s_i,g_j)=0 & \text{if } s_i = g_j \\ w_s(s_i,g_j)>0 & \text{otherwise} \end{cases} \tag{3.6}$$

where,

$i,j \geq 1$;

$d(s,g)$ is the total cost of equalization of s ($= s^m$) with g ($= g^n$);

$d(s^i,g^j)$ is the cost of equalization of s^i with g^j, cumulated from the equalization of s^0 to g^0.

Equation (3.2) indicates that there is no predecessor of the corner cell. Equations (3.3) and (3.4) imply that only one predecessor is given to each cell in the margins s and g, representing the deletion and insertion, respectively. Equation (3.5) returns the minimum value of the alignment cumulated from $d(s^0, g^0)$ to $d(s^i, g^j)$. Equation (3.1) gives the overall minimum cumulated effort until the last cell (m,n). The 'weighted' Levenshtein distance defines dissimilarity as the *smallest sum of operation weighting values* required to change sequence s to sequence g.

A specific set of weighting values can be assigned to reflect a particular analysis context. A variety of weighting schemes exists in biology and computational linguistics. They include various mutation probabilities among amino acids and among positions in the sequence (Thompson, *et al.*, 1994), generalized gap costs for speech recognition and long deletions and insertions of introns (Bradley & Bradley, 1983; Russel, *et al.*, 1986; Gusfield, 1997a), etc. In this section, however, we stick to the elementary operation weights; $w_e(s_i, g_j) = 0$, $w_d(s_i, \phi) = w_i(\phi, g_j)$, and $w_s(s_i, g_j) = w_d(s_i, \phi) + w_i(\phi, g_j) \ \forall \ i, j$. This is partly because we simply do not have enough information to utilize a more flexible weighting scheme for the analysis of activity-travel behavior and because we wish to more clearly manifest the effect of deletion and insertion by keeping the alignment as simple and close to the original sequence alignment method as possible.

This section assumes the simplest form of the Levenshtein distance, where the cost for substitution is the simple sum of the costs for deletion and insertion ($Q_{ij} = W + W = 2W \ \forall i, j$ if $s_i \neq g_j$), implying that a substitution is always decomposable into an elementary deletion and an insertion. This recursive formula of the Levenshtein distance can be achieved by the following (pseudo) computer code.

```
for i = 0 to m
begin
   for j = 0 to n
   begin
      if j = 0 and i = 0 then d(sⁱ,gʲ) = 0
      else if j = 0 and i > 0 then d(sⁱ,gʲ) = W × i
      else if j > 0 and i = 0 then d(sⁱ,gʲ) = W × j
      else
      begin
         Dᵢ = d(sⁱ⁻¹,gʲ) + W
         Iⱼ = d(sⁱ,gʲ⁻¹) + W
         if sᵢ = gⱼ then Qᵢⱼ = 0 else Qᵢⱼ = 2W
         Gᵢⱼ(sⁱ,gʲ) = d(sⁱ⁻¹,gʲ⁻¹) + Qᵢⱼ
         d(sⁱ,gʲ) = min[Dᵢ,Iⱼ,Gᵢⱼ]
      end
   end
end
```

An interesting feature of this Levenshtein distance is that the resulting distance measure always contains the maximum number of identity operations, which are cost-free.

Let F and T be an arbitrary number of cost-Free operations (identity) and an arbitrary number of cost-Taking operations (deletion and insertion) that are used, in sum, for changing sequence s into sequence g of lengths m and n, respectively. Let F^* and T^* respectively be the number of cost-free and cost-taking operations taken by the optimum alignment based on the above formula. Let $d(s,g)$ and $d(s,g)^*$ be the resulting distances from arbitrary and optimum alignments, respectively. Then:

$$(F^*,T^*) \in \{(F,T)\} \tag{3.7}$$

and

$$2F + T = m + n \tag{3.8}$$

and

$$d(s,g) = W \times T \tag{3.9}$$

and

$$d(s,g)^* = W \times T^* \tag{3.10}$$

Equation (3.8) states that, in terms of the number of operations, one identity is equivalent to a set of a deletion and an insertion. Given the definition of the Levenshtein distance:

$$d(s,g)^* \leq d(s,g) \tag{3.11}$$

or
$$W \times T^* \leq W \times T \tag{3.12}$$

or

$$T^* \leq T \qquad \forall\, T \tag{3.13}$$

Hence, by equations (3.7) and (3.8),

$$F^* \geq F \qquad \forall\, F \tag{3.14}$$

Capturing the largest number of cost-free identities results in the preservation of the largest *structural skeleton* consisting of the elements common to both sequences. The common structural skeleton implies not only the same list of elements but also the same order of the elements between the sequences. The measure then computes the amount of effort for deleting and inserting the remaining elements to equalize two sequences. Accordingly, the resulting measure of distance captures the difference between sequences in both terms of element composition and sequential order of the elements. This is the very

property that distinguishes sequence alignment methods from the conventional position-based distance measures.

In classification studies, the Hamming distance measure (Gower, 1971) has been widely used for comparing activity attribute sequences (e.g., Burnett & Hanson, 1982; Koppelman & Pas, 1985). It involves matching the activity attributes of the corresponding positions of the two sequences that are compared and summing the results to calculate the distance. This position-based distance measure does not capture the sequential information embedded in the activity-travel behavior. The difference between the Hamming distance measure and the sequence alignment method is illustrated in the following examples. Note that each activity is represented as an element of the activity sequence.

Example 1: Comparison based on the Hamming distance

pos	1	2	3	4	5	6
g	p_care	breakfast	work	shopping	dinner	sport
	╫	╫	╫	╫	╫	╫
s	breakfast	work	shopping	dinner	h_keeping	p_care

The Hamming distance measure in Example 1 indicates that activity patterns *s* and *g* are completely different because all six activities of corresponding positions differ between the two activity patterns. The sequence alignment method in Example 2 on the other hand regards the two patterns as very similar because most activities are sequenced in a common order. The required changes to equalize *s* with *g* only involve a substitution of h_keeping (housekeeping) with sport and a deletion and an insertion (or a change of the position) of p_care (personal care).

Example 2: Comparison based on the sequence alignment method
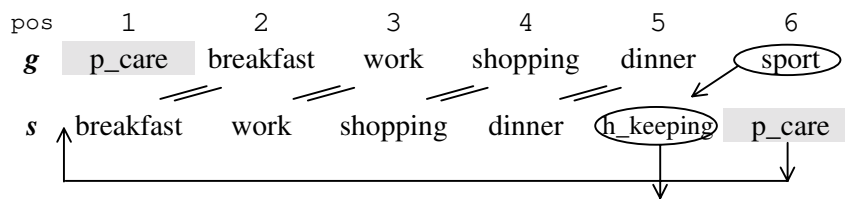
A numerical example can also be given. Consider the following pairs of sequences.

Pair 1
g = [A,B,C,D,E,F]
*s*1 = [D,E,F]

Pair 2
g = [A,B,C,D,E,F]
*s*2 = [D,E,F,G,H,I]

In equation, the Hamming distance is defined as:

$$d(\boldsymbol{s}, \boldsymbol{g}) = \sum_{i}^{Z} d(s_i, g_i) + |m - n| \qquad (3.15)$$

with

$$d(s_i, g_i) = \begin{cases} 0 & \text{if } s_i = g_i \\ 1 & \text{otherwise} \end{cases} \qquad (3.16)$$

$$Z = \min[m, n]. \qquad (3.17)$$

Based on this Hamming distance measure, two pairs give the same result as:

$$d(\boldsymbol{s}1, \boldsymbol{g}) = \sum_{i}^{3} d(s_i, g_i) + |3 - 6| = 6$$

and

$$d(\boldsymbol{s}2, \boldsymbol{g}) = \sum_{i}^{6} d(s_i, g_i) + |6 - 6| = 6.$$

The sequence alignment method, on the other hand, gives different results, $d(\boldsymbol{s}1, \boldsymbol{g}) = 3$, and $d(\boldsymbol{s}2, \boldsymbol{g}) = 6$, as the method inserts three elements from sequence $\boldsymbol{g}$ and deleting three elements from sequence $\boldsymbol{s}2$ in the second pair while simply inserting three elements from sequence $\boldsymbol{g}$ in the first pair. The origin of this difference is evident from the fact that in the first pair the sequence alignment method does not count the costs for deleting D, E and F because the sub-sequence D-E-F is identical in both sequences, and only inserting A, B and C from sequence $\boldsymbol{g}$ into sequence $\boldsymbol{s}1$ is required to change $\boldsymbol{s}1$ into $\boldsymbol{g}$. As such, the sequence alignment method detects the 'similarity' between $\boldsymbol{s}1$ and $\boldsymbol{g}$ compared to the $\boldsymbol{s}2$ and $\boldsymbol{g}$ pair and likewise, recognizes the 'difference' between $\boldsymbol{s}2$ and $\boldsymbol{g}$ compared to the $\boldsymbol{s}1$ and $\boldsymbol{g}$ pair.

These simple examples demonstrate that the sequence alignment method considers two kinds of differences when comparing sequences: the difference in sequential order of the elements, and the difference in element composition. The ability to measure the degree of difference in sequential order is a strong point of the sequence alignment method; conventional position-based distance measures, including Euclidean, Minkowski, Block and Hamming distances (e.g., Gower, 1971; Kruskal, 1983), do not share this property.

3.3 An extension of the alignment method

3.3.1 Problem

In order to capture difference in element composition, the Sequence Alignment Method (SAM) differentiates between 'common elements' and 'unique elements.' *Common elements* are the elements that appear in both sequences, while *unique elements* appear in either the source or the target sequence only. The unique elements are simply deleted from the source sequence and inserted from the target sequence into the source sequence. Common elements are also deleted (or inserted) but then again inserted (respectively deleted) and, as a result, preserved during the alignment. Exceptions are the common elements whose number differs between the sequences that are compared. For example, if the source sequence has four common elements and the target has two of the same element, then two of the four common source elements are regarded as being unique and removed during the alignment. Similarly, when the source sequence has two common elements and the target has three, one of the three common target elements is regarded as being unique and newly inserted. In other words, SAM measures the degree of difference between the two sequences in terms of their element composition by deleting the unique elements from the source sequence and inserting these from the target sequence into the source sequence. At the same time, it measures the degree of difference between the two sequences in terms of the sequential order of the elements by changing the order of the common elements of the source sequence if it differs from that of the common elements of the target.

However, this mechanism implies that the conventional SAM is not sensitive to the distance (number of positions), by which the sequential order of the source elements is changed. Consider the following examples. In both examples, the sequence pairs have sixteen common elements of eight activities and are identical in terms of the element composition. The paired sequences are different only in terms of the sequential order of the elements, and the SAM is now equalizing them by changing the order of a common element, shopping. The resulting distance measure is exactly the same between these two sequence pairs. The fact that in Example 4, shopping occupies position 8 rather than 4 as in Example 3, does not affect the distance measure at all. Thus, $s1$ and $s2$ would be considered equally distant from g. However, this seems counter-intuitive in some application domains such as activity scheduling, where not only the relative positions or order of elements but also the difference between the absolute positions of each element before and after the alignment are of interest. Methodologically, this means that some hybrid form of a Euclidean and a biological distance measure would be desirable in the domain of activity scheduling.

Example 3

pos	1	2	3	4	5	6	7	8
g	p_care	shopping	breakfast	h_keeping	work	sport	dinner	banking
*s*1	p_care	breakfast	h_keeping	shopping	work	sport	dinner	banking

Example 4

pos	1	2	3	4	5	6	7	8
g	p_care	shopping	breakfast	h_keeping	work	sport	dinner	banking
*s*2	p_care	breakfast	h_keeping	work	sport	dinner	banking	shopping

3.3.2 Conceptualization

As a solution to the above problem, we introduce the concepts of reordering and reordering distance. Let us thus first define these concepts.

DEFINITION 1*: Reordering* is the change of the order of a known element of a sequence, which is achieved by consecutive deletion-insertion or insertion-deletion operations on that element. If an element is deleted from (or inserted into) a certain position in a sequence and again inserted (respectively deleted) during the alignments, it is said to be *reordered.*

DEFINITION 2*: Reordering distance* is the number of positions by which a known element of a sequence is reordered. As reordering is related to change in the order of concerned elements, reordering distance can be defined only if there is any reordering.

Note that the reordering concerns only the 'known' elements as the reordering of 'unknown' elements does not make sense. Consequently, the method assumes that when a missing character s_i is to be substituted with a missing character g_j, the substitution operation is applied. In the following, let the value of the reordering distance be denoted by h and measured as $h = |i-j|$, where i and j are the positions of the reordered elements in the source and target sequences, respectively. To operationalize this concept, it is necessary to specify 'when' the reordering is initiated and 'which elements' are reordered in the reordering situation.

When are the reorderings initiated?

The reordering will be initiated if the order of two or more common elements is not identical in the two sequences that are compared. The following diagrams are useful to illustrate this principle, where the common elements of the same letter are connected with lines between two sequences.

When the order of elements differs between two sequences, the lines must cross. Hence, the intersection of the lines of *g*1-*s*1 pair of Example 5 indicates that there are reordering(s), and either A or B is reordered, while the absence of any intersection of *g*2-*s*2 pair of Example 6 indicates no reordering.

Example 5   Example 6
```
    1  2              1  2  3  4  5  6  7
g1  A  B          g2  B  C  D  E  F  G  A

s1  B  A          s2  H  K  J  B  M  A  I
```
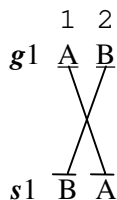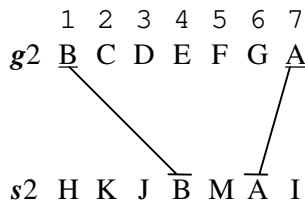
Which elements are reordered?

It is obvious that whether A or B in the $g1$-$s1$ pair of Example 5 is reordered does not affect the result. In both cases, the number of reorderings is 1, and the difference in positions is 1. In general, however, the reordering situation is more complex. Consider the following example.

Example 7
```
    1  2  3  4  5  6  7
g   B  C  D  E  F  G  A

s   H  I  J  K  L  A  B
```
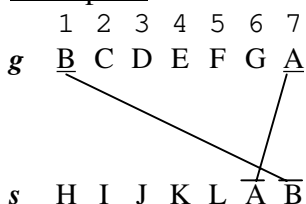
In this example, there are two common elements, B and A. Their relative positions are reversed, thus reordering is required. If A is reordered, B stays non-reordered, and the difference in positions is $h = |6-7| = 1$. However, the difference in positions is $h = |7-1| = 6$ if B is reordered and A stays non-reordered. Thus, depending on which element is reordered, the result may change significantly. We therefore need to develop a principle to cope with this problem of ambiguity.

   A solution may be found by considering the purpose of including the reordering distance effect into the conventional SAM. The underlying principle is that in changing the *order* of elements, we assume that larger differences in *positions* require more effort. In order words, the amount of alignment effort should, ceteris paribus, monotonically increase as the difference in positions increases. The envisioned distance measure should be able to describe such situations, and to this end, we need a rule to decide which elements are to be regarded reordered (and thereby which elements remain non-reordered).

   We will derive a guiding principle for this decision problem from the fundamental characteristics of conventional sequence alignment methods, which indicates that if some common elements are arranged in the same order in the two compared sequences, their arrangement represents the two sequences' structural integrity (McClure, *et al*., 1994) or structural skeleton as mentioned in Section 3.2. In other words, sequence alignment methods try to identify the sequential order of the elements and their positions that are identical between two sequences compared.

This fact appears in Examples 3 and 4. It is clear that 'shopping' has been reordered in both examples, instead of 'breakfast-h_keeping' and 'breakfast-h_keeping-work-sport-dinner-banking'. There are two reasons for this conclusion. First, the sub-sequences, 'breakfast-h_keeping' and 'breakfast-h_keeping-work-sport-dinner-banking', are larger than the sub-sequence, 'shopping'. The sequence alignment method prefers the larger set of elements for the application of identity operation among the common elements to preserve the structural skeleton as large as possible during the alignments. Secondly, the shopping activities in the source sequences are more distant from those in the target sequence, compared to 'breakfast-h_keeping' and 'breakfast-h_keeping-work-sport-dinner-banking'. The sequence alignment method prefers the similar positions for the application of identity operation among the positions of common elements to preserve the structural skeleton's positions as closely as possible during the alignments. Thus, for the case of two sets of common elements, one of which is to be reordered, the set of elements that consists of a smaller sub-sequence and/or involves more change in their positions is regarded as the set of reordered elements. Following this guiding principle, in Example 7, B is regarded reordered, and A remains non-reordered.

Having such a guiding principle, the next question is what would happen if these two criteria were in conflict? We need another guiding principle to cope with this situation. We suggest giving the size of sub-sequence priority over the number of positions to be changed because an alignment method basically emphasizes more the sub-sequences of the same order than the sub-sequence positions. Suppose that we have two common sub-sequences, one of which has to be chosen for reordering. If one has a shorter reordering distance but a smaller sub-sequence, and the other has a longer reordering distance but a larger sub-sequence, the smaller one will then be considered reordered, in spite of its shorter reordering distance.

This principle is illustrated in Example 8. In this example, there are two sets of common elements (B and G-H-I). Their relative positions are reversed. Consequently, reordering is initiated. The sub-sequence G-H-I has a longer reordering distance, but its size is also larger than sub-sequence B. Hence, we consider B to be reordered. Some readers may find this result counter-intuitive. Although we partly incorporate the concept of the changing positions of common elements, we wish to stay close to the principles, underlying the conventional sequence alignment method. Therefore, we argue in favor of the alignment, which prefers preserving the structural skeleton as much as possible. Thus, this discussion leads to the following rules for determining the set of elements to be reordered.

Example 8

```
    1 2 3 4 5 6 7 8 9
g   A B C D E F G H I

s   G H I B J K L M N
```
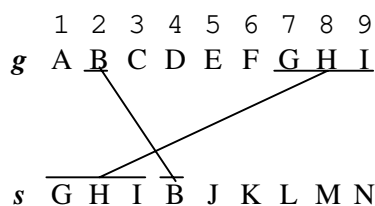
REORDERING RULE 1*: If one of two sets of common elements is to be reordered, and if the number of common elements differs between the two sets, the set with the smaller number of elements will be reordered.*

REORDERING RULE 2*: If one of two sets of common elements is to be reordered, and if the number of common elements in the two sets is the same, the set with the larger reordering distance will be reordered.*

Where to be reordered?

Another problem arises when the common elements are not in a one-to-one relationship between the source and target sequences, and elements may be assigned in a variety of ways. In this case, the position to which a common element is to be reordered is not unique, which is unfortunately often the case in the comparison of actual activity patterns. Consider, for example, the following sequence pair.

Example 9

```
   1  2  3  4  5  6
g  A  B  C  D  E  F



s  A  C  D  B  E  B
```
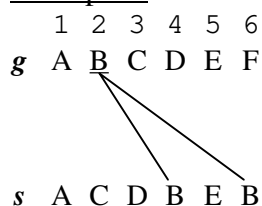
Obviously, A, C-D and E remain non-reordered, while B is to be reordered in this example. However, the position to which the inserted B is to be reordered is not unique. It may be deleted from the 4th or from the 6th position of the source sequence to be inserted to the 2nd position. We therefore need to specify the positions from and/or to which the elements are to be reordered. We propose the following rule for positioning the reordered elements.

POSITIONING RULE: *If common elements that need to be reordered have a one-to-many, many-to-one or many-to-many relationship between source and target sequences, the reordering positions are chosen such that the sum of reordering distances is minimized.*

3.3.3   A position-sensitive method

Finding the set of reordered common elements

Given the reordering rules, the problem then is how to obtain the set of reordered common elements to calculate the reordering distances. By definition, reordered elements are always associated with subsequent deletion-insertion or insertion-deletion operations. Because the

conventional SAM identifies the largest structural skeleton, the set of reordered common elements can be found by tracing the history of deletions and insertions of the common elements in the comparison table of the conventional SAM if there is only one largest set of common elements. The comparison table of Example 8 in Figure 3.2 illustrates this. The figure shows that the SAM detects the largest structural skeleton (G-H-I) and reorders (inserts-deletes) the smaller one (B), following Reordering Rule 1. Note that the identity operation applied to B is outside the optimum trajectory. The optimum trajectory was obtained by back-tracking the recursive equations (3.1) to (3.6) from cell (*m,n*) to (0,0) as follows.

$$d(s^i,g^j) \rightarrow \min\ [d(s^{i-1},g^j)+w_d(s_i,\phi),\ \ d(s^i,g^{j-1})+w_i(\phi,g_j),\ \ d(s^{i-1},g^{j-1})+w(s_i,g_j)] \tag{3.5a}$$

$$d(s^0,g^j) \rightarrow d(s^0,g^{j-1})+w_i(\phi,g_j) \tag{3.4a}$$

$$d(s^i,g^0) \rightarrow d(s^{i-1},g^0)+w_d(s_i,\phi) \tag{3.3a}$$

where, '$\rightarrow$' implies that the predecessor (RHS) was chosen by the successor (LHS).

Unfortunately, however, the conventional SAM does not uniquely determine which set of common elements is to stay non-reordered and which one is to be reordered, if two or more of the largest common element sets of the same size exist. The comparison table of Example 7, for instance, gives both possibilities (Figure 3.3). In the upper trajectory, A stays non-reordered, and B is reordered (inserted-deleted). This situation is reversed in the lower trajectory. The largest number of common elements staying non-reordered is the same in both trajectories (A in the upper one and B in the lower one), and hence, Reordering Rule 2 is to be applied. However, the sizes of two common element sets are the same in this case, and the information of the reordering distance is not available in the conventional SAM's comparison table. Which one of the two sets of common elements is to be reordered is therefore not determined.

```
pos            0      1      2      3      4      5      6      7      8      9
          |  null     A      B      C      D      E      F      G      H      I
---------------------------------------------------------------------------------
0  null|   0.00 <- 1.00   2.00   3.00   4.00   5.00 — 6.00  <- 7.00   8.00   9.00
1     G|   1.00   2.00   3.00   4.00   5.00   6.00   7.00   6.00   7.00   8.00
2     H|   2.00   3.00   4.00   5.00   6.00   7.00   8.00   7.00   6.00   7.00
3     I|   3.00   4.00   5.00   6.00   7.00   8.00   9.00   8.00   7.00   6.00
4     B|   4.00   5.00   4.00   5.00   6.00   7.00   8.00   9.00   8.00   7.00
5     J|   5.00   6.00   5.00   6.00   7.00   8.00   9.00  10.00   9.00   8.00
6     K|   6.00   7.00   6.00   7.00   8.00   9.00  10.00  11.00  10.00   9.00
7     L|   7.00   8.00   7.00   8.00   9.00  10.00  11.00  12.00  11.00  10.00
8     M|   8.00   9.00   8.00   9.00  10.00  11.00  12.00  13.00  12.00  11.00
9     N|   9.00  10.00   9.00  10.00  11.00  12.00  13.00  14.00  13.00  12.00
```

Figure 3.2: Conventional SAM's comparison table of sequences *g*=[ABCDEFGHI] and *s*=[GHIBJKLMN] of Example 8.

Note: Identities are applied to the cells of underlined numbers, while deletion-insertions or insertion-deletions are applied to the cells of bold-italic numbers. The bold line denotes the optimum trajectory of the alignments. The operation weights are assigned as $w_d = w_i = 1$, $w_s = w_d+w_i$, and $w_e = 0$.

```
pos              0      1      2      3      4      5      6      7
        |      null     B      C      D      E      F      G      A
     ---------------------------------------------------------------------
     0 null|   0.00 ← 1.00 — 2.00 — 3.00 — 4.00 — 5.00 — 6.00    7.00
     1   H|   1.00    2.00   3.00   4.00   5.00   6.00   7.00    8.00
     2   I|   2.00    3.00   4.00   5.00   6.00   7.00   8.00    9.00
     3   J|   3.00    4.00   5.00   6.00   7.00   8.00   9.00   10.00
     4   K|   4.00    5.00   6.00   7.00   8.00   9.00  10.00   11.00
     5   L|   5.00    6.00   7.00   8.00   9.00  10.00  11.00 ← 12.00
     6   A|   6.00    7.00   8.00   9.00  10.00  11.00  12.00   11.00
     7   B|   7.00 ↖  6.00 ← 7.00 — 8.00 — 9.00 — 10.00 — 11.00 — 12.00
```

Figure 3.3: Conventional SAM's comparison table of sequences g=[BCDEFGA] and s=[HIJKLAB] of Example 7.

Note: The operation weights are assigned as $w_d = w_i = 1$, $w_s = w_d + w_i$, and $w_e = 0$.

The problem here is that many optimal trajectories for any sequence pair prevent us from finding a fast solution. When computer time is not a concern, this might not be a real problem. When we use the distance measure as we intend to do in real time, however, the combinatorial problem presents a problem.

To solve this problem, we suggest modifying the identity weight in the conventional SAM to identify common parts and also to differentiate their reordering distances. Because the identity operation is always applied to any pair of identical elements as in the conventional SAM, the largest set of common elements can be detected, and Reordering Rule 1, if applicable, can be applied. At the same time, as the modified identity weight detects the longer reordering distance between sets of common elements, Reordering Rule 2, if applicable, can be applied. We shall call a SAM, based on a modified identity (*equality*) weight, the *e*SAM. The relevant modified equations for the *e*SAM are:

$$d(s, g) = d(s^m, g^n) \tag{3.18}$$

$$d(s^0, g^0) = 0 \tag{3.19}$$

$$d(s^i, g^0) = d(s^{i-1}, g^0) + w_d \tag{3.20}$$

$$d(s^0, g^j) = d(s^0, g^{j-1}) + w_i \tag{3.21}$$

$$d(s^i, g^j) = \min[d(s^{i-1}, g^j) + w_d, d(s^i, g^{j-1}) + w_i, d(s^{i-1}, g^{j-1}) + w(s_i, g_j)] \tag{3.22}$$

with

$$w(s_i, g_j) = \begin{cases} w_{e'}(s_i, g_j) = \dfrac{w_o}{\max[m, n]^2} \cdot v & \text{if} \quad s_i = g_j \\ w_s(s_i, g_j) = w_d + w_i & \text{otherwise} \end{cases} \tag{3.23}$$

where,

$i,j \geq 1$;

$w_d = w_i = w_o > 0$;

$w_{e'}$ is the modified identity weight;

$v = |i{-}j|$ ($v \leq \max[m{-}1,n{-}1]$).

The v in equation (3.23) depicts position differences, and is a measure of the amount of difference in a common element's positions between the source and target sequences. The position difference v is the same as the reordering distance h. We nevertheless give it a name, and use a different notation to make explicit the fact that it is used to find the common element set. The modified identity weight $w_{e'}$ reflects the amount of difference in a common element's source and target positions that are paired during the alignments. The $w_{e'}$ is, however, doubly (but linearly) restricted so that:

(i) any of the position differences is smaller than a single deletion or insertion weight

$$(\frac{v}{\max[m,n]} \cdot w_o < w_o = w_d = w_i), \text{ and}$$

(ii) any sum of the modified identity weights is smaller than a single deletion or insertion

weight ($\sum_{z}^{Z} \frac{v_z}{\max[m,n]^2} w_o < w_o = w_d = w_i$; where Z ($Z \leq \min[m,n]$) is the total number

of modified identities along an alignment trajectory).

Like other dynamic programming algorithms, the eSAM returns the optimum value. It applies the $w_{e'}$ to the paired source and target positions of each common element, and finds the *largest* set of common elements (Reordering Rule 1) of the *minimum* sum of position differences (Reordering Rule 2). As a result, the set of common elements to be reordered is determined, which is the smaller sets of common elements deleted-inserted and/or inserted-deleted along the eSAM's alignment trajectory. Figure 3.4 presents an example of the eSAM, which fixes the problem that appeared in Figure 3.3. (The backtracking method stays the same as before).

```
pos             0       1       2       3       4       5       6       7
        |     null      B       C       D       E       F       G       A
        -------------------------------------------------------------------
0 null|     0.00    1.00    2.00    3.00    4.00    5.00    6.00    7.00
1    H|     1.00    2.00    3.00    4.00    5.00    6.00    7.00    8.00
2    I|     2.00    3.00    4.00    5.00    6.00    7.00    8.00    9.00
3    J|     3.00    4.00    5.00    6.00    7.00    8.00    9.00   10.00
4    K|     4.00    5.00    6.00    7.00    8.00    9.00   10.00   11.00
5    L|     5.00    6.00    7.00    8.00    9.00   10.00   11.00   12.00
6    A|     6.00    7.00    8.00    9.00   10.00   11.00   12.00   11.02
7    B|     7.00    6.12    7.12    8.12    9.12   10.12   11.12   12.02
```

Figure 3.4: eSAM's comparison table of g=[BCDEFGA] and s=[HIJKLAB] of Example 7.
Note: A is staying non-reordered, while B is reordered. The bold line is chosen by the eSAM. The operation

weights are assigned as $w_d = w_i = w_o = 1$, $w_s = w_d{+}w_i$, and $w_{e'} = \dfrac{w_o}{\max[m,n]^2} \cdot v$.

There may, of course, be two or more optimal trajectories of the same reordering distance for *e*SAM as well. Compared to the conventional SAM, however, the number of trajectories is fairly small. Thus, we will use this property for determining the set of reordered elements.

Once the set of common reordered elements is identified, their reordering distances can be calculated. The final solution, representing the overall costs in the equalization process, can then be found by combining the costs for deleting and inserting the unique elements and reordering the common elements. This principle is further elaborated in the next section.

A method for calculating the costs of a position-sensitive SAM

We propose to measure the position-sensitive distance between activity sequences by using the costs provided by the conventional SAM (*c*SAM) and the set of reordered elements identified by the *e*SAM. In particular, we propose the following equations for calculating the position-sensitive SAM (*p*SAM) costs.

$$d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}} = \min[d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}_1}, \; ..., \; d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}_k}, \; ..., \; d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}_K}] \tag{3.24}$$

with

$$d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}_k} = (w_d D + w_i I) + (w_d L + w_i L) + \eta \sum_{l}^{L} h_l - (w_d L + w_i L) \tag{3.25}$$

or

$$d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}_k} = d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{CS}} + \eta \sum_{l}^{L} h_l - (w_d L + w_i L) \tag{3.26}$$

where,

$d(\boldsymbol{s}, \boldsymbol{g})_{\mathrm{PS}_k}$ is the *p*SAM costs derived from the *e*SAM's k^{th} optimal trajectory;
$d(\boldsymbol{s},\boldsymbol{g})_{\mathrm{CS}}$ is the costs measured by the *c*SAM ($w_d = w_i > 0$, and $w_s = w_d + w_i$.);
D and *I* are the number of deleted, respectively inserted unique elements;
L is the number of reordered elements (the number of pairs of deletion-insertion and insertion-deletion, each applied to the same element; $L \leq \min[m-1, n-1]$);
h_l is the distance of reordering the lth common element ($h_l \geq 0$);
η is the reordering weight, a positive constant determined by the researcher ($\eta \geq 0$).

Equations (3.25) and (3.26) imply first that the costs calculated by the *c*SAM consist of the costs for deleting and inserting unique elements and the costs for deleting-inserting and inserting-deleting common elements that need to be reordered. That is, $d(\boldsymbol{s},\boldsymbol{g})_{\mathrm{CS}} = (w_d D + w_i I) + (w_d L + w_i L)$. Secondly, the *p*SAM cost calculation does *not* regard the sum of weights of deletions and insertions, $w_d L + w_i L$, but the sum of weights of reorderings, each

multiplied by the reordering distance, $\sum^{L}(\eta \cdot h_l)$, as the costs for reordering common elements. Hence, the equations subtract the costs for deleting and inserting L common elements that have been unnecessarily added to the cSAM costs and, at the same time, add the costs for reordering them. Hence, $d(\boldsymbol{s},\boldsymbol{g})_{CS} - (w_dL+w_iL) + \eta\sum^{L}h_l$. The sequence pair in Example 6, for instance, involves 5 deletions and 5 insertions of unique elements, 1 reordering of a common element, and 1 identity of another common element. Consequently, the costs calculated by the cSAM is:

$$d(\boldsymbol{s},\boldsymbol{g})_{CS} = (w_dD+w_iI) + (w_dL+w_iL) = (1\times5+1\times5) + (1\times1+1\times1) = 12.$$

Figure 3.4 shows that there is only one optimal trajectory for the eSAM, which implies that A stays non-reordered and B is reordered. Assuming $\eta = 1$, the cost for reordering B is:

$$\eta\sum^{L}h_l = \sum^{1}h_l = |7-1| = 6.$$

The costs for inserting and deleting B, w_dL+w_iL, have unnecessarily been added to $d(\boldsymbol{s},\boldsymbol{g})_{CS}$. Thus, we subtract them from $d(\boldsymbol{s},\boldsymbol{g})_{CS}$:

$$d(\boldsymbol{s},\boldsymbol{g})_{CS} - (w_dL+w_iL) = 12 - (1\times1+1\times1).$$

Finally, we obtain the overall cost as:

$$d(\boldsymbol{s},\boldsymbol{g})_{PS} = d(\boldsymbol{s},\boldsymbol{g})_{PS_1} = d(\boldsymbol{s},\boldsymbol{g})_{CS} +\eta\sum^{L}h_l - (w_dL + w_iL) = 12 + 6 - 2 = 16.$$

A further specification

An operational problem with the term $\eta\sum^{L}h_l$ in equation (3.26) arises when the position to which a common element is to be reordered is not unique due to the off-one-to-one relationship between the source and target sequences. We continue our discussion using the sequence pair of Example 9, which is illustrated in Figure 3.5 using the eSAM's comparison table.

Confronting this situation, the positioning rule proposed in Section 3.3.2 implies that equation (3.26) needs to be modified as follows:

$$d(\boldsymbol{s},\boldsymbol{g})_{PS_k} = d(\boldsymbol{s},\boldsymbol{g})_{CS} +\eta\sum^{L}h_l^{*} - (w_dL + w_iL) \qquad (3.27)$$

```
pos          0      1      2      3      4      5      6
       |   null     A      B      C      D      E      F
----------------------------------------------------------------
0 null |   0.00    1.00   2.00   3.00   4.00   5.00   6.00
1    A |   1.00    0.00   1.00   2.00   3.00   4.00   5.00
2    C |   2.00    1.00   2.00   1.03   2.03   3.03   4.03
3    D |   3.00    2.00   3.00   2.03   1.06   2.06   3.06
4    B |   4.00    3.00   2.06   3.03   2.06   3.06   4.06
5    E |   5.00    4.00   3.06   4.03   3.06   2.06   3.06
6    B |   6.00    5.00   4.06   5.03   4.06   3.06   4.06
```

Figure 3.5: *e*SAM's comparison table of *g*=[ABCDEF] and *s*=[ACDBEB] of Example 9.

Note: The operation weights are assigned as $w_d = w_i = w_o = 1$, $w_s = w_d + w_i$, and $w_{e'} = \dfrac{w_o}{\max[m,n]^2} \cdot v$.

where, $\eta \sum\limits^{L} h_l^*$ is the reordering cost of the minimum sum of reordering distances among $\eta \sum\limits^{L} h_l$'s.[1]

Equation (3.27) based on Positioning Rule provides the general solution to every comparison case. To illustrate, consider the sequence pair of Example 9, which involves 1 deletion and 1 insertion of unique elements, 1 reordering of a common element, and 4 identities of other common elements. Hence, the *c*SAM cost is:

$$d(s,g)_{CS} = (w_d D + w_i I) + (w_d L + w_i L) = (1 \times 1 + 1 \times 1) + (1 \times 1 + 1 \times 1) = 4.$$

Assuming $\eta = 1$, we obtain the cost for reordering B as:

$$\eta \sum\limits^{L} h_l^* = \min\left[\eta \sum\limits^{L} h_l \right] = \min[|4-2|,|6-2|] = 2.$$

The costs for inserting and deleting B have unnecessarily been added to $d(s,g)_{CS}$. Thus, we subtract it from $d(s,g)_{CS}$, giving:

$$d(s,g)_{CS} - (w_d L + w_i L) = 4 - (1 \times 1 + 1 \times 1).$$

Finally, the overall cost of the single optimal trajectory is:

$$d(s,g)_{PS} = d(s,g)_{PS_1} = d(s,g)_{CS} + \eta \sum\limits^{L} h_l^* - (w_d L + w_i L) = 4 + 2 - 2 = 4.$$

---

[1] We describe a method in Appendix 3.1 to obtain $\sum h_l^*$ for any comparison case, and its appropriateness in Appendix 3.2.

A measure of the relevance of the proposed method

To check the relevance of the proposed method of measuring the position-sensitive sequential difference on the basis of the sequence alignment method, we suggest employing correlation analysis, as it measures the degree of linearity of the relation between the concerned measures, regardless of the overall scale of their values. Before providing the results of such an analysis in Section 3.4.2, we will first theoretically explore the behavior of the correlation coefficient.

Given $w_d = w_i = w_o = 1$, and $w_s = w_d + w_i$, let $\boldsymbol{D}(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}}$ and $\boldsymbol{D}(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}}$ respectively be the vectors of the pSAM and cSAM costs, and N be the number of comparisons. Pearson's correlation coefficient for our analysis then is defined as follows.

$$r = \frac{\text{cov}(\boldsymbol{D}(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}}, \boldsymbol{D}(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}})}{\sqrt{\text{var}(\boldsymbol{D}(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}})}\sqrt{\text{var}(\boldsymbol{D}(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}})}} \tag{3.28}$$

or

$$r = \frac{\sum_a \left(d(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}a} - \frac{1}{N}\sum_a d(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}a} \right)\left(d(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}a} - \frac{1}{N}\sum_a d(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}a} \right)}{\sqrt{\sum_a \left(d(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}a} - \frac{1}{N}\sum_a d(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}a} \right)^2}\sqrt{\sum_a \left(d(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}a} - \frac{1}{N}\sum_a d(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}a} \right)^2}} \tag{3.29}$$

where:

$$d(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}a} - \frac{1}{N}\sum_a d(\boldsymbol{s}, \boldsymbol{g})_{\text{PS}a} = \eta\left(\left(\sum_l^{L_a} h_l^* \right)_a - \frac{1}{N}\sum_a \left(\sum_l^{L_a} h_l^* \right)_a \right)$$

$$+ w_o\left((D+I)_a - \frac{1}{N}\sum_a (D+I)_a \right);$$

$$d(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}a} - \frac{1}{N}\sum_a d(\boldsymbol{s}, \boldsymbol{g})_{\text{CS}a} = 2w_o\left(L_a - \frac{1}{N}\sum_a L_a \right)$$

$$+ w_o\left((D+I)_a - \frac{1}{N}\sum_a (D+I)_a \right);$$

$$a = 1, \ldots, N.$$

Let $X_a = \left(\sum_l^{L_a} h_l^* \right)_a - \frac{1}{N} \sum_a \left(\sum_l^{L_a} h_l^* \right)_a$, $Y_a = L_a - \frac{1}{N} \sum_a L_a$ and $Z_a = (D+I)_a - \frac{1}{N} \sum_a (D+I)_a$,

for convenience. Then, equation (3.29) can be rewritten as:

$$r = \frac{\sum_a (\eta X_a + w_o Z_a)(2 w_o Y_a + w_o Z_a)}{\sqrt{\sum_a (\eta X_a + w_o Z_a)^2} \sqrt{\sum_a (2 w_o Y_a + w_o Z_a)^2}} \tag{3.30}$$

where,

X_a represents the deviation of the sum of reordering distances of the ath sequence pair's comparison from the average across N comparisons;
Y_a represents the deviation of the number of reorderings of the ath sequence pair's comparison from the average across N comparisons;
Z_a represents the deviation of the number of deletions and insertions of the ath sequence pair's comparison from the average across N comparisons.

      The reordering weight η may significantly affect the size of r. Although an appropriate size of η is to be determined by the researcher, we need to delimit the maximum and minimum sizes of η that are reasonable regarding the context of the application. The minimum reordering weight can be set as $\eta = 0$, assuming that reordering an element by any distance does not require an alignment effort at all (A negative reordering weight is surely nonsense. All elements in the sequence would be reordered endlessly to reduce the alignment costs.). The maximum η may be set to $2w_o$ ($= w_d + w_i$), reflecting the notion that the amount of effort of reordering an element by one position cannot exceed the effort of deleting and inserting the element. With $\eta > 2w_o$, the common elements would be better deleted and inserted rather than reordered. In practice, the reordering weight may therefore be determined somewhere in between.

      Additionally, it is to note that the correlation coefficient r is constant regardless of the size of reordering weight η when all Z_a's are zero. In other words, when activity sequences of each pair of the data have the same set of elements, and hence, there are no deletions and insertions of unique elements, the size of reordering weight does not affect the correlation. In such cases, the correlation is even not defined if the reordering weight is zero, which is evident from equations (3.25) and (3.30).

3.4   Illustration

The illustration in this section provides two analyses of activity sequences focusing on the original sequence alignment method and the extended method, respectively. The analysis using the original method will highlight the fundamental characteristics of the method as

developed in biology, whereas the analysis using the extended method will present a possible way of modification and use of this imported method for the activity-scheduling problem.

3.4.1 An analysis of sequences using the original sequence alignment method

A set of store sequences data is available. A store choice sequence is an array of stores that an individual visited for shopping, given a period of time. The data is a special case of a more general activity-travel pattern, which collected only the attribute of shopping destinations over time in sequence. A limited number of store names, denoted by pre-defined nominal codes, repeatedly appear in the order that the individual visited. All sequences convey the information of single alphabet or single attribute, but the order of stores visited and the number of visitations differ between the sequences. The data structure is simple, but the sequential information embedded in these data will provide the alignment method with the basis for clearly illustrating the general characteristics of activity patterns.

Data

Scanner panel data provided by A.C. Nielsen Inc. is used for analysis. The data consists of grocery shopping trips made by households for a period of three years (1986 through 1988) in Springfield, Missouri, USA. Data are available for all shopping trips made by 945 households to five different store chains. On average customers made, in a total of 169661 shopping trips, 179.5 shopping trips with the minimum of 49 and maximum of 909 (std. = 87.5). As it appears, shopping behavior is characterized by a considerable amount of store switching, while few households are completely store loyal. Store chain A consists of a larger number of medium sized stores that have a combined market share of 40%, chains B and D consist of a small number of larger stores with market shares of 23% and 18%, respectively. Chain C consists of a few smaller sized stores with a share of 12%, while chain E is an independent store with a market share of 7%.

Analysis scheme

It will be illustrated whether the alignment method as developed in molecular biology that is applied to the measuring of shoppers' purchase sequences actually results in different segments, compared to the results based on conventional position-based distance measures. To this end, this section compares the two measures in terms of (1) the set of pairwise distances, (2) the cluster membership and (3) the set of influential properties distinguishing between segments.

First, different sets of pairwise distances would lead to different segmentation results. The cluster analysis however concerns only the relative pairwise distances between objects, but not the overall scale of the distances. Hence, the correlation between the two measures was analyzed, as the correlation coefficient is scale-irrelevant. The pairwise distances

between 945 shoppers' purchase histories were calculated by a position-based distance measure (Hamming distance) and the alignment method (SAM), respectively.

Secondly, a direct way of illustrating the difference in segment solution between approaches is to compute the degree of matching in the cluster membership. This section compared the individual purchase sequences' segment memberships between the two measures by examining a (pseudo) confusion matrix. The pairwise distance matrices, obtained by the Hamming distance and the SAM, were respectively input to a cluster analysis as the proximity matrices. The individual purchase sequences' segment memberships based on the SAM were then compared with Hamming memberships.

Thirdly, different segment solutions from the same data set reflect different sets of data properties. As seen in the previous section, conventional position-based distance measures concern only the information of corresponding elements, while the SAM concerns the sequential information as well. We identified, for each measure, which purchase properties play an important role in distinguishing among segments, in particular whether the SAM's segments reflect the sequential properties. To this end, this section defined relevant dimensions associated with cross-sectional and sequential properties of the shoppers' purchase sequences, respectively. A stepwise discriminant analysis then identified the influential purchase properties important to the discriminating of the segments.

Results

Pairwise distances: For calculating the distances between shoppers' purchase sequences, the empirical analysis used alphabetic letters, A, B, C, D and E, to distinguish among five different grocery store chains that the shoppers visited for shopping. Consequently, the sequence of a shopper h's purchase history is represented as:

$$\boldsymbol{s}_h = [s_{0_h}, ..., s_{i_h}, ..., s_{m_h}] \tag{3.31}$$

where,

s_{i_h} is shopper h's i^{th} visited store chain ($s_{i_h} \in \{A, B, C, D, E\}$);
m_h is the overall shopping frequency of shopper h.

The comparisons of the 945 shoppers' purchase sequences yielded 446040 pairwise distances. The statistics about the resultant pairwise distances calculated by the two measures are shown in Table 3.1. The analysis of the correlation between the two measures returned Pearson's correlation coefficient of 0.853. This result indicates that although the two measures are highly correlated, the correlation is not perfect.

Table 3.1: Pairwise distances by two measures

	Mean	STD	Min	Max	skewness	kurtosis
Hamming	188.77	93.88	2	901	1.93	7.82
SAM	221.36	104.36	2	1164	1.23	3.16

We observed in the previous section that unlike the conventional position-based distance measure, the SAM uses the information of the elements in the longer part of the longer sequence for the comparison of two sequences, instead of simply ignoring it. We again use the following example.

Pair 1
g = [A,B,C,D,E,F]
$s1$ = [D,E,F]

Unlike the position-based distance measure that compares the first three positions between the two strings and ignores the three elements of the longer part of g, the SAM uses the longer part information and matches it between the strings, which results in the different distances between the measures. This implies that the alignment method is less affected by the length and is more sensitive to the structural properties of information arrangement of the strings.

Accordingly, we additionally examined whether the longer part information used by the SAM significantly affects the pairwise comparison results in general. To this end, the correlation between pairwise distance and difference in sequence length was computed for each measure. If the distance is strongly related to the difference in the length between sequences, this would imply that the sequential information embedded in the longer part is virtually ignored, and the measure takes only the number of elements in the longer part into account in determining the distance. Because the pairwise distance is primarily affected by the sum of the two sequences' lengths, however, we normalized the distance and length gap by dividing them by the sum of sequence lengths, respectively.

Pearson's correlation coefficients are 0.826 and 0.194 for the Hamming distance and the SAM, respectively. The very small coefficient of 0.194 of the SAM indicates that the SAM is much less affected by the difference in sequence length compared to the Hamming distance, while indeed making use of the longer part's sequential information. Based on these observations, we expect that the SAM's pairwise comparison results provide a substantial amount of variation compared to the conventional measure's results that lacks the sequential information, which will in turn affect the results of the shopper segmentation.

Segment membership: From the wide variety of available clustering algorithms (Punji & Stewart, 1983; Wedel & Kamakura, 2000), the non-overlapping hierarchical Ward's clustering algorithm was used to derive segments. The resulting dendrograms provide a clear difference in the hierarchical structure of the solution between the two measures. To study the difference in detail, we examined the proportion of the matching of the segment membership between the two measures in a (pseudo) confusion matrix for each segment solution. Note that a segment label that particular cases belong to is arbitrary. In other words, segment 1 based on one distance measure may be labeled as, for example, segment 2 of the other measure. We therefore calculated the matching proportion by enumerating all possible segment label combinations of a measure, matching each of them to the other measure's segment label combination and finding the highest matching proportion. Given the number of clusters to compute the matching proportion between the measures, the number of segment label combinations to compute is defined as the factorial of the number of clusters.

Table 3.2: Matching proportions of the segment membership between Hamming and SAM

segment solution*	matching proportion %	segment solution*	matching proportion %
2	72.3	6	57.6
3	43.7	7	60.4
4	44.2	8	49.0
5	52.5		

Note: '*' denotes the number of segments of the solution.

The matching proportion P of a segment solution following such a procedure was therefore computed as:

$$P = \frac{\max_{k \in \{1,\ldots,NC!\}} [MC_k]}{TC} \qquad (3.32)$$

where,

TC is the total number of cases (purchase sequences);

NC is the number of clusters;

MC_k is the number of cases that belong to the same segments between the two measures, counted for the kth segment label combination between the two measures.

As Table 3.2 shows, the matching proportions range from 43.7 to 72.3%, which indicate significant differences in segments between the measures.

Influential purchase properties: A critical test of the alignment method is whether it has the property, unlike the conventional position-based distance measures, to handle not only cross-sectional but also sequential information embedded in the activity sequences. We expect that the variables representing sequential characteristics of the strings distinguish segments better for the SAM than for a conventional position-based distance measure. To test this, relevant dimensions associated with cross-sectional and sequential properties of the shoppers' purchase sequences were defined as follows.

- Variables for cross-sectional dimension: n_A, n_B, n_C, n_D and n_E are a shopper's shopping frequency for store chains A, B, C, D and E, respectively, and *Leng* is a shopper's shopping frequency for all store chains (i.e., sequence length).

- Variables for sequential dimension: A, B, C, D and E are for a shopper, the number of changes from store chains A, B, C, D and E to other chains, respectively, and *Vseek* is for a shopper, the total number of store chain changes that is defined as:

$$\underline{Vseek}_h = \sum_{i_h=2}^{m_h} V_{i_h} \qquad (3.33)$$

with

$$V_{i_h} = \begin{cases} 0 & \text{if } s_{i_h} = s_{i-1_h} \\ 1 & \text{otherwise} \end{cases} \tag{3.34}$$

where, $\underline{Vseek_h}$ is the total number of shopper h's store chain changes, whereas s_{i_h} and m_h are defined as in equation (3.31).

Given the set of explanatory variables, a stepwise discriminant analysis was used to find the variables important to discriminating among segments. The sequential dimension is particularly relevant to the illustration, as the store-chain changing behavior well represents the sequential characteristics of activity behavior. Note that the sequence length is the sum of the shopping frequencies for individual store chains visited. Likewise, the total number of store chain changes is the sum of individual store chain changes. The discriminant analysis after all filters out redundant variables through the stepwise processes.

In addition, we will also test whether the solutions differ significantly from a random segmentation and which distance measure leads to the better solution. Arnold (1979) mentioned that the objective of cluster analysis (at least a partitioning technique) is to minimize the within-group variance and maximize the between-group variance and suggested a measure, $C = \log(\max |\mathbf{T}|/|\mathbf{W}|)$, where $\mathbf{T}$ is the total sum of variances, and $\mathbf{W}$ is the sum of within-group variances. The only numeric information about the sequences at hand is however the distances between the purchase sequences, and we cannot compute the variance of the sequences without having the sequences' numeric values that are not defined. Hence, any direct test of statistical significance of the segment solution seems not feasible. Instead, discriminant analysis provides information about how well the shoppers' purchase sequences are segmented in terms of the defined dimensions, as denoted by "% correctly classified cases". We shall use this information as a surrogate of segment homogeneity.

Having explained this, we state the following hypotheses to test the relevance of the biological alignment method to our activity pattern study.

Hypothesis 1: The sequential characteristics of activity sequences (purchase sequences in this illustration) will be better represented for the alignment method than for the conventional position-based distance measure in the resulting segmentations.

Hypothesis 2: The overall segment homogeneity will be better achieved by the alignment method than by the conventional position-based distance measure in the resulting segmentations.

Table 3.3: Statistics about the variables included in the discriminant analysis

	n_A	n_B	n_C	n_D	n_E	*Leng*	*A*	*B*	*C*	*D*	*E*	*Vseek*
Mean	70.4	41.8	22.3	31.8	13.0	179.5	29.9	19.9	13.8	18.0	8.3	90.1
STD	60.6	61.7	39.8	39.8	28.6	87.5	22.8	23.1	21.0	18.5	15.1	66.5

Note: n_A=number of visits to store chain A, *A*=number of changes from store chain A to others.

Table 3.4: Correlation between the variables characterizing the purchase sequence

	n_A	n_B	n_C	n_D	n_E	*Leng*	*Vseek*
n_B	-.127						
n_C	*-.040*	*-.011*					
n_D	-.187	-.149	-.108				
n_E	-.135	*-.081*	*.005*	*.044*			
Leng	.456	.518	.372	.185	.199		
Vseek	.209	.348	.452	.207	.277	.781	
VseekR	-.094	*.035*	.265	.108	.212	.199	.697

Note: Italic figures denote that the correlation is not significant at $\alpha = 0.01$ level. The *VseekR*, representing variety-seeking tendency (=*Vseek*/*Leng*), is included in this table to see its correlation with cross-sectional variables, but not included in the discriminant analysis.

Tables 3.3 and 3.4 respectively provide the statistics about the variables included in the discriminant analysis and the correlation between them measured on 945 sequences. Table 3.4 shows that, except for some correlations involving sequence length, correlations are low. For checking the unbiased discriminant power concerned with hypothesis 2, we randomly divided the set of 945 sequences into analysis and holdout sets of size 630 (66.6 %) and 315 (33.3 %), respectively.

The results of the analysis are given in Table 3.5. The stepwise method entered at each step the variable that minimizes the overall Wilks' Lambda. The minimum partial *F* to enter was set to 3.84 and the maximum partial *F* to remove to 2.71. Table 3.5 shows that the sets of important dimensions listed by the stepwise discrminant analysis procedure are to a large extent the same between the segment solutions for each measure. The table further demonstrates that the Hamming segments were distinguished by cross-sectional dimensions (primarily by the sequence length indicating the shopping frequency in general and mostly by shopping frequency for each store chain) and by only few sequential dimensions (changes from store chain B). On the other hand, the segments based on the SAM were distinguished by both cross-sectional and sequential dimensions. Note that the variable '*Vseek*' reflecting the overall variety-seeking level of a shopper was included in the four-clusters solution of the SAM's segments, but included in *none* of the Hamming solutions.

This finding is consistent with the correlation analysis where the Hamming distance measure was strongly correlated with the difference in sequence length between sequences, whereas the SAM has low correlations. In addition, the '% correctly classified cases' shows that across segment solutions, the SAM led to better segment solutions than the Hamming solutions. The holdout set does not show any big downfall of the correct classification ratio compared with the analysis set, implying that the analysis set is not biased. In words, the variable '*Leng*' is the most influential determinant of the Hamming segments across solutions, while many other variables including the sequential variables are characterizing the SAM's segments in combination with the '*Leng*'.

We further studied the characteristics of each segment by testing the canonical discriminant functions on the analysis set of sequences. As the sets of important dimensions are largely the same between the solutions for each measure, the four-segment solution was arbitrarily chosen for the illustration for both the Hamming distance and the SAM, and the results are shown in Table 3.6.

Table 3.5: Stepwise discriminant analysis on several segment solutions

#	Hamming solution			SAM solution		
	Variables included in the stepwise analysis	$\%_1$	$\%_2$	Variables included in the stepwise analysis	$\%_1$	$\%_2$
2	$Leng, n_B, n_C, \cancel{B}$	88.3	89.2	$Leng, n_A, n_B, \cancel{B}, \cancel{C}$	94.3	94.3
3	$Leng, n_B, n_C, \cancel{B}$	88.6	86.7	$Leng, n_A, n_B, n_C, \cancel{B}, \cancel{C}, \cancel{D}$	91.9	88.6
4	$Leng, n_B, n_C, n_D, \cancel{B}$	87.6	90.5	$Leng, n_A, n_B, n_D, \cancel{B}, \cancel{C}, \cancel{D}, \underline{Vseek}$	89.7	89.8
5	$Leng, n_A, n_B, n_C, \cancel{B}$	85.1	87.9	$n_A, n_B, n_C, n_D, n_E, \cancel{A}, \cancel{B}, \cancel{C}, \cancel{D}$	89.4	87.6
6	$Leng, n_A, n_B, n_C, \cancel{B}$	83.7	86.0	$n_A, n_B, n_D, n_C, n_E, \cancel{A}, \cancel{B}, \cancel{C}, \cancel{D}$	86.0	85.1
7	$Leng, n_A, n_B, n_C, \cancel{B}$	83.0	83.5	$n_A, n_B, n_C, n_D, n_E, \cancel{A}, \cancel{B}, \cancel{C}, \cancel{D}$	83.2	83.8
8	$Leng, n_A, n_B, n_C, \cancel{B}$	83.2	82.9	$n_A, n_B, n_C, n_D, n_E, \cancel{A}, \cancel{B}, \cancel{C}, \cancel{D}$	83.5	79.7

Note: '#' means the number of segments of the solution, '$\%_1$' percent correctly classified cases of analysis set and '$\%_2$' percent correctly classified cases of holdout set.

First, the canonical discriminant function eigenvalue that represents the discriminant function's power of explaining the amount of difference between segments, demonstrates that only function 1 appears to be significant in the Hamming segmentation, while all three functions are significant in the SAM's segmentation.

Secondly, the standardized canonical discriminant function coefficient that represents the relative importance of each variable in each discriminant function, shows that for the Hamming segmentation function 1 is associated with longer sequence length, function 2 with higher frequency for store chain B and shorter sequence length, and function 3 with higher frequency for store chain C. In case of the SAM's segmentation, on the other hand, a more diverse set of variables is used for characterizing each function. Function 1 is associated with higher frequency for store chains B, A and D, shorter sequence length, and more changes from store chains B and C. Function 2 is associated with higher frequency for store chains A and D, shorter sequence length, more changes from store chain C, and less variety-seeking behavior in general. Function 3 is associated with lower frequency for store chain D, higher frequency for store chain A, and more changes from store chain D.

Finally, the segment centroids of discriminant functions that represent the characteristics of the segments (each segment's mean discriminant score for each function) indicate for the Hamming segmentation that the shoppers with the longest purchase histories constitute segment 4, those of smallest frequency for store chains constitute segment 2, and those in the middle represent segments 1 and 3. Note that in the case of Hamming segmentation, function 1 was the only significant discriminant function identified by canonical eigenvalues, and sequence length was the only variable having a recognizable importance in function 1. SAM's segmentation, however, involves more diverse distinguishable characteristics, as the SAM's discriminant functions were all found significant. The shoppers of segment 1 shop less frequently at store chains A, B and D, and more often in general. They also show more variety-seeking behavior. Shopper segment 2 is characterized by more frequent shopping at store chains A and B, a lower shopping frequency in general, and less variety-seeking behavior. Likewise, Shopper segment 3 can be described in terms of a higher frequency for store chains B and D, a lower shopping frequency in general, and higher variety-seeking behavior. Shopper segment 4, finally is characterized by more variety-seeking behavior in general.

Table 3.6: Segment characteristics identified by discriminant function

Canonical discriminant function eigenvalues

	Hamming distance				SAM		
function	eigen-value	% variance	canonical correlation	function	eigen-value	% variance	canonical correlation
1	3.036	83.1	.867	1	1.797	39.7	.802
2	.592	16.2	.610	2	1.490	32.9	.774
3	.027	.7	.161	3	1.240	27.4	.744

Standardized canonical discriminant function coefficients

	Hamming distance				SAM		
variable	discriminant function			variable	discriminant function		
	1	2	3		1	2	3
n_A				n_A	1.185	1.645	.707
n_B	.148	.745	.039	n_B	1.551	.485	.337
n_C	-.101	.292	1.076	n_C			
n_D	.122	-.163	.349	n_D	.968	.854	-1.165
n_E				n_E			
Leng	.874	-.588	-.292	*Leng*	-2.235	-1.781	-.275
A				*A*			
B	.232	.365	.109	*B*	.587	.031	-.219
C				*C*	.801	.688	.073
D				*D*	-.001	.499	.723
E				*E*			
Vseek				*Vseek*	-.476	-.865	-.053

Discriminant functions at segment centroids

	Hamming distance				SAM		
segment	discriminant function			segment	discriminant function		
	1	2	3		1	2	3
1	.774	-1.093	-.223	1	-2.108	-1.565	-.165
2	-1.245	-.045	.090	2	-.353	1.228	.887
3	.384	1.555	-.211	3	.416	.752	-2.143
4	4.273	.099	.225	4	1.849	-1.179	.478

Based on the analyses in this subsection reported in Tables 3.5 and 3.6, we draw the following conclusions. First, compared to the conventional position-based distance measure, the alignment method better discriminates among segments regarding the sequential characteristics of the purchase histories. Secondly, compared to the conventional measure, the alignment method achieves higher overall homogeneity in the resultant segmentation in terms of the defined dimensions representing both the cross-sectional and sequential characteristics of the purchase histories. Both hypotheses 1 and 2 are therefore accepted.

In sum, the conventional position-based distance measure and the alignment method of comparing activity sequences (purchase sequences in this illustration) generate different segments. First, the segmentation based on the Hamming distance identifies mostly the cross-sectionally differentiated segments only, while the segmentation based on the SAM induces not only cross-sectionally but also sequentially differentiated segments. Consequently, SAM's segmentation provides richer information. Perhaps equally important

is the fact that the SAM's segmentation is less affected by the sequence length. In other words, the segments based on the SAM are distinguished not only by the sequence length but also more by the proportions of individual activities (store chains in this illustration), which is the structural skeleton of the activity sequence, another key aspect of interest. This property of the distance measure results from the fact that the SAM captures the cross-sectional and sequential information of particular store chains at the same time.

3.4.2   An analysis of sequences using the extended sequence alignment method

This subsection analyzes activity diary sequences. An activity diary sequence is an array of activities that an individual implemented for a given period of time. A limited number of activity categories repeatedly appear. All sequences convey the information of the order of activities implemented and the number of activities that differs between the sequences. Compared with the sequence data in the previous subsection, the current sequences do not distinguish between different stores visited but encode 'grocery shopping' or 'non-grocery shopping' for them all. Instead, the sequence also includes all other activities implemented given a time horizon. The analysis of these sequences will show the impact of the incorporation of the position sensitiveness into the original alignment method on the alignment measures and the subsequent classification results.

Data

The data used in the analysis are part of a recent Dutch activity diary survey, collected in 1997 in two cities, Hendrik-Ido-Ambacht and Zwijndrecht. Both belong to the south Rotterdam region. The survey was conducted as part of Albatross research project. The respondents were asked to report all their activities conducted during two consecutive days. Each day begins at 3 a.m. and ends at 3 a.m. of the next day. The diary used open time intervals. A total of 2974 activity-travel patterns were included in the data set. The empirical analysis of this section used a sub-set of 77 activity diary sequences that were randomly selected from the full data set and involved 2926 pairwise comparisons. The questionnaire classification of the survey lists a total of 47 activities (Arentze & Timmermans, 2000, p. 466). The sequences used in the current empirical analysis simplified these into 17 activity categories. An extra code, 'unknown,' was included when activities were not identified. A total of 18 activity categories include work, bring/get of person/goods, grocery shopping, non-grocery shopping, service, medial, sport, tour, eating, sleeping, out-of-home leisure, out-of-home non-leisure, receiving visit, paying visit, other work, other activities, doing nothing and unknown activities. The substitution operation was applied to any alignment with the element of 'unknown' activity. The average length of the activity sequences was 15.86 with a maximum of 29, a minimum of 8 and a standard deviation of 4.90 activities.

Analysis scheme

This sub-section will examine whether the position-sensitive SAM (*p*SAM) is sensitive to the various reordering distances when compared to the conventional SAM (*c*SAM) and whether the identified position-sensitiveness of the *p*SAM, if any, affects the results of an activity-travel behavior analysis. To this end, we will first measure the correlation between the two SAMs dependent on the size of reordering weight. We expect on the basis of equation (3.27) that the two SAMs give different results, as the size of the second term of the RHS of equation (3.27) will often differ from the size of the third term. Furthermore, the difference is expected to be amplified as the reordering weight increases.

Next, we will examine the specific contribution of the reordering distance to the alignment costs. For the latter analysis, we compare the *p*SAM with a SAM that takes only the reordering weight but not the reordering distance into account. For convenience, we shall call the SAM of the latter case the *nr*SAM, as it is only concerned with the *n*umber of *r*eorderings, weighted by the reordering weight. Note that *nr*SAM and *c*SAM are equivalent if the reordering weight is set to two units (i.e. $\eta = 2w_o$). The correlation coefficients $r(\eta)$ between *c*SAM and *p*SAM and between *c*SAM and *nr*SAM will therefore be compared. We also expect on the basis of equation (3.27) that the correlation between *c*SAM and *p*SAM is lower than the correlation between *c*SAM and *nr*SAM. This is because by taking both the number of reorderings and the reordering distances into account the sum of the second and third terms of RHS of equation (3.27) will likely result in greater diversity than in the case of taking into account only the number of reorderings.

Secondly, the set of pairwise distances respectively measured by *c*SAM and *p*SAM will be used for classifying activity diaries as an example of the analysis of activity-travel behavior. We will test whether cluster solutions differ much between the two measures by comparing the cluster memberships.

The equations used to calculate different SAM costs are based on equations (3.24) to (3.27). The variants of SAM are defined as:

$$c\text{SAM}: d(\boldsymbol{s},\boldsymbol{g})_{\text{CS}} = w_o(D+I) + 2w_o L \tag{3.35}$$

$$p\text{SAM}: d(\boldsymbol{s},\boldsymbol{g})_{\text{PS}} = w_o(D+I) + \eta\left(\sum_{l}^{L_a} h_l^*\right) \tag{3.36}$$

$$nr\text{SAM}: d(\boldsymbol{s},\boldsymbol{g})_{\text{nr}} = w_o(D+I) + \eta L \tag{3.37}$$

The illustration uses twenty-one different reordering weights, ranging from 0 to $2w_o$ as mentioned in Section 3.3.3. When $\eta = 0$, the costs of *p*SAM of equation (3.36) and of *nr*SAM of equation (3.37) become the same and are always smaller than the *c*SAM costs, if any reordering happens (that is, $L_i > 0$). As discussed before, when $\eta = 2w_o$, the costs of *c*SAM of equation (3.35) and of *nr*SAM of equation (3.37) become the same and are always smaller than or equal to the *p*SAM costs. Other nineteen reordering weights are evenly distributed over this range.
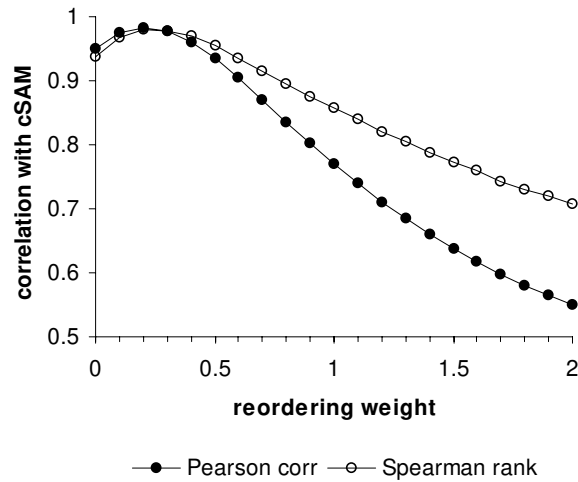
Figure 3.6: Correlation between *p*SAM and *c*SAM

Results

Correlation coefficients: Figure 3.6 shows the correlation coefficients between *p*SAM and *c*SAM. The X-axis in this figure represents *p*SAMs with varying reordering weight. The figure demonstrates that *p*SAM is highly, positively correlated with *c*SAM, but the correlation is not perfect. The two sequence alignment measures are highly correlated because the sum of reordering distances likely increases as the number of reorderings increases. Their correlation is, however, not perfect, indicating that the sum of reordering distances is not a perfectly linear increment of the number of reorderings.

Figure 3.6 also shows that the functional curve of the correlation coefficient is globally concave. This result can also be deducted by comparing the second terms of the RHS of equations (3.35) and (3.36). When the sizes of reordering weights are very small, the cost for reorderings becomes near to zero regardless of the reordering distances, and the correlation between the two SAMs is mostly determined by the relation between the sum of the first and second terms of equation (3.35) and the first term of equation (3.36). The correlation is increasing as the relative sizes of the second terms of the RHS of equations (3.35) and (3.36) are getting close to each other by the increment of the reordering weight. The correlation, however, starts decreasing as the reordering weight decreases after a certain point. A more detailed examination showed that the critical value of the reordering weight inducing the stationary point of the correlation coefficient is determined near to $2w_o$ multiplied by the ratio of standard deviations of the number of reorderings and the sum of reordering distances. This is because the impact of disagreement between the sum of reordering distances and the number of reorderings on the costs of deletions and insertions of unique elements will be amplified as the reordering weight is increased.
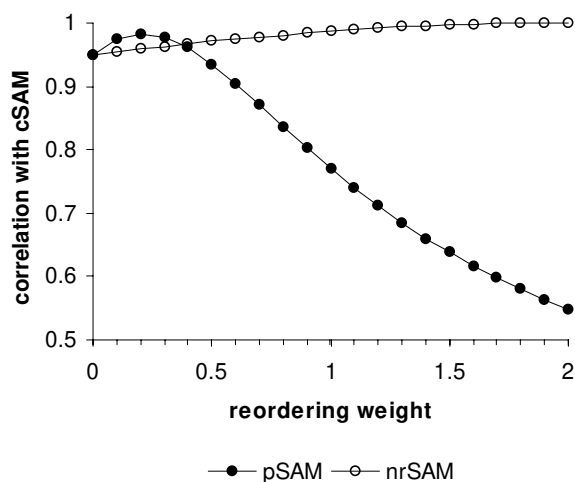
Figure 3.7: Pearson's correlation between *p*SAM, *nr*SAM and *c*SAM

The correlation between *p*SAM and *c*SAM and the correlation between *nr*SAM and *c*SAM using the same data set are compared in Figure 3.7. The figure clearly indicates that *nr*SAM is more strongly correlated with *c*SAM than *p*SAM is and that the effect of reordering distances systematically increases as the reordering weight increases. The result demonstrates, our earlier expectation, that the reordering distances provide greater diversity, and it is amplified by the increment of the reordering weight.

Cluster membership: Finally, how well *p*SAM matches *c*SAM in a cluster based on pairwise distances was examined. To this end, the following procedures were performed. First, the pairwise distance matrices produced by the two measures were respectively input to the SPSS cluster analysis as the proximity matrix. The Ward method was used as the clustering algorithm. A total of four clusters could be identified in both measures. Then, the individual activity diary cases that each *c*SAM cluster contains were identified. Next, for each *c*SAM cluster, the individual activity diary cases that each *p*SAM cluster contains were identified. Finally, the number of individual cases of the biggest *p*SAM cluster for each *c*SAM cluster was identified.

Table 3.7: Comparison of *p*SAM's membership with *c*SAM's membership

*c*SAM solution		*p*SAM solution	Matching
cluster	cases	match-cases[*]	(%)
1	15	9	60.0
2	20	13	65.0
3	23	19	82.6
4	19	12	63.2

Note: '*' denotes the number of cases of the biggest *p*SAM cluster matching with the corresponding *c*SAM cluster.

As shown in Table 3.7, the resultant matching ratios of cluster membership range from 60.0 to 82.6 %, which demonstrate a substantial difference in the cluster solution between the two measures and affirm the findings of the correlation analysis.

Based on these observations, it can be concluded that the reordering distance indeed affects the cluster solution. It is necessary to take this conclusion into account because the properties of sub-sequence do matter in the analysis of activity-travel behavior as discussed in the introduction.

3.5   Conclusions and discussion

This chapter has introduced the sequence alignment method, originally developed in the molecular biology to measure the biological distance between DNA, RNA or protein sequences. Because, by definition, sequential information is of crucial importance in analyzing the activity-travel patterns, which consist of sequences of activities, sequence alignment methods have potential for the analysis of activity-travel patterns.

The current chapter extensively explored the application of sequence alignment methods to particular problems of activity analysis. More specifically, the original alignment method was applied to the identification of shopper segments on the basis of their purchase histories. It was found that conventional Euclidean distance measures only capture the cross-sectional (dis)similarity of corresponding elements between the sequences compared. This may lead to a significant loss of information about the sequential (dis)similarity between sequence of information. We therefore suggested using sequential alignment methods for the analysis of activity sequences.

This is not to say that the method cannot be improved specifically for activity-based analysis in transportation and urban planning research. To this effect, an extension of the original method was proposed. It measures the difference between sequences in terms of both the sequential order and the positioning of common elements in the sequence as well as the composition of the overall sequence. The proposed method includes (1) reordering rules by which particular common elements are selected for the reordering, (2) a repositioning rule by which particular positions are determined as the destinations of the selected common elements and (3) rules for finding the set of common elements to be reordered. Based on these, a position-sensitive distance measure is defined. The sizes of weights for the deletion and insertion of unique elements and reordering of common elements are the parameters of the method.

An empirical application of this method to activity diary data led to the following conclusions. First, the proposed method does differ from the conventional sequence alignment method. Furthermore, the degree of difference between the two sequence alignment methods varies with the size of reordering weight. This implies that one may incorporate the effect of the difference in positions of common elements into the overall difference between sequences, dependent on the application. Secondly, the size of the reordering distance, in addition to the reordering weight, affect the results, confirming the importance of an appropriate reordering weight in the context of the analysis. Additionally, a

mathematical interpretation of the correlation equation indicates that the results of the proposed method would be less sensitive to the reordering weight as the element composition becomes more homogeneous between sequences compared. In such cases, the determinant of the position sensitiveness of the proposed method is the difference between the number of reorderings and the sum of reordering distances itself rather than the sum of reordering distances multiplied by the reordering weight. Finally, the cluster solutions substantially differ between the conventional position-irrelevant sequence alignments and the proposed measure.

Based on these findings, we conclude that the proposed method is useful to calculate the degree of difference between sequences of information for both classification and goodness-of-fit test purposes. However, the original as well as the extended method assumes uni-dimensional strings. This implies that although we argue that the position-sensitive method may be a valuable method to measure the similarity between uni-dimensional facets of activity sequences, it does not suffice to analyze multi-attribute activity-travel patterns. Therefore, in the next chapter a multidimensional sequence alignment method will be developed and it will be this measure, instead of the position-sensitive uni-dimensional method that will be used in the context of the model to be developed in this project.

Appendix 3.1: A mathematical method for calculating the minimum sum of reordering distances

When the source common elements of a letter to be reordered do not have one-to-one relationships with the target elements, as mentioned in Example 9, the pairs of common elements of the source and target sequences are to be selected such that the sum of reordering distances is minimized. To calculate the minimum sum of the reordering distances, we developed a mathematical method, and we shall call this a *Minimum Reordering Distance Calculator* (MRDC).

We will introduce the MRDC by using a calculation example. Consider the following operation set consisting of deletion and insertion operations applied to eight common elements of the same letter, as well as the positions to which those operations are applied, identified by the *e*SAM.

$$\{\text{i2, d4, i5, d7, i8, d9, i15, i17}\}$$

where, d and i represent deletion and insertion operations, respectively; the attached numbers indicate the positions to which the concerned operations are applied.

There are three deletions and five insertions. In other words, all of three source elements must be reordered (deleted-inserted) to particular positions of the target elements, while two of five target elements are simply inserted. As such, the number of reorderings is determined by the operation of the smaller number, and hence, we shall call the operation of the smaller number the *anchor operation*, and the operation of the larger number the *counterpart operation*. Summing across the reordering sets the number of anchor operations returns *L* of equation (3.27). We may rewrite the above operation set such that the anchors come first, and the counterparts next.

$$\{\text{d4, d7, d9; i2, i5, i8, i15, i17}\}$$

Each reordering distance is measured as $h = |i–j|$, where i and j are the positions of the reordered elements in the source and target sequences, respectively. The reordering distance hence is calculated by pairing each anchor operation with a counterpart operation. There are many ways of doing this, and the purpose of the *MRDC* is to find the 'best' set of pairs of d and i such that the sum of reordering distances is minimized.

Note that the anchor operations should maintain their order when paired with their counterparts. For example, d7-i2 and d4-i5 pairings, which lead to the distance $|7–2|+|4–5| = 6$, are worse than d4-i2 and d7-i5 pairings of the distance $|4–2|+|7–5| = 4$. This fact introduces the following table of the common element pairing. The positions to which the anchor operations (deletions in this example) are applied are arranged in rows, and the counterpart operation positions are represented in columns. Note that the positions are arranged in an increasing order of positions, and the reordering operations are not applied to the shadowed cells because of the pairing order mentioned above.

	2	5	8	15	17	i ← *counterpart*
4	①	②	③			
7		④	⑤	⑥		
9			⑦	⑧	⑨	
d						

anchor
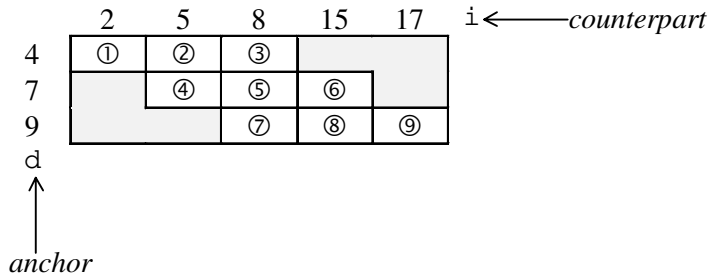
where, each cell represents a pair of positions of the common elements deleted (d) and inserted (i).

Consequently, the reordering of this common element set should end with one of three cells, ⑦,⑧ and ⑨, and there are ten possible reordering combinations to reach them as shown below.

⑦ ← ①-④	⑧ ← ①-④	⑨ ← ①-④
	①-⑤	①-⑤
	②-⑤	①-⑥
		②-⑤
		②-⑥
		③-⑥

Also, the pairwise reordering distances are identified as:

	2	5	8	15	17	i
4	2	1	4			
7		2	1	8		
9			1	6	8	
d						
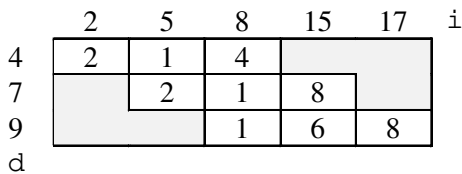
The *MRDC* then finds the reordering history of the minimum distance as defined as.

$$r_d(\boldsymbol{p},\boldsymbol{q}) = \min[r_d(\boldsymbol{p}^x,\boldsymbol{q}^x),...,r_d(\boldsymbol{p}^x,\boldsymbol{q}^y)] \qquad\qquad (3A1\text{-}1)$$

$$r_d(\boldsymbol{p}^0,\boldsymbol{q}^0) = 0 \qquad\qquad (3A1\text{-}2)$$

$$r_d(\boldsymbol{p}^u,\boldsymbol{q}^0) = 0 \qquad\qquad \forall\, u \qquad (3A1\text{-}3)$$

$$r_d(\boldsymbol{p}^0,\boldsymbol{q}^v) = 0 \qquad\qquad \forall\, v \qquad (3A1\text{-}4)$$

$$r_d(\boldsymbol{p}^u,\boldsymbol{q}^v) = \min[r_d(\boldsymbol{p}^{u-1},\boldsymbol{q}^{u-1}),...,r_d(\boldsymbol{p}^{u-1},\boldsymbol{q}^{v-1})] + r_d(p_u,q_v)$$
$$1 \le u \le x\,;\, i \le v \le y-(x-u) \qquad (3A1\text{-}5)$$

where, p_u and q_v are the positions of the *u*-th anchor and *v*-th counterpart operations in their sequences, respectively; $r_d(p_u,q_v)$ is the *r*eordering *d*istance between the *u*-th anchor

operation and the v-th counterpart operation ($p_u < p_{u'}$ where $u < u'$, and $q_v < q_{v'}$ where $v < v'$); x and y are the number of anchor and counterpart operations of the concerned reordering set, respectively ($x \leq y$); $r_d(p^u,q^v)$ is the minimum reordering distance cumulated from $r_d(p^0,q^0)$ to $r_d(p^u,q^v)$; $r_d(p,q)$ is the final solution of the minimum sum of reordering distances.

Note that p^u and q^v do *not* dictate the initial parts of the source and target sequences BUT the initial parts of the *anchor* and *counterpart* operations. To emphasize this, we denoted the anchor and counterpart operations of positions u and v by p_u and q_v, respectively. Thus, we use p^u and q^v instead of s^i and g^j to avoid any confusion. Equations (3A1-2) to (3A1-4) imply that no reordering operation is applied to the null cells. Equation (3A1-5) finds the best history of reordering operations out of the possible combinations of the reordered predecessors defined by the conditions of u and v that maintain the pairing order. Equation (3A1-1) finally finds the minimum sum of reordering distances among the cell values of the last anchor operation.

We continue the above example to illustrate how the *MRDC* actually works.

pos		0	1	2	3	4	5	q_v
		2	5	8	15	17		i
0		0	0	0	0	0	0	
1	4	0	2	1	4			
2	7	0		4	2	9		
3	9	0			5	8	10	
p_u	d							

The values of the cells are:

$$r_d(p^1,q^1) = r_d(p^0,q^0) + r_d(p_1,q_1) = 0 + 2 = 2;$$
$$r_d(p^1,q^2) = \min[r_d(p^0,q^0), r_d(p^0,q^1)] + 1 = 1;$$
$$r_d(p^1,q^3) = \min[r_d(p^0,q^0), r_d(p^0,q^1), r_d(p^0,q^2)] + 4 = 4;$$
$$r_d(p^2,q^2) = r_d(p^1,q^1) + 2 = 4; \qquad\qquad\text{:from } (p_1,q_1)$$
$$r_d(p^2,q^3) = \min[r_d(p^1,q^1), r_d(p^1,q^2)] + 1 = 2;$$
$$r_d(p^2,q^4) = \min[r_d(p^1,q^1), r_d(p^1,q^2), r_d(p^1,q^3)] + 8 = 9;$$
$$r_d(p^3,q^3) = r_d(p^2,q^2) + 1 = 5; \qquad\qquad\text{:from } (p_2,q_2)$$
$$r_d(p^3,q^4) = \min[r_d(p^2,q^2), r_d(p^2,q^3)] + 6 = 8;$$
$$r_d(p^3,q^5) = \min[r_d(p^2,q^2), r_d(p^2,q^3), r_d(p^2,q^4)] + 8 = 10;$$

Hence,

$$r_d(p,q) = \min[r_d(p^3,q^3), r_d(p^3,q^4), r_d(p^3,q^5)] = 5. \qquad\text{:from } (p_3,q_3)$$

The minimum sum of reordering distances includes the reordering history of $r_d(p_1,q_1)$, $r_d(p_2,q_2)$ and $r_d(p_3,q_3)$ (①→④→⑦). Summing the weights of the minimum sums of reordering distances across the reordering sets returns the $\sum_{l}^{L} r_l^*$ in terms of equation (3.27).

Appendix 3.2: Appropriateness proof

It can be proven that under the condition that the proposed method remains an alignment method that keep the skeleton of original sequence as much as possible, the position-sensitive SAM matches our intuition about reordering in the sense that the elements of a smaller number or of a bigger reordering distance are reordered, and that the cost of position-sensitive SAM monotonically increases as the reordering distance increases, ceteris paribus.

THEOREM. Let $s = [s_1 \ldots s_m]$ and $g = [g_1 \ldots g_n]$ respectively be the source and target sequences. Let $o = \{p_1, \ldots, p_d, \ldots, p_D, q_1, \ldots, q_i, \ldots, q_I, f_1, \ldots f_z, \ldots f_Z\}$ be an arbitrary alignment of any pair of s and g, consisting of D deletions, I insertions, and Z modified identities ($D \leq m$; $I \leq n$; $Z \leq \min[m,n]$). Let Z_{CS} and Z_{ES} respectively be the number of identities of the optimum alignment of original SAM and the number of modified identities of the optimum alignment of eSAM. Let v_z^*, $w_{e'_z}^*$ and h_l^* respectively be the position difference and the modified identity weight of f_z of the optimum alignment of eSAM and the reordering distance of $(p_d, q_i)_l$ of the optimum reordering calculation ($l = 1, \ldots, L$). Let $w_o = w_d = w_i > 0$. Let $d(s,g)_{CS}$, $d(s,g)_{ES}$ and $d(s,g)_{PS}$ respectively be the optimum alignment cost of original SAM and eSAM and position-sensitive SAM. Let $A = \{ p_{1_a}, \ldots, p_{D_a}, q_{1_a}, \ldots, q_{I_a}, f_{1_a}, \ldots, f_{Z_a} \}$ and $B = \{ p_{1_b}, \ldots, p_{D_b}, q_{1_b}, \ldots, q_{I_b}, f_{1_b}, \ldots, f_{Z_b} \}$ respectively be the optimum alignment of eSAM for the pairs of s_a and g_a and of s_b and g_b. Then, $Z_{CS} = Z_{ES}$, and $(D+I)w_o + \sum\limits^{Z_{ES}} v_z^* \leq (D+I)w_o + \sum\limits^{Z_{ES}} v_z$ $\forall$ $(D+I)w_o + \sum\limits^{Z_{ES}} v_z$, $\{(D+I)w_o + \sum\limits^{Z_{ES}} v_z \} \ni (D+I)w_o + \sum\limits^{Z_{ES}} v_z^*$, and if $D_a + I_a = D_b + I_b$, and $\sum\limits^{L_a} h_{l_a}^* > \sum\limits^{L_b} h_{l_b}^*$, then $d(s_a, g_a)_{PS} > d(s_b, g_b)_{PS}$.

Proof. It will be shown that the set of elements staying unreordered in an eSAM represents one of the optimal trajectories of original SAM, as the number of modified identities applied by eSAM is the same as the number of identities applied by original SAM, that the sum of position differences obtained by the optimum alignment is the smallest one among others in eSAM, and that the cost of position-sensitive SAM monotonically increases as the reordering distance increases, ceteris paribus. Then, we will show that the proposed method incorporating the reordering distance effect into original SAM, is appropriate.

LEMMA 1. Given $o = \{p_1, \ldots, p_d, \ldots, p_D, q_1, \ldots, q_i, \ldots, q_I, f_1, \ldots f_z, \ldots f_Z\}$, defined as any modified identity-applied arbitrary alignment of a pair of s and g, Z_{CS} and Z_{ES}, respectively defined as the number of identities of the optimum alignment of original SAM and the number of modified identities of the optimum alignment of eSAM, $w_{e'_z}^*$, defined as the modified identity weight of f_z of the optimum alignment of eSAM, w_o, defined as $w_o = w_d = w_i > 0$, and $d(s,g)_{CS}$ and $d(s,g)_{ES}$, respectively defined as the optimum alignment costs of original SAM and eSAM, then $Z_{CS} = Z_{ES}$.

Proof. Given $o=\{p_1,\ldots,p_d,\ldots,p_D, q_1,\ldots,q_i,\ldots,q_I, f_1,\ldots,f_z,\ldots,f_Z\}$, $d(s,g)_{CS}$ and $d(s,g)_{ES}$, according to the definitions of original SAM and *e*SAM,

$$n(o) = D+I+Z \tag{3A2-1}$$

and

$$d(s,g)_{CS} = \min\left[(D+I)w_o + Zw_e\right] \tag{3A2-2}$$

and

$$d(s,g)_{ES} = \min\left[(D+I)w_o + \sum^{Z} w_{e'_z}\right] \tag{3A2-3}$$

Since,

$$\max\left[Zw_e\right] = 0 < w_o \tag{3A2-4}$$

we have

$$d(s,g)_{CS} = \min\left[(D+I)w_o\right] + Z_{CS}w_e \tag{3A2-5}$$

Because

$$\max\left[\sum^{Z} w_{e'_z}\right] < w_o \tag{3A2-6}$$

we also have

$$d(s,g)_{ES} = \min\left[(D+I)w_o\right] + \sum^{Z_{ES}} w_{e'_z}^* \tag{3A2-7}$$

According to equations (3A2-5), (3A2-7) and (3A2-1),

$$\min\left[D+I\right] + Z_{CS} = \min\left[D+I\right] + Z_{ES} \tag{3A2-8}$$

Hence,

$$Z_{CS} = Z_{ES} \tag{3A2-9}$$

LEMMA 2. Given $o=\{p_1,\ldots,p_d,\ldots,p_D, q_1,\ldots,q_i,\ldots,q_I, f_1,\ldots,f_z,\ldots,f_Z\}$, defined as any modified identity-applied arbitrary alignment of a pair of *s* and *g*, Z_{ES}, defined as the number of

modified identities of the optimum alignment of eSAM, v_z^* and $w_{e'_z}^*$, respectively defined as the position difference and the modified identity weight of f_z of the optimum alignment of eSAM, w_o, defined as $w_o = w_d = w_i > 0$, and $d(s,g)_{ES}$, defined as the optimum alignment cost of eSAM, $(D+I)w_o + \sum^{Z_{ES}} v_z^* \leq (D+I)w_o + \sum^{Z_{ES}} v_z \quad \forall \quad (D+I)w_o + \sum^{Z_{ES}} v_z, \quad \{(D+I)w_o + \sum^{Z_{ES}} v_z\} \ni$

$(D+I)w_o + \sum^{Z_{ES}} v_z^*$.

Proof. Given $o=\{p_1,\ldots,p_d,\ldots,p_D, q_1,\ldots,q_i,\ldots,q_I, f_1,\ldots,f_z,\ldots,f_Z\}$ and $d(s,g)_{ES}$, according to equation (3A2-7) of Lemma 1,

$$d(s,g)_{ES} = \min[(D+I)w_o] + \sum^{Z_{ES}} w_{e'_z}^* \leq (D+I)w_o + \sum^{Z} w_{e'_z} \tag{3A2-10}$$

Since,

$$\{(D+I)w_o + \sum^{Z} w_{e'_z}\} \supset \{\min[(D+I)w_o] + \sum^{Z_{ES}} w_{e'_z}\} \tag{3A2-11}$$

we have

$$\min[(D+I)w_o] + \sum^{Z_{ES}} w_{e'_z}^* \leq \min[(D+I)w_o] + \sum^{Z_{ES}} w_{e'_z} \tag{3A2-12}$$

According to equation (3A2-1) of Lemma 1,

$$(D+I)w_o + \sum^{Z_{ES}} w_{e'_z}^* \leq (D+I)w_o + \sum^{Z_{ES}} w_{e'_z} \tag{3A2-13}$$

Given $w_{e'} = \dfrac{w_o}{\max[m,n]^2} \cdot v$,

$$(D+I)w_o + \sum^{Z_{ES}} \frac{w_o}{\max[m,n]^2} \cdot v_z^* \leq (D+I)w_o + \sum^{Z_{ES}} \frac{w_o}{\max[m,n]^2} \cdot v_z \tag{3A2-14}$$

Hence, since $\dfrac{w_o}{\max[m,n]^2}$ is a non-negative constant for each comparison case,

$$(D+I)w_o + \sum_{z}^{Z_{ES}} v_z^* \le (D+I)w_o + \sum_{z}^{Z_{ES}} v_z \qquad (3A2\text{-}15)$$

LEMMA 3. Given $A = \{ p_{1_a}, \ldots, p_{d_a}, \ldots, p_{D_a}, \ q_{1_a}, \ldots, q_{i_a}, \ldots, q_{I_a}, \ f_{1_a}, \ldots, f_{Z_a} \}$ and $B = \{ p_{1_b}, \ldots, p_{d_b}, \ldots, p_{D_b}, \ q_{1_b}, \ldots, q_{i_b}, \ldots, q_{I_b}, \ f_{1_b}, \ldots, f_{Z_b} \}$, respectively defined as the optimum alignment of eSAM for the pairs of $\boldsymbol{s}_a$ and $\boldsymbol{g}_a$ and of $\boldsymbol{s}_b$ and $\boldsymbol{g}_b$, h_l^*, defined as the reordering distance of $(p_d,q_i)_l$ of the optimum reordering calculation ($l = 1,\ldots,L$), and $d(\boldsymbol{s},\boldsymbol{g})_{CS}$, $d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{PS}$ and $d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{PS}$, respectively defined as the cost of original SAM and position-sensitive SAM of the optimum alignment of the pairs of $\boldsymbol{s}_a$ and $\boldsymbol{g}_a$ and of $\boldsymbol{s}_b$ and $\boldsymbol{g}_b$, $d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{PS} > d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{PS}$ if $D_a+I_a = D_b+I_b$, and $\sum^{L_a} h_{l_a}^* > \sum^{L_b} h_{l_b}^*$.

Proof. Given $d(\boldsymbol{s},\boldsymbol{g})_{PS}$,

$$d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{PS} = d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{CS} + \eta \sum^{L_a} h_{l_a}^* - (w_d L_a + w_i L_a) \qquad (3A2\text{-}16)$$

or

$$d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{PS} = (w_d D_a + w_i I_a) + (w_d L_a + w_i L_a) + \eta \sum^{L_a} h_{l_a}^* - (w_d L_a + w_i L_a) \qquad (3A2\text{-}17)$$

or

$$d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{PS} = (w_d D_a + w_i I_a) + \eta \sum^{L_a} h_{l_a}^* \qquad (3A2\text{-}18)$$

Similarly,

$$d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{PS} = d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{CS} + \eta \sum^{L_b} h_{l_b}^* - (w_d L_b + w_i L_b) \qquad (3A2\text{-}19)$$

or

$$d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{PS} = (w_d D_b + w_i I_b) + (w_d L_b + w_i L_b) + \eta \sum^{L_b} h_{l_b}^* - (w_d L_b + w_i L_b) \qquad (3A2\text{-}20)$$

or

$$d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{\text{PS}} = (w_d D_b + w_i I_b) + \eta \sum^{L_b} h^{*}_{l_b} \tag{3A2-21}$$

Given $D_a + I_a = D_b + I_b$, and $w_d = w_i$,

$$w_d D_a + w_i I_a = w_d D_b + w_i I_b \tag{3A2-22}$$

Hence, according to equations (3A2-18), (3A2-21), and (3A2-22), and given $\sum^{L_a} h^{*}_{l_a} > \sum^{L_b} h^{*}_{l_b}$,

$$d(\boldsymbol{s}_a,\boldsymbol{g}_a)_{\text{PS}} > d(\boldsymbol{s}_b,\boldsymbol{g}_b)_{\text{PS}} \tag{3A2-23}$$

4   A Multidimensional Sequence Alignment Method

4.1   Introduction

In Chapter 3, a sequence alignment method was introduced for the analysis of activity sequences. Unlike Euclidean distance measures, the sequence alignment method can also measure the sequential similarities between activity patterns. As repeatedly stated in Chapter 2, this implies that the suggested measure captures not only the compositional information but also, more importantly, the contextual information embedded in activity patterns. Moreover, the original sequence alignment method was extended to a position-sensitive measure that captures not only the nominal difference between corresponding elements of two sequences but also the information of how many positions they are apart. The empirical analyses reported in Chapter 3 provide evidence of the potential of these measures for a variety of applications in transportation and urban planning research, where sequential information is of importance.

Nevertheless, an analysis of activity-travel behavior should consider not only the sequence of activities, which the uni-dimensional alignments can handle, but also the interdependency relations across attributes of an activity, which cannot be captured by the uni-dimensional alignments. Given the background work on the uni-dimensional sequence alignment method, in this chapter we will propose such a multidimensional extension of the original sequence alignment method. A crucial challenge here is how to incorporate interdependency between activity attributes while maintaining the central property of the alignment methods of capturing sequential information.

This chapter is organized as follows. Section 4.2 explains what the multidimensional extension of the uni-dimensional methods means to the analysis of activity-travel behavior. Section 4.3 accordingly defines the problem of multidimensional activity-travel pattern comparison. A way to handle the interdependency between attributes is suggested, which is subsequently formalized as an *operational method*. An example of an application of the method is given to illustrate the method. Because the computing time for calculating similarity in terms of an exhaustive search will be prohibitive for any realistic data set, Section 4.4 develops efficient *implementation algorithms* to compute the suggested method in reasonable time. As there are several ways to implement the suggested method in practice, the section addresses the details of the alternative algorithms at some length. Section 4.5 uses activity-travel data collected in The Netherlands to show the fundamental properties of the suggested method in activity-travel analysis in comparison with the conventional Euclidean measures. In Section 4.6, the new and existing alternative algorithms are compared in terms of accuracy of the solution and computing time using a recent Dutch activity-diary data set. The chapter ends with some conclusions and discussion.

4.2   Implication of multidimensional extension of uni-dimensional method

The problem that arises in activity analysis is that the alignment costs for *multidimensional* activity-travel patterns having two or more attribute sequences is not the simple sum of uni-dimensional alignment costs because of the interrelations between activity elements of different attributes. A variety of interdependency relationships between attributes complicate the problem of calculating the minimum-effort equalization.

In the absence of an algorithm for such multidimensional sequence alignment, Wilson (1998) suggested combining the attribute levels of interest and then performing a conventional uni-dimensional sequence alignment. For example, a three-dimensional profile of an activity, [activity type=Shopping, location=Amsterdam, travel mode=CarDriver]′ can be encoded as a single activity code, (Shopping-Amsterdam-CarDriver), which is nominally different from another activity code, (Shopping-Amsterdam-CarPassenger). The comparison problem then is simply a question of uni-dimensional alignment of uni-dimensional strings of multidimensional information. By differentiating substitution weights between activity code pairs based on their degree of correspondence, the uni-dimensional code system can detect the difference in a subset of elements between activities at the level of single activities.

The positive feature of this approach is its simplicity. Unfortunately, however, this uni-dimensional encoding scheme presents a problem at the level of comprehensive patterns. Assume, for example, that two four-dimensional source patterns *s*1 and *s*2, consisting of activity-type, location, travel-mode and accompanying-person attributes, are compared with a target pattern *g*. The activity-travel patterns can be represented by either a uni-dimensional sequence of multidimensional activity information or a set of multiple sequences of uni-dimensional attribute information, as shown in Figures 4.1 and 4.2. In the figures, the grayed cells indicate elements that involve mismatches with the target pattern *g*.

Activity1 and Activity2 of *s*1 partly share the activity contexts (Car-Alone and Work-Rotterdam) with Activity1 of *g*, while only Activity1 of *s*2 does this. Despite this fact, the costs for uni-dimensional alignments of uni-dimensional pattern pairs, *s*1-*g* and *s*2-*g*, are both 2+4 = 6 units for the mismatch (Figure 4.1).

g

Activity 1			
Work —	Rotterdam —	Car —	Alone

*s*1

Activity1				Activity2			
Shopping —	Amsterdam —	Car —	Alone	Work	Rotterdam —	Bus —	WithOthers

*s*2

Activity1				Activity2			
Shopping —	Amsterdam —	Car —	Alone	SocialVisit —	Maastricht —	Bus —	WithOthers

Figure 4.1: Comparison of multidimensional activity-travel patterns based on uni-dimensional encoding scheme

g
Activity1
Work
Rotterdam
Car
Alone

*s*1	
Activity1	Activity2
Shopping	Work
Amsterdam	Rotterdam
Car	Bus
Alone	WithOthers

*s*2	
Activity1	Activity2
Shopping	SocialVisit
Amsterdam	Maastricht
Car	Bus
Alone	WithOthers

Figure 4.2: Comparison of multidimensional activity-travel patterns based on multidimensional encoding scheme

The uni-dimensional encoding scheme conducts a full deletion of Activity2 of both *s*1 and *s*2. On the other hand, an alignment based on a multidimensional encoding scheme allows one to distinguish the alignment costs for multidimensional pattern pairs as 2+2 = 4 units for the mismatch between *s*1 and *g*, and 2+4 = 6 units for the mismatch between *s*2 and *g* (Figure 4.2). This encoding scheme conducts a full deletion of Activity2 of *s*2 but a partial deletion of Activity2 of *s*1. Thus, it allows one to differentiate between various interdependency relationships in the sequential alignments. Employing the multidimensional encoding scheme that copes with the interdependency relationships is therefore critical to the development of a multidimensional distance measure.

4.3   Method

4.3.1   Problem definition

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 of m, respectively n elements for source and target pattern. The activity patterns to be compared can also concern a day, week, month, year, or any other time horizon. The source and target patterns to be compared can then be represented by $K \times m$ and $K \times n$ matrices, respectively, as:

$$source\ pattern\ \boldsymbol{s} = [\boldsymbol{s}_{1\bullet} \ \ldots \ \boldsymbol{s}_{k\bullet} \ \ldots \ \boldsymbol{s}_{K\bullet}]'$$

with

$$\boldsymbol{s}_{k\bullet} = [s_{k0} \ \ldots \ s_{ki} \ \ldots \ s_{km}]$$

and

target pattern $\boldsymbol{g} = [\boldsymbol{g}_{1\bullet} \; \ldots \; \boldsymbol{g}_{k\bullet} \; \ldots \; \boldsymbol{g}_{K\bullet}]'$

with

$$\boldsymbol{g}_{k\bullet} = [g_{k0} \; \cdots \; g_{kj} \; \cdots \; g_{kn}]$$

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 j^{th} element of the kth attribute sequence of the source and target pattern, respectively ($i = 0, \ldots, m; j = 0, \ldots, n; k = 1, \ldots, K$);

$s_{ki} \in A_k$, and $g_{kj} \in A_k$.

Consequently, row vectors $\boldsymbol{s}_{k\bullet} = [s_{k0} \; \ldots \; s_{ki} \; \ldots \; s_{km}]$ and $\boldsymbol{g}_{k\bullet} = [g_{k0} \; \ldots \; g_{kj} \; \ldots \; g_{kn}]$ represent the sequential order of elements of the kth attribute of the source and target pattern, respectively, while column vectors $\boldsymbol{s}_{\bullet i} = [s_{1i} \; \ldots \; s_{ki} \; \ldots \; s_{Ki}]'$ and $\boldsymbol{g}_{\bullet j} = [g_{1j} \; \ldots \; g_{kj} \; \ldots \; g_{Kj}]'$ potentially represent the interdependency between the dimensions of the ith and j^{th} 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 $\boldsymbol{s} = [\boldsymbol{s}_{1\bullet} \; \ldots \; \boldsymbol{s}_{K\bullet}]'$ into $\boldsymbol{g} = [\boldsymbol{g}_{1\bullet} \; \ldots \; \boldsymbol{g}_{K\bullet}]'$ as a measure of similarity.

4.3.2 Conceptualization

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.

Consider the comparison case shown in Figure 4.3. Note that Pattern 1 is equalized to Pattern 2 by using deletion and insertion operations. The elements 'B' of attribute 1 and '3' of attribute 2 are independently deleted and inserted, because they occupy different positions. In contrast, elements 'D' and '4' are deleted from and inserted into the same positions in both sequences, and hence, the alignments of these elements can be combined into a single segment.
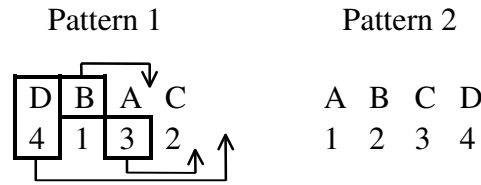
Pattern 1   Pattern 2

Figure 4.3: A comparison of two-dimensional patterns

Assuming unit weights for both the deletion and insertion operations, this combined alignment requires six units (deletions and insertions of 'B', '3' *and* 'D and 4'), while the independent uni-dimensional alignments require eight units (deletions and insertions of 'B', '3', 'D' *and* '4').

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. For example, let w_d be the weight attached to the deletion of an element, and β_k be the weight attached to the kth attribute. Then, the deletion of segment 'D and 4' in Figure 4.3 costs $max(\beta_1,\beta_2) \times w_d$ because these elements are aligned together instead of $(\beta_1 + \beta_2) \times w_d$. This results in a cost reduction of $(\beta_1 + \beta_2) \times w_d - max(\beta_1,\beta_2) \times w_d = min(\beta_1,\beta_2) \times w_d$. In general, the alignment of two multidimensional activity patterns will involve varying degrees of cost reductions. 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. We will develop such a method in the following section.

4.3.3   Specification of the method

The multidimensional alignment method proposed in this chapter 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. The method is detailed below.

Uni-dimensional operation set

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. As discussed in Section 3.2, 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:

$$O_{k,l} = \{p|p{=}\mathtt{d}(i,k) \vee p{=}\mathtt{i}(j,k) \vee p{=}\mathtt{s}(i,j,k)\} \tag{4.1}$$

with

$$i \in \{1, .., m\}, \ j \in \{1, .., n\}, \ 1 \le k \le K$$

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 j^{th} 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 4.4 represents the 2nd attribute of an arbitrary activity pattern. The alignment represented by the trajectory in that figure is summarized as:

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

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.

Figure 4.4: Comparison Table (An example)

As this set representation is derived from the optimum trajectories, we shall call the proposed method the uni-dimensional Optimum Trajectories-based MultiDimensional Sequence Alignment Method (OT-MDSAM).

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 4.5. The uni-dimensional operation sets corresponding to the trajectories are:

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

and

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

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.[1]

Figure 4.5: Two different trajectories of the same operation set

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[1] The algorithm and its optimality proof are detailed in Appendix 4.1.

Multidimensional operation set

The proposed OT-MDSAM 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:

$$T = \prod_{k=1}^{K} T_k \tag{4.2}$$

For each combination, t ($t = 1, \ldots, T$), we have K operation sets, $O^t_{1,l'}, \ldots, O^t_{k,l}, \ldots, O^t_{K,l''}$, 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:

$$O^t = \{p | p = d(i,k) \vee p = i(j,k) \vee p = s(i,j,k)\} \tag{4.3}$$

where, k identifies the set of attributes to which the concerned operation was applied.

Thus, the set 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:

$O^t_{1,l'}$ = {d(2,1), i(4,1), s(5,6,1)},
$O^t_{2,l}$ = {d(3,2), i(4,2), s(5,5,2)},
$O^t_{3,l''}$ = {d(2,3), i(4,3), s(5,5,3)},

then the tth multidimensional operation set is:

O^t = {d(2,{1,3}), d(3,{2}), i(4,{1,2,3}), s(5,5,{2,3}), 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.

Multidimensional similarity

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 $\boldsymbol{k}$. Hence, the alignment cost calculated from the tth multidimensional operation set, C^t, is:

$$C^t = \sum_{p \in O_t} c_p \qquad (4.4)$$

with

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

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 $w_s = w_d + w_i$);
β_k^{max} is the maximum weight across attributes in the set $\boldsymbol{k}$.

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

$$C^* = \min [C^1, ..., C^t, ..., C^T] \qquad (4.5)$$

That is, the minimum cost across trajectory combinations is taken as a measure of multidimensional similarity.[2]

Illustration

Consider the following example, where $K = 4$, and length of the source and target patterns is $m=4$ and $n=5$, respectively. We assume that $\beta_1=2$, and $\beta_2=\beta_3=\beta_4=1$.

source pattern	*target pattern*		
A D B C	A B C D E	$\rightarrow$	activity-type sequence
1 6 2 3	1 2 3 4 5	$\rightarrow$	activity-location sequence
a b c f	a b c d e	$\rightarrow$	transport-mode sequence
α δ φ γ	α φ γ δ ε	$\rightarrow$	accompanying-person sequence

The optimum trajectories are shown in Figure 4.6. In the figure, activity type, location and accompanying person sequences have one optimum trajectory, respectively, while the transport mode sequence has five. Hence, the number of trajectory combinations in this example is:

---

[2] Multidimensional sequence alignment should not be confused with the multiple sequence alignments developed in molecular biology. For interested readers, this difference is explained in Appendix 4.2.

activity type

	nul	A	B	C	D	E	g_1
nul	0	1	2	3	4	5	
A	1	0	1	2	3	4	
D	2	1	2	3	2	3	
B	3	2	1	2	3	4	
C	4	3	2	1	2	3	

s_1

activity location

	nul	1	2	3	4	5	g_2
nul	0	1	2	3	4	5	
1	1	0	1	2	3	4	
6	2	1	2	3	4	5	
2	3	2	1	2	3	4	
3	4	3	2	1	2	3	

s_2

transport mode

	nul	a	b	c	d	e	g_3
nul	0	1	2	3	4	5	
a	1	0	1	2	3	4	
b	2	1	0	1	2	3	
c	3	2	1	0	1	2	
f	4	3	2	1	2	3	

s_3

accompanying person

	nul	α	φ	γ	δ	ε	g_4
nul	0	1	2	3	4	5	
α	1	0	1	2	3	4	
δ	2	1	2	3	2	3	
φ	3	2	1	2	3	4	
γ	4	3	2	1	2	3	

s_4
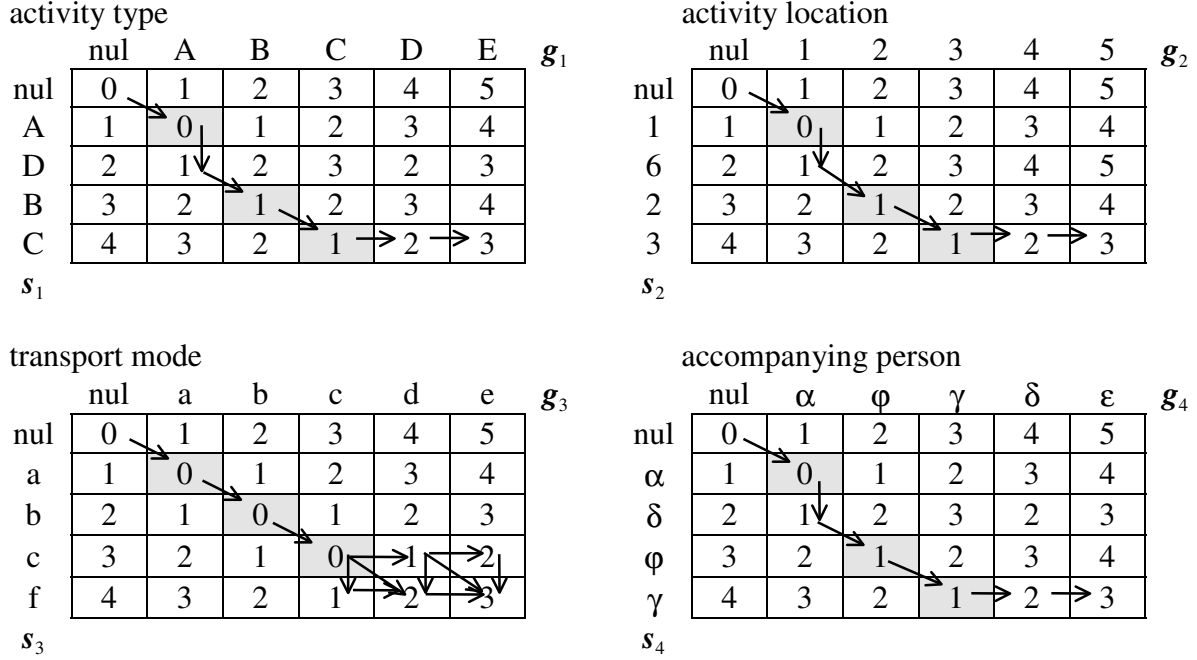
Figure 4.6: Optimum trajectories of each attribute sequence

$T = 1 \times 1 \times 5 \times 1 = 5$.

The operation sets for the first combination are:

$O_{1,1} = \{\texttt{d(2,1)}, \texttt{i(4,1)}, \texttt{i(5,1)}\}$, $O_{1,2} = \{\texttt{d(2,2)}, \texttt{i(4,2)}, \texttt{i(5,2)}\}$,
$O_{1,3} = \{\texttt{i(4,3)}, \texttt{i(5,3)}, \texttt{d(4,3)}\}$, $O_{1,4} = \{\texttt{d(2,4)}, \texttt{i(4,4)}, \texttt{i(5,4)}\}$,

the operation sets for the second combination:

$O_{2,1} = \{\texttt{d(2,1)}, \texttt{i(4,1)}, \texttt{i(5,1)}\}$, $O_{2,2} = \{\texttt{d(2,2)}, \texttt{i(4,2)}, \texttt{i(5,2)}\}$,
$O_{2,3} = \{\texttt{i(4,3)}, \texttt{s(4,5,3)}\}$, $O_{2,4} = \{\texttt{d(2,4)}, \texttt{i(4,4)}, \texttt{i(5,4)}\}$,

the operation sets for the third combination:

$O_{3,1} = \{\texttt{d(2,1)}, \texttt{i(4,1)}, \texttt{i(5,1)}\}$, $O_{3,2} = \{\texttt{d(2,2)}, \texttt{i(4,2)}, \texttt{i(5,2)}\}$,
$O_{3,3} = \{\texttt{i(4,3)}, \texttt{d(4,3)}, \texttt{i(5,3)}\}$, $O_{3,4} = \{\texttt{d(2,4)}, \texttt{i(4,4)}, \texttt{i(5,4)}\}$,

the operation sets for the fourth combination:

$O_{4,1} = \{\texttt{d(2,1)}, \texttt{i(4,1)}, \texttt{i(5,1)}\}$, $O_{4,2} = \{\texttt{d(2,2)}, \texttt{i(4,2)}, \texttt{i(5,2)}\}$,
$O_{4,3} = \{\texttt{s(4,4,3)}, \texttt{i(5,3)}\}$, $O_{4,4} = \{\texttt{d(2,4)}, \texttt{i(4,4)}, \texttt{i(5,4)}\}$,

and the operation sets for the fifth combination:

$O_{5,1} = \{\texttt{d(2,1)}, \texttt{i(4,1)}, \texttt{i(5,1)}\}$, $O_{5,2} = \{\texttt{d(2,2)}, \texttt{i(4,2)}, \texttt{i(5,2)}\}$,
$O_{5,3} = \{\texttt{d(4,3)}, \texttt{i(4,3)}, \texttt{i(5,3)}\}$, $O_{5,4} = \{\texttt{d(2,4)}, \texttt{i(4,4)}, \texttt{i(5,4)}\}$.

By equation (4.3), the unique operation set for each combination is:

$O_1 = \{\texttt{d}(2,\{1,2,4\}), \texttt{d}(4,\{3\}), \texttt{i}(4,\{1,2,3,4\}), \texttt{i}(5,\{1,2,3,4\})\},$
$O_2 = \{\texttt{d}(2,\{1,2,4\}), \texttt{i}(4,\{1,2,3,4\}), \texttt{i}(5,\{1,2,4\}), \texttt{s}(4,5,\{3\})\},$
$O_3 = \{\texttt{d}(2,\{1,2,4\}), \texttt{d}(4,\{3\}), \texttt{i}(4,\{1,2,3,4\}), \texttt{i}(5,\{1,2,3,4\})\},$
$O_4 = \{\texttt{d}(2,\{1,2,4\}), \texttt{i}(4,\{1,2,4\}), \texttt{i}(5,\{1,2,3,4\}), \texttt{s}(4,4,\{3\})\},$
$O_5 = \{\texttt{d}(2,\{1,2,4\}), \texttt{d}(4,\{3\}), \texttt{i}(4,\{1,2,3,4\}), \texttt{i}(5,\{1,2,3,4\})\}.$

By equation (4.4), the alignment costs calculated from these operation sets are:

$C^1 = 2\times1 + 1\times1 + 2\times1 + 2\times1 = 7,$
$C^2 = 2\times1 + 2\times1 + 2\times1 + 1\times2 = 8,$
$C^3 = 2\times1 + 1\times1 + 2\times1 + 2\times1 = 7,$
$C^4 = 2\times1 + 2\times1 + 2\times1 + 1\times2 = 8,$
$C^5 = 2\times1 + 1\times1 + 2\times1 + 2\times1 = 7.$

By equation (4.5), the optimum alignment costs, C^*, are:

$$C^* = \min [C^1, C^2, C^3, C^4, C^5] = 7.$$

This example illustrates OT-MDSAM's fundamental property discussed in the conceptualization of Section 4.2.2. The costs of the MDSAM in a perfectly independent case would be 6+3+3+3 = 15, in a perfectly interdependent case, 15/4. The reduction of 8-units cost according to the proposed method, compared to the perfectly independent case, is achieved by the integration of operations, $\texttt{d}(2,\{1,\underline{2},\underline{4}\})$ (2-units reduction), $\texttt{i}(4,\{1,\underline{2},\underline{3},\underline{4}\})$ (3-units reduction) and $\texttt{i}(5,\{1,\underline{2},\underline{3},\underline{4}\})$ (3-units reduction).

In general, the interdependency relationships between attributes may be quite variable, leading to different MDSAM results that the integration of uni-dimensional optimum alignments cannot perfectly project. To date, the only possible way to guarantee the optimality of the multidimensional comparison result is to try all possible alignments of each attribute (i.e., all uni-dimensional operation sets that lead to a solution), generate all possible combinations of the alignments across attributes and then find the minimum costs. Unfortunately, the enumeration of all possible alignments of even a single attribute already requires an enormous amount of computing time. This is the reason why we proposed the OT-MDSAM, as a principle of the heuristic sequence alignment method to guide the development of the implementation algorithms that approximate the true solution of the problem at our hand by reducing search space in the way that the guiding principle defines. The implementation algorithm to achieve the proposed method can however be manifold. The question is, which one is more efficient regarding the accuracy and the computing time. In the following sections, we suggest alternative heuristic approaches and examine their performance.

4.4   Algorithms

We develop several alternative heuristic algorithms in this section to implement the suggested method. This will include a genetic algorithms-based heuristic algorithm that employs an evolutionary search technique in Section 4.4.1, and a heuristic that is based on a dynamic programming technique using domain knowledge of uni-dimensional sequence alignments in Section 4.4.2. From the algorithmic nature of the two proposed approaches, genetic algorithms and dynamic programming, we derive a hybrid algorithm that integrates the two previous algorithms in Section 4.4.3 to seek possible improvements. The performances of these three alternatives will then be examined and illustrated in Section 4.5.2.

4.4.1   A heuristic based on genetic algorithms

Genetic Algorithms (GAs) constitute a heuristic algorithm, inspired by Darwinian evolution theory. Its *solution representation* and search mechanism are modeled in analogue to evolutionary processes of biological species. In this approach, a possible solution is represented as an *organism* consisting of one or more *chromosomes*. A chromosome is a string of *genes* containing genetic information. GAs do not search the entire space of a possibly infinite number of solution candidates, but consider only a *population*: a pre-defined, tractable number of organisms. It starts with initializing the population (called the 0th *generation*) by using a random generator and evaluates all organisms of the population according to some mathematical function, resulting in a fitness value of each organism. A certain number of organisms are then probabilistically selected from the population, based on their fitness values. The higher the fitness of an organism, the greater the probability of being selected. GAs then generate a new population by applying genetic operators such as reproduction, crossover and mutation to the selected organisms. This cyclic procedure of evaluation-selection-application of genetic operators continues over generations until the evaluation result meets a pre-defined stop condition. The new organisms genetically modified from the selected old ones often represent further improvement of the fitness values.

The principle underlying GAs can be expressed using a pseudo code (Buckles & Petry, 1992) as in the following box. The structure is common to all GAs. The specific challenge in any application domain concerns ① the specification of a representation scheme of the possible solutions, ② the specification of the fitness function, ③ the choice of genetic operators, and ④ the choice of stop condition. Note that each generation selects and applies only one genetic operator. Equally important is a list of parameters, to be set by the researcher, that controls the algorithmic flow. It includes ⑤ the size of a population, ⑥ the selection probabilities of genetic operators in each generation, ⑦ the number of organisms to be selected from a population, and ⑧ the application probabilities of reproduction and crossover to each selected organism and the mutation probability of each gene of the selected organism.

```
begin
   initialize population
   evaluate initial population
   while not (stop condition) do
   begin
      select organisms
      select a genetic operator
      generate new population by applying a genetic operator
      evaluate newly generated population
   end
end
```

We will develop a Genetic Algorithms-based MultiDimensional Sequence Alignment Method (GA-MDSAM) by incorporating some problem-specific modifications of these principles.

Representation scheme

The terms underlying GAs are used as follows for our problem at hand:

generation   →   generation
population   →   population
organism   →   trajectory set (consisting of K uni-dimensional trajectories)
chromosome   →   trajectory
gene   →   move (vertical, horizontal and diagonal)

where, a set of moves in the comparison table constitutes a trajectory of alignments of an attribute, a set of trajectories composes a trajectory set as a solution of multidimensional alignments, and a set of trajectory sets constitutes a population of the current generation. The population then is represented as:

$$E(t) = \{E_1 ... E_y ... E_Y\} \tag{4.6}$$

$$E_y = [E_{1y} ... E_{ky} ... E_{Ky}]' \tag{4.7}$$

$$E_{ky} = [X_{1k} ... X_{lk} ... X_{(m+n)k}] \tag{4.8}$$

where,

$E(t)$ is the population of the tth generation ($t \geq 0$);
E_y is the yth trajectory set of $E(t)$ defined as an ordered set of K trajectories ($K > 0$);
Y is the number of trajectory sets in $E(t)$ ($0 < Y << TY$);
E_{ky} is the kth trajectory of E_y defined as an ordered set of moves in the comparison table;
X_{lk} is the lth move of the kth trajectory encoded as V, H or D representing the vertical, horizontal or diagonal move, respectively.

When two *K*-dimensional activity-travel patterns of lengths *m* and *n* are compared, the number of operations is fixed and equal to *m+n* for all trajectories as expressed in equation (4.8). In other words, GA-MDSAM employs a 'fixed-format' representation scheme although the lengths of actual trajectories in the comparison tables may vary because the lengths of the trajectories having diagonal moves of identity operation are shorter than those of off-diagonal moves. GAs in general and this heuristic in particular separate random population generation (initialization and genetic operator application) from problem-specific evaluation of the resulting population. The offspring trajectories generated by initialization and genetic operators are always of the same length, *m+n* (as said 'fixed format') as their parent trajectories, but may fail to constitute real trajectories. Any alignment of two sequences must yield a trajectory that ends with the last pair of source and target elements (the *m*th and the *n*th) in the comparison table. However, a randomly initialized or genetically randomly modified fixed-format trajectory may not satisfy this condition. Nevertheless, allowing illegal trajectories can dramatically improve the results in later generations by keeping the diversity of the solutions.

Fitness function and trajectory-set selection

Assuming that the trajectory sets with lower multidimensional alignment costs are the better ones, GA-MDSAM selects the best-of-generation solution for producing the offspring (Koza, 1992) in each generation. Each trajectory E_{ky} of E_y, consisting of vertical, horizontal and diagonal moves, is converted into the corresponding uni-dimensional operation set that contains deletion and insertion operations. Unlike vertical and horizontal moves that are always converted into deletion and insertion operations, it is checked whether a diagonal move implies identity (in the case where the source and target elements compared are the same) or substitution (otherwise). The diagonal move is then decomposed into vertical and horizontal moves if it is identified as substitution. The uni-dimensional operation sets are then integrated into multidimensional operation sets. The fitness values C^y of individual trajectory sets E_y are defined as the sum of the costs for the deletions and insertions included in the multidimensional operation sets. Finally, the fitness of population C^* at the tth generation is determined. Note that the number of multidimensional operation sets of GA-MDSAM of each generation is much smaller than a complete set of all possible solutions of the exhaustive MDSAM.

Now the problem is how to evaluate particular trajectory sets whose uni-dimensional trajectories do not end with the element pair (*m,n*). Dracopoulos (1997) suggested three alternative techniques for handling the 'illegal children' problem: ① Repair illegal solutions, ② Cancel the illegal solutions and initialize a new one, and ③ Redesign the algorithm so that it produces legal solutions only. We choose the first technique because the second requires too much computing time, and the third does not seem appropriate for our problem. In particular, we will handle this 'illegal children' problem by temporarily ignoring and/or amending for evaluation the trajectories that do not satisfy this requirement.

Consider, for example, a trajectory of alignments, involving two sequences of lengths 3 and 4 (Figure 4.7). The trajectory resulting from a random generation is E_{ky} = [D V H V D̲ V̲ V̲] in the comparison table of the left hand side of Figure 4.7, where n(E_{ky}) = *m+n* = 3+4 = 7.
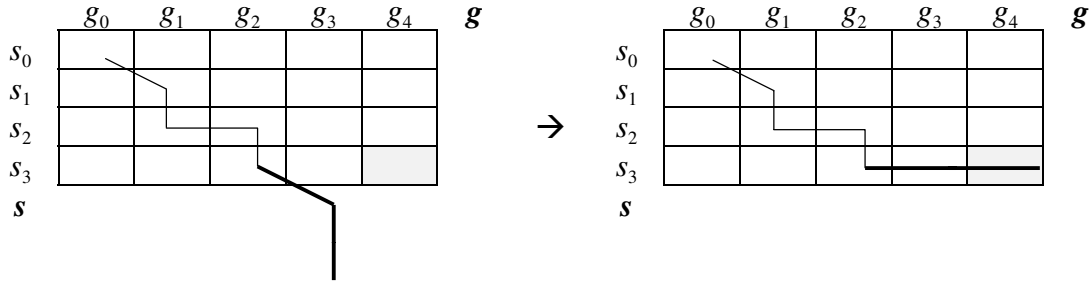
Figure 4.7: 'Illegal' trajectories and their correction for evaluation

The underlined elements in the trajectory vector are the moves not in the comparison table, which are thus ignored by the evaluation procedure. Instead, new moves are assumed as in the right hand side of Figure 4.7, and E_{ky} = [D V H V H̲ H̲] is evaluated.

Note that these changes are temporarily assumed only for the evaluation purpose, while the illegal trajectories remain unchanged and applied as they are for the successive genetic operators. One may find this counterintuitive as the 'illegal' individuals still have the right to be selected to contribute to the next generation. Interpreting an illegal trajectory as the one that has some defected part instead of being dead and utilizing its information instead of dumping it provide however substantial benefits. First, it increases the possibility of sudden improvement of the illegal trajectories genetically modified by context-free operators. Secondly, and more importantly, it maintains the size of population to be tested that would sharply decrease otherwise. Furthermore, the fact that a particular part of a trajectory set is defected is in itself informative. An illegal trajectory that has some part outside the comparison table is therefore not changed or deleted from the current generation in advance of the trajectory-sets selection for the next population generation. The employed GAs strictly separate random application of genetic operators from problem-specific evaluation and maintains the diversity of trajectory-set candidates.

The employed GAs probabilistically select the trajectory sets for generating new populations in proportion to their fitness values. While there are some other important methods such as tournament selection and rank selection (Mitchell, 1997), this so-called roulette wheel selection scheme (Goldberg, 1989) is rather standard (Davis, 1991a). The employed selection scheme can be expressed as:

$$S(E_y) = \left.\frac{\sum_{y'}^{Y} C^{y'}}{C^y}\right/ \sum_{y'}^{Y}\frac{\sum_{y'}^{Y} C^{y'}}{C^{y'}} \tag{4.9}$$

where, $S(E_y)$ is the selection probability, also called survival rate, of the yth trajectory set.

Note that equation (4.9) holds for each selection of a trajectory set in the current generation. In other words, the selection of trajectory sets is made *with* replacement, and gives higher chances to better solutions of being selected.

Genetic operators

GA-MDSAM employs reproduction, crossover and mutation operators that are commonly used in GAs. It is well known however that these genetic operators may vary considerably, depending on the data (e.g., Syswerda, 1991). We therefore explored several combinations of genetic operators of different forms to identify the best for our problem.

First, we explored three different kinds of crossover operators: a one-point, two-point and uniform crossover, as illustrated in Figure 4.8. One-point crossover is an operator that exchanges one piece of information between two selected trajectories, designated by a single cutting point somewhere in the sequence. Two-point crossover is an operator that exchanges one or two pieces of information between two selected trajectories, designated by two cutting points somewhere in the sequence. Uniform crossover is an operator that exchanges the information of each corresponding position between two selected trajectories by chance. It is a crossover operator, possibly involving multiple cutting points (Davis, 1991b).

Secondly, we explored two kinds of mutation operators: a point and order-based mutation. Point mutation is an operator that changes by chance the kind of move. Order-based mutation is an operator that randomly selects two moves and exchanges them within a single trajectory.
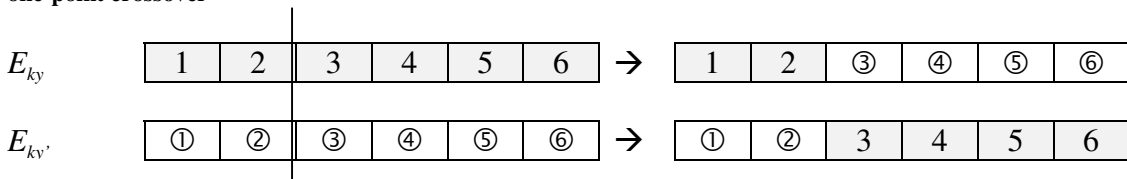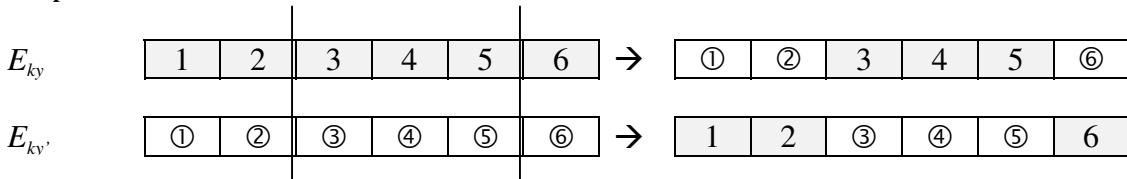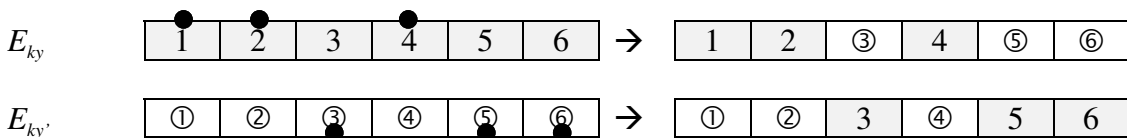
Figure 4.8: Illustration of the employed crossover operators.
Note: The vertical lines represent crossover points. Each cell may represent a vertical, horizontal or diagonal move. The number of cells (moves) of a trajectory is $m+n$. Each crossover event works on a pair of trajectories for the same attribute. That is, $k = k'$ in any pair of E_{ky} and $E_{k'y'}$ where $y \neq y'$.

Finally, we used the reproduction operator as it is commonly done in conventional GAs. Once a selection of trajectory sets has been made on the basis of fitness values, the reproduction operator simply copies the selected trajectory sets to the next generation.

Stop condition

In general, three different stop conditions can be identified. First, the number of generations for a run can be a priori given. Secondly, a certain threshold value of the fitness of an organism may be employed. Finally, a certain degree of stability or convergence rate across consecutive generations can be specified. We decided to use as the stop condition a convergence rate, or a certain number of consecutive generations that do not represent an improvement. A particular rate of convergence was determined based on some preliminary experiments that we conducted.

Parameters

Three additional parameters are particularly relevant. First, we specified the choice probability of the diagonal move in initializing the population and in point mutating trajectory sets. Because we have vertical, horizontal and diagonal moves, a choice probability of 1/3 given to every mutated move may be considered reasonable. However, since many diagonal moves involve, rather than an identity, a substitution operation that is decomposed into deletion (vertical move) and insertion (horizontal move), the equal choice probability is not fair for the problem at hand. We therefore introduced an additional parameter of diagonal move choice probability for initialization and point mutation that is bigger than 1/3.

Secondly, we defined a parameter to select the best trajectory set(s) for the next generation. The best trajectory set of the current generation contains all the efforts accumulated from the first generation. When the best combination(s) of a generation is not selected by chance, the algorithm may put in the same effort again and again over generations (Davis, 1991b). To prevent this inefficiency, we specified the number of best trajectory sets to be preserved for the next generation, instead of being selected by chance.

Finally, we were concerned about the possible limitation of conventional genetic operators with respect to their ability to derive better trajectory sets from the selected ones. In our problem context, the random application of genetic operations with fixed format representation may produce a trajectory set that is often worse than the selected one. To increase the probability to find a locally better trajectory set, we generated several offspring around the selected trajectory set and picked the best. This nearest neighbor search selects the locally superior alternatives at each search step (Rich & Knight, 1991; Reeves & Höhn, 1996). Of course, not all neighbors of a selected trajectory set were tried as all possible crossover or mutation of a trajectory set would involve too much computing time. Instead, we examined a few neighbors by introducing a parameter for the number of neighbors. Thus, GA-MDSAM can now be summarized as in the following box.

```
begin
   t = 0                                          // t indicates the tth generation //
   no_improve = 0
   initialize E(t)
   calculate C*(t)
   Best_Fitness = C*(t)
   while not (no_improve ≥ convergence_rate) do
   begin
      select a genetic operator
      create E1(t) by selecting and copying a subset of E(t)
      t = t+1
      no_improve = no_improve+1
      create E1(t) by applying the selected genetic operator to E1(t−1)
      create E2(t) by selecting and copying a subset of E(t−1)
      create E(t) by summing E1(t) and E2(t)
      calculate C*(t)
      if C*(t) < Best_Fitness then Best_Fitness = C*(t) and no_improve = 0
   end
end
```

Note: $C^*(t)$ denotes the fitness of $E(t)$. Note that $E_1(t)$ consists of the trajectory sets newly generated by the single or multiple applications of a genetic operator to each of the selected trajectory sets and that $E_2(t)$ includes the best trajectory set(s) of the $(t-1)^{th}$ generation.

4.4.2 A heuristic based on dynamic programming

GA-MDSAM separates the solution search procedure from the solution evaluation procedure and keeps the solution search context-free. This general-purpose search may find better solutions by avoiding premature application of the knowledge about uni-dimensional alignments to the integration of operation sets. In theory, the uni-dimensional optimum alignments are not necessarily an appropriate basis for the multidimensional integration of operation sets in terms of the optimality of the solutions. In practice, however, we may expect that the integration of uni-dimensional optimum trajectories will result in a solution that is near to the multidimensional optimum as those trajectories involve the largest number of cost-free identity operations. Even then, there are often many possible optimum trajectories, and the number of combinations of trajectories across attributes to consider may become intractably large. We may therefore employ a more simplified heuristic approach that considers, for each attribute dimension, only one optimum trajectory along the diagonal region of the comparison table. The optimum trajectory was sought by a dynamic programming (DP) technique, as used for the uni-dimensional optimum alignments of the OT-MDSAM.

    This heuristic approach was inspired by the fact that most uni-dimensional optimum trajectories run along the diagonal region of the comparison table (Kruskal & Sankoff, 1983; States & Boguski, 1991). The reason is that the diagonal moves often involve identity operations, which do not involve any costs. The integration of diagonal-oriented trajectories across attribute dimensions is therefore expected to produce a good solution.
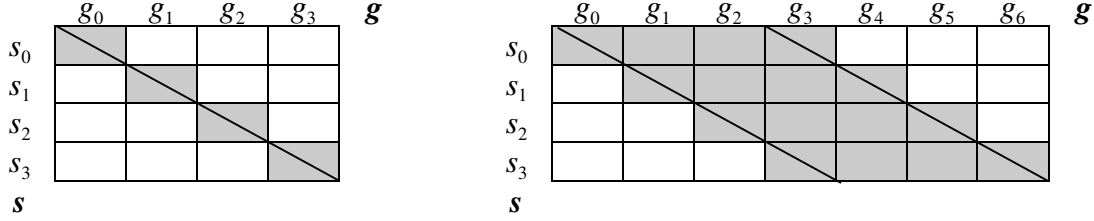
Figure 4.9: Diagonal region of the comparison table

More similar loci or trajectories across different attribute dimensions imply more similar sets of operations that result in more occasions of operation integration in the multidimensional space. Examples of the diagonal region are shown as shadowed cells in Figure 4.9.

The general solution of the MDSAM problem involves the existence of multiple uni-dimensional operation sets and, hence, assumes the existence of multiple multidimensional operation sets. Although reducing the number of multidimensional operation sets to test, the previously discussed GA-MDSAM searches multiple opportunities for the solution because it also involves multiple uni-dimensional operation sets. In contrast, the proposed Dynamic Programming-based MultiDimensional Sequence Alignment Method (DP-MDSAM) considers only one multidimensional operation set. In other words, whereas GA-MDSAM searches multiple uni-dimensional trajectories that are not necessarily optimal, DP-MDSAM searches only one trajectory that is optimum and is within or closest to the diagonal of the comparison table. The only uni-dimensional operation set of each attribute dimension that is selected for the inclusion in a single multidimensional operation set is defined as:

$$O_k = \{p|p=\mathtt{d}(i,k) \vee p=\mathtt{i}(j,k)\} \tag{4.10}$$

with

$$O_k = conv(Q_k) \tag{4.11}$$

and

$$Q_k = \{q|q = \mathtt{e}(i,j,k)_1, \ldots, \mathtt{e}(i,j,k)_r, \ldots, \mathtt{e}(i,j,k)_{R_k}\} \tag{4.12}$$

and

$$F(Q_k) = F(Q_{v_k^*}) = \max[F(Q_{1_k}), \ldots, F(Q_{v_k}), \ldots, F(Q_{V_k})] \tag{4.13}$$

and

$$F(Q_{v_k}) = \sum_r^{R_k} e_{r_v} \tag{4.14}$$

and

$$e_{r_v} = \begin{cases} 1 & \text{if } \ominus(i,j,k)_{r_v} \in D\{\ominus(i,j,k)\} \\ 0 & \text{otherwise} \end{cases} \qquad (4.15)$$

where,

O_k is the cost-taking deletion and insertion operation set of the kth attribute dimension;

$\ominus(i,k)$ and $\mathbb{i}(j,k)$ are respectively the deletion and insertion operations applied to the ith and j^{th} elements of the kth attribute dimension;

Q_k is the cost-free identity operation set of an optimum alignment of the kth attribute dimension;

$conv(Q_k)$ is a procedural function that converts Q_k into O_k;

$\ominus(i,j,k)_r$ is the rth identity operation applied to the ith source element and the jth target element of the kth attribute dimension;

R_k is the number of identity operations of the optimum trajectory of the kth attribute dimension;

Q_{v_k} is the identity operation set of the vth optimum trajectory of the kth attribute dimension;

V_k is the number of optimum trajectories that can be traced in the comparison table of the kth attribute dimension; (All optimum trajectories of an attribute dimension have the same number of identity operations as shown in Appendix 4.1.)

$F(Q_{v_k})$ is a 'diagonal' function measuring how much Q_{v_k} is involved with the diagonal region of the kth attribute dimension, denoted by $D\{\ominus(i,j,k)\}$;

e_{r_v} is a dichotomous value denoting whether the coordinate of the rth identity operation of the vth optimum trajectory falls in the diagonal region;

$\ominus(i,j,k)_{r_v}$ is $\ominus(i,j,k)_r$ of the vth optimum trajectory.

More specifically, the value of e_{r_v} in equation (4.15) is determined as:

$$e_{r_v} = \begin{cases} 1 & \text{if } p \leq q \leq (|m-n|+p) \\ 0 & \text{otherwise} \end{cases} \qquad (4.16)$$

where, p and q are the positions of the shorter pattern and the longer pattern appeared in $\ominus(i,j,k)_{r_v}$, respectively.

Q_k can be easily converted into O_k by comparing the coordinates of two adjacent identity operations. All the source and target elements in-between these are identified as the elements that are respectively deleted and inserted. When there are multiple Q_{v_k}'s, with the maximum value of the 'diagonal' function, one of such Q_{v_k}'s is arbitrarily selected as $Q_{v_k^*}$.

The major difference of the DP approach from the previously suggested GAs is that the DP approach considers, for each attribute dimension, only a single *optimum* trajectory within or nearest to the diagonal region, while the GAs seek, for each attribute dimension, more possibilities also including *non-optimum* trajectories.

4.4.3   A hybrid algorithm

The nature of the above two approaches stimulates the design of this hybrid alternative. This section addresses this alternative to possibly improve the heuristics. First, if the accuracy of the DP-MDSAM's results is rather acceptable given its 'single-hit' nature, this would indeed prove that most of the different combinations of uni-dimensional trajectories induce the same set of operations in the multidimensional space. Then, bounding the search space to the diagonal region of the comparison table should be a better starting point than randomly picking up the initial search points. Secondly, unless being extremely lucky to obtain exactly the true value, the method would gain benefit from further search starting from the DP-MDSAM's single hit. The method could make use of the ability of the search built in GA-MDSAM. This suggests that a hybrid algorithm, which uses the DP solution as an initial GA solution and the random application of genetic operators for further search, may combine the best of speed and accuracy.

The hybrid alternative maintains the overall framework of genetic algorithms as discussed in Section 4.3.1 but replaces the random initialization by the solution of the DP-MDSAM as in Section 4.3.2. This change requires a few subsequent modifications of the algorithm. This section introduces the details of these modifications, and Section 4.5.2 examines the performance of the suggested Hybrid MultiDimensional Sequence Alignment Method (Hy-MDSAM).

Changes in representation scheme

The multidimensional operation sets associated with the DP-MDSAM's solutions are of various lengths. Hy-MDSAM, employing the DP solution as the initial solution, therefore represents the trajectories and trajectory sets that are no longer of fixed format. Consequently, the representation of a trajectory of equation (4.8) should be modified to a flexible length-format as follows:

$$E_{ky} = [X_{1k} \ldots X_{lk} \ldots X_{Lk}]$$
(4.17)

where, L is the number of moves of a trajectory ($L \leq m+n$), which can vary with attribute dimensions of even the same activity-travel pattern.

Changes in crossover

Two trajectories of different lengths could be crossed over. Crossover points within the range of the shorter trajectory would then always allow crossover to happen. One-point, two-point and uniform crossovers are illustrated in Figure 4.10, instead of Figure 4.8. Similarly, mutation is also applied to the positions within the range of shorter trajectory.

4.5   Illustration

Section 4.3 discussed the fundamental features of the proposed method of multidimensional activity pattern comparison with an illustration of its application in a simple example. Section 4.4 subsequently developed alternative algorithms to implement the method in real time. This section will provide a practical illustration of how the suggested method works with empirical data of activity-travel patterns collected in The Netherlands to show the method's fundamental properties and also reports the results of the comparative analysis of the performance of three alternative search algorithms regarding the solution's accuracy and the computing time.

4.5.1   Fundamental properties of the method examined by the OT-MDSAM application

Analysis scheme

The fundamental properties of the proposed multidimensional sequence alignment method are studied by examining whether the method is capable of capturing the interdependency between attributes in empirical data.
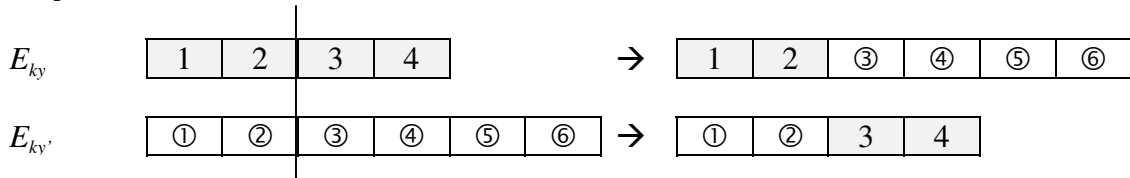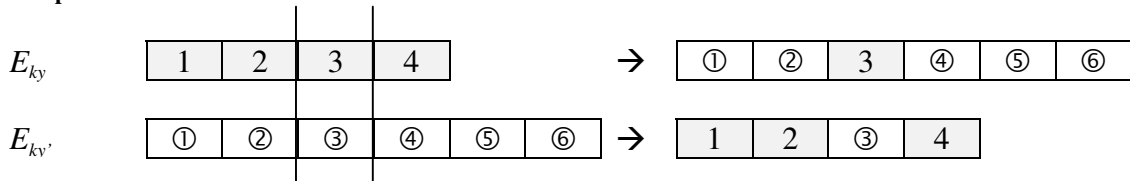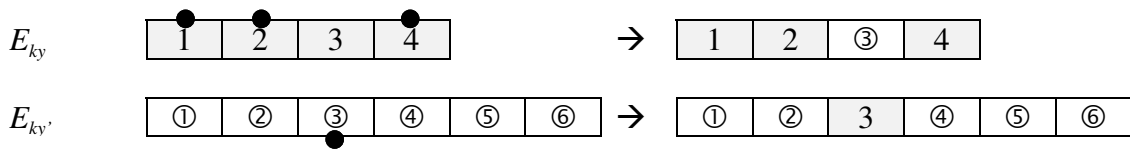
Figure 4.10: Illustration of the crossover operators of Hy-MDSAM.

Note: The number of cells (moves) of a trajectory is $L \leq m+n$. (Compare with Figure 4.8.)

To this end, we compare the amount of cost reduction achieved by the proposed method with the *sum* of costs of the original Uni-Dimensional sequence alignment method (UDsum). In addition, the correlation between the two methods will be examined because the relative (rather than absolute) pairwise distances are relevant to the classification and the goodness-of-fit measurement. A significant cost reduction would demonstrate that the proposed method captures interactions between attribute dimensions. An imperfect correlation would also suggest a variety of interdependency relationships between attributes. Empirical proof along these lines would be indicative of the superiority of the additional value of the proposed method.

Data

The same activity diary data collected in 1997 in Hendrik-Ido-Ambacht and Zwijndrecht is used as in Section 3.4.2. The empirical analysis of this section used only a sub-set of 71 activity-travel patterns that were randomly selected from the full data set consisting of a total of 2974 activity-travel patterns. The selection involves 2485 pairwise comparisons. Unlike in Section 3.4.2 that used only single dimension of activity type, however, this section analyzed three dimensions of activity-travel patterns including activity type, location and transport mode. The patterns involve twenty-five out-of-home activities, thirty-two out-of-home locations and four transport modes including car, walk, bike and car passenger. An extra code, 'unknown,' was included to represent the attribute elements that were not identified. The substitution operation was applied to any alignment with the unknown element. The average length of the activity patterns was 6.80 with a maximum of 17, a minimum of 1 and a standard deviation of 3.77 activities. Figure 4.11 shows an example.

Results

The UDsum costs and the OT-MDSAM costs were calculated on 2485 pairs of activity-travel patterns. The deletion and insertion weights were given the value of 1, and the substitution weight was assumed to be the sum of deletion and insertion weights. All attribute weights were also given the value of 1.

The results are shown in Table 4.1. The difference in cost reduction between the two methods is 14.63, which is fairly large considering the size of the UDsum costs (reduction is 52.75 % of 27.7336). This finding provides empirical evidence of the fact that the proposed method captures interdependency in multidimensional activity profiles. Moreover, this result suggests that interdependencies are significant.

actual pattern				*encoded pattern*		
in-home activity at home unknown mode	grocery shopping at location 3342 walk	in-home activity at home walk	➔	99 0 9999	20 3342 2	99 0 2
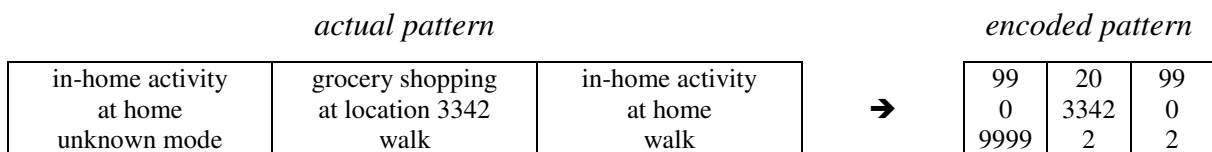
Figure 4.11: An example of the encoding of activity pattern

Table 4.1: Pairwise comparison results

	# comparisons	Mean	Min	Max	STD
Sum of UDSAMs	2485	27.7336	2	73	12.2389
OT-MDSAM	2485	13.1038	2	32	5.1867

The constant amount of cost reduction across different weights of the primary attribute should be evident from equation (4.4). It occurs because a change in the weight of the primary attribute does not affect the total amount of cost reduction, which is caused by the integration operation that is applied only to the alignments of smaller-weight attribute elements. Consequently, as the primary attribute weight increases, the ratio of the OT-MDSAM cost to the UDsum costs becomes larger, and the cost reduction becomes less important. This finding implies that a fine-tuning of the size of the primary attribute weight is required, depending on the context of analysis. Given a proper size of the primary attribute weight, OT-MDSAM should be expected to significantly change the similarity between activity-travel patterns as compared to the UDsum.

The next step in the analysis involved the examination of the correlation between the two methods to investigate whether the significant amount of cost reduction changes the relative distances between activity patterns. The Pearson correlation coefficient and rank correlation coefficient are 0.951 and 0.953, respectively. This finding indicates that although the two measures are highly correlated, the correlation is not perfect.

Evidence of the decreasing effect of cost reduction can be found in Figure 4.12. The left-hand side of the figure shows that the correlation between UDsum and OT-MDSAM becomes close to 1 as the weight of the primary attribute becomes 3 or higher. The effect of the cost reduction caused by the integration of operations applied to the second and third attributes is virtually disappearing as illustrated by the right-hand side of the figure that shows the diminishing ratio of cost reduction to the UDsum.
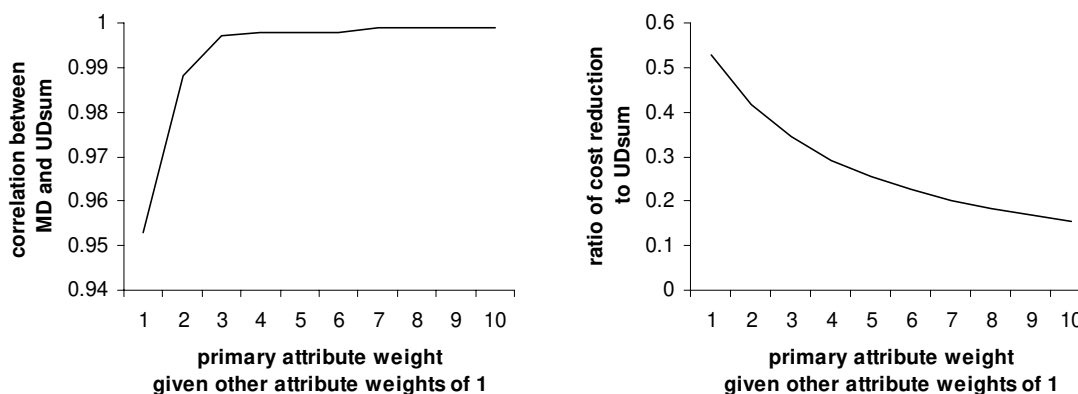
Figure 4.12: Correlation between UDsum costs and OT-MDSAM cost with varying weights of activity-type attribute.

Table 4.2: Correlation between UDsum and two-dimensional OT-MDSAM

Attributes included in the activity patterns	Pearson's r	Spearman's r
activity type, activity location	0.977	0.977
activity type, transport mode	0.970	0.973
activity location, transport mode	0.967	0.969

To investigate the interdependency between attributes in more detail, we further examined which pairs of attribute dimensions demonstrate co-existences of attribute elements. The correlation between UDsum and OT-MDSAM costs employing two attribute sequences was computed for this purpose (Table 4.2). A higher correlation is indicative of a weaker interdependency. The attribute weights were all assigned the value of 1. Table 4.2 shows that the simultaneous alignment of activity types and transport modes occurs more often than the simultaneous alignment of activity types and activity locations. These different degrees of coexistence of attribute elements suggest that the transport modes to reach particular activity locations are rather fixed, while the locations to conduct particular activities are more flexible. The fact that there are more locations encoded than transport modes encoded as choice alternatives may also have affected these results. Furthermore, the lowest correlation between activity location and transport mode provides evidence of the effect of physical constraints on mobility.

4.5.2   Performance of alternative algorithms

Analysis scheme

The MDSAMs employing alternative heuristics (DP, GAs and Hybrid) were compared in terms of how close their solutions were to the 'true' distances, calculated by an exhaustive algorithm, and in terms of the computing time required to reach the solution. The importance of the accuracy of the solution and the computing time is paramount in the analysis of activity-travel behavior. In classification study, the accurate relative distances between activity-travel patterns is crucial for the subsequent clustering procedure. In prediction of actual activity-travel patterns using simulated patterns, the correct measure of goodness-of-fit is a pre-requisite of the model establishment.

Table 4.3: GA-MDSAMs and Hy-MDSAMs to test

	one-point crossover		two-point crossover		uniform crossover	
	point mutation	order-based mutation	point mutation	order-based mutation	point mutation	order-based mutation
1 neighbor	(1-1-1)	(1-2-1)	(2-1-1)	(2-2-1)	(3-1-1)	(3-2-1)
5 neighbors	(1-1-5)	(1-2-5)	(2-1-5)	(2-2-5)	(3-1-5)	(3-2-5)

Note: The first numeral in the bracket represents the kind of crossover (1=one-point, 2=two-point, 3=uniform), the second the kind of mutation (1=point, 2=order-based), and the last the number of neighbor trajectory sets to try.

Table 4.4: Parameters commonly used for twelve GA-MDSAMs

parameter	value	parameter	value
# trajectory sets	100	trajectory set proportion for reproduction	30 %
# best trajectory sets	1	trajectory set proportion for crossover	40 %
convergence rate	50	trajectory set proportion for mutation	20 %
vertical move choice prob.	20 %		
horizontal move choice prob.	20 %		
diagonal move choice prob.	60 %		
reproduction selection prob.	20 %	reproduction application prob.	100 %
crossover selection prob.	70 %	crossover application prob.	100 %
mutation selection prob.	10 %	mutation application prob.	1 %

A reasonable amount of computing time with acceptable accuracy should allow the study. Different crossover and mutation operators and a different number of neighbors of each selected trajectory set were examined for the genetic algorithms, yielding twelve GA-MDSAMs and Hy-MDSAMs, respectively (Table 4.3).

Table 4.4 presents a summary of the other operational decisions. Based on preliminary experiments, population size was restricted to 100 trajectory sets. The convergence rate was set to 50 so that the GAs procedure stopped when no improvement in the best-of-generation fitness was reported over 50 generations since the last improvement. The choice of diagonal move for initialization and point mutation was given a higher probability than the choice of a horizontal or vertical move. The selection of crossover that is known as the main engine of genetic evolution was given a higher probability than the selection of reproduction and mutation. In addition, we conducted multiple runs of each measure on the same data set and averaged the results to avoid that a single run could lead to a lucky hit or an improbable miss (Davis, 1991a).

Data

A total of 20 runs involving 1540 pairwise comparisons of 56 three-dimensional activity-travel patterns consisting of activity type, location and travel mode sequences and averaged the results were conducted for each measure. As the exhaustive search requires a considerable amount of computing time, only this small number of activity-travel patterns was analyzed. The set of 56 activity-travel patterns was arbitrarily selected from a total of 1128 diaries, representing two-days records of 670 individuals from 333 households, collected in Voorhout in The Netherlands in 1997 (Arentze, *et al*, 2001b). The 1128 diaries distinguish 17 activity types, 252 locations and 6 transport modes. The activity locations were encoded by four-digit zip codes, except for the home location that was encoded '0'. In addition, the analysis in this section includes an extra code representing the attribute elements that were not identified. The substitution operation was applied to the alignment of the unknown element. The analysis also included an extra activity type, 'in-home activities.' This activity type was identified if an activity was conducted at home. Once identified, each set of consecutive in-home activities was encoded as a single in-home activity. The activity-travel patterns distinguish 13 activity types (in-home activities, out-of-home work/school, bring/get person or goods, grocery shopping, non-grocery shopping, service activity, medical

visit, eat, sleep, out-of-home leisure, out-of-home non-leisure, paying social visit and others), 52 locations and 6 transport modes (car, walk, bike, car pool, car passenger and public transport mode including bus, tram, train and subway). The average length of the 56 activity-travel patterns was 5.57 with a maximum of 16 and a minimum of 1 activities, while the average of the full set of 1128 activity-travel patterns was 5.32 with a maximum of 19 and a minimum of 1.

Results

Table 4.5 shows the performance of DP-MDSAM, GA-MDSAMs and Hy-MDSAMs. It clearly shows that the MDSAMs of all three alternative algorithms dramatically reduce the computing time compared to the exhaustive search, while providing relatively accurate solutions. The performance of the heuristic algorithms is good. We first report the comparison of DP-MDSAM and GA-MDSAM, and then discuss the performance of the Hy-MDSAM, which is a hybridization of the DP- and GA-MDSAMs.

As for relative performance, the DP-MDSAM clearly outperforms the GA-MDSAM in terms of computing time. DP-MDSAM completed the 1540 comparisons in just 2 seconds on average across runs, while the GA-MDSAM's algorithms took, on average, 4 minutes 52 seconds across runs, and even the best GA-MDSAM (2-1-1), took 3 minutes 15 seconds across runs. Although the convergence rate is a critical determinant of the computing time of the GA-MDSAM's, the incremental procedure underlying a GA will never be faster than the 'single-hit' procedure of a DP. The difference in computing time between the two approaches is indeed proven substantial.

In contrast, the comparison of the solution accuracy between DP- and GA-MDSAMs does not produce consistent results. While some GA-MDSAMs show a higher accuracy than the DP-MDSAM, the difference between the two heuristic approaches is relatively small. The best GA-MDSAM (3-2-5) outperforms the DP-MDSAM by 4.3%, but this may not compensate the difference in computing time (7 minutes 5 seconds versus 2 seconds). Whether obtaining a slightly better accuracy at the expense of a significantly higher computing time is worthwhile will depend on the aim of the study. While one might expect that computing time is not critical in classification studies, if the alignment measure is used to calibrate an activity-based model, the larger computing time may be prohibitive.

Next, an examination of the results of the Hy-MDSAM compared with the results of the previous two algorithms leads to the following observations. First, a surprisingly high increase in accuracy (about 20%-up) has been achieved. Secondly, computing time also increased, but not as sharp as the increase in accuracy. Thirdly, the deviation and the average difference are sharply reduced, indicating that a more stable similarity measure has been obtained. Finally, the differences in accuracy between the MDSAMs become very small.

The reason of this success of Hy-MDSAM can be explained as follows. First, DP-MDSAM's result was rather accurate given its 'single-hit' nature, and therefore, bounding the search space to the diagonal region of the comparison table indeed provided a good starting point to the GA-MDSAM. Secondly, as demonstrated by the significant differences in accuracy between single-neighborhood and multiple-neighborhoods GA-MDSAMs, more search leads to a better accuracy. Multiple-neighbors GA-MDSAMs on average outperform single neighbor GA-MDSAMs by 6%. Single-neighbor GA-MDSAMs are inferior to DP-

MDSAM in terms of solution accuracy, while searching for more neighbors reverses relative performance. Similarly, a further investigation showed that, in 49.4% of the cases, the DP-MDSAM solutions were better than the solutions of the 1st iterations of GA-MDSAMs that start with the random initializations, while being inferior in only 8.1%. Given the high speed of the DP algorithm, the suggested hybrid algorithm, which uses the DP solution as an initial GA solution and the random application of genetic operators for further search, succeeded in combining the best of speed and accuracy. However, the computing time could still be a problem in conducting a Hy-MDSAM in real time for a large set of comparisons. In these situations, one might still wish to employ the DP algorithm and accept less accuracy.

Table 4.5: Performance of alternative MDSAMs(20 runs of 1540 comparisons for each measure)

MDSAMs		=[I]	range[II]	avedif[III]	Computing time[IV]
exhaustive search		-	-	-	1 hour 16min 54sec
DP-MDSAM		929 (60.3%)	0 - 4.00	.423	2 sec
GA-MDSAMs	(1-1-1)	*853 (55.4%)*	0 - 6.35	.575	3 min 16 sec
	(1-1-5)	935 (60.7%)	0 - 5.95	.435	6 min 3 sec
	(1-2-1)	857 (55.6%)	*0 - 7.15*	*.580*	3 min 16 sec
	(1-2-5)	944 (61.3%)	0 - 5.45	.434	6 min 1 sec
	(2-1-1)	879 (57.1%)	0 - 6.50	.559	*3 min 15 sec*
	(2-1-5)	964 (62.6%)	0 - 5.70	.402	6 min 9 sec
	(2-2-1)	864 (56.1%)	0 - 7.10	.564	3 min 16 sec
	(2-2-5)	956 (62.1%)	0 - 5.45	.408	6 min 5 sec
	(3-1-1)	890 (57.8%)	0 - 6.35	.546	3 min 27 sec
	(3-1-5)	994 (64.5%)	*0 - 5.10*	*.391*	*7 min 10 sec*
	(3-2-1)	893 (58.0%)	0 - 6.70	.554	3 min 23 sec
	(3-2-5)	*995 (64.6%)*	0 - 5.45	.394	7 min 5 sec
	best	3-2-5	3-1-5	3-1-5	2-1-1
	worst	1-1-1	1-2-1	1-2-1	3-1-5
Hy-MDSAMs	(1-1-1)	*1276 (82.9%)*	0 - 3.90	.157	*4 min 55 sec*
	(1-1-5)	1286 (83.5%)	0 - 3.90	.141	9 min 28 sec
	(1-2-1)	1276 (82.9%)	*0 - 4.00*	*.167*	4 min 57 sec
	(1-2-5)	1281 (83.2%)	0 - 4.00	.161	8 min 55 sec
	(2-1-1)	1277 (82.9%)	0 - 3.95	.155	5 min 5 sec
	(2-1-5)	*1291 (83.8%)*	0 - 3.80	.137	9 min 5 sec
	(2-2-1)	*1272 (82.6%)*	0 - 4.00	.163	5 min 13 sec
	(2-2-5)	1283 (83.3%)	0 - 4.00	.157	8 min 58 sec
	(3-1-1)	1278 (83.0%)	0 - 3.75	.157	5 min 14 sec
	(3-1-5)	1283 (83.3%)	*0 - 3.75*	*.141*	10 min 3 sec
	(3-2-1)	1275 (82.8%)	0 - 4.00	.165	5 min 22 sec
	(3-2-5)	1282 (83.2%)	0 - 4.00	.159	*10 min 55 sec*
	best	2-1-5	3-1-5	3-1-5	1-1-1
	worst	2-2-1	1-2-1	1-2-1	3-2-5

I: Heuristic MDSAM distances are the same as the true distances from the exhaustive search.
II: Range of deviation of each measure's results from the true distances, averaged on 20 runs.
III: Average deviation from the true distances, averaged on 20 runs.
IV: Computations based on a 450MHz Pentium II processor, averaged on 20 runs.

4.6   Comparative analysis of measurement methods

4.6.1   Introduction

In this chapter, we proposed a new method to measure the similarity between activity-travel patterns in terms of their compositional, sequential and interdependency properties. The method is theoretically appealing, and its potential was proven by analyzing real multidimensional activity diary data. This section investigates whether this potentially powerful method indeed offers comparative advantages over other existing distance measures by empirically analyzing the performance of the method in a classification study.

The classification of activity-travel patterns has traditionally been a topic in activity analysis that has received considerable attention. The classification of activity-travel patterns provides the foundation for more theoretically or empirically oriented research activities, and sometimes the basis for subsequent modeling work in the sense that most modeling approaches require some simplification of the complexity underlying observed activity-travel patterns to derive a feasible model. The aim of the classification may either be to identify typical activity-travel patterns or to arrive at some segmentation of more homogeneous activity-travel patterns.

In this section, we will examine (1) whether sequential relationships and interdependency play a significant role in determining the dissimilarity of activity-travel patterns, and if so, (2) whether the newly suggested multidimensional sequence alignment measure results in cluster solutions that better discriminate the cross-sectional information embedded in activity-travel patterns and are better correlated with individuals' socio-demographic characteristics. It should be noted that most of the first question was already dealt with in Sections 3.4.1 and 4.5.1, where the fundamental properties of the uni-dimensional alignment methods were illustrated and compared with Euclidean measures, and the proposed multidimensional extension was compared with the simple sum of uni-dimensional alignments. We nevertheless repeat this analysis but in a broader context where the proposed method is compared with other existing methods in activity analysis. Particular attention is given to the comparison of the suggested multidimensional sequence alignment method with a Euclidean distance measure (Koppelman & Pas, 1985) and a signal detecting method (Recker *et al.*, 1985, 1986a, 1986b).

In the following, a brief introduction to the various measures is provided in Section 4.6.2, and the results of the empirical analysis using recent Dutch activity-diary data are reported in Section 4.6.3.

4.6.2   Empirical analysis

The empirical analysis employs the Dynamic Programming-based MultiDimensional Sequence Alignment Method (DP-MDSAM) introduced in Section 4.4.2.

Objectives

The empirical analysis reported in this chapter considers the question whether the structural information (sequential relationships and interdependency) embedded in activity-travel patterns is well reflected by the multidimensional sequence alignment method and, if so, whether the incorporation of the structural information affects the final cluster solutions. To this end, we first examine the overall relationships between distances calculated based on the different measures. We then investigate whether sequential relationships between activities are captured by the sequence alignment method by comparing uni-dimensional sequence alignment and Euclidean measures calculated for each attribute sequence, respectively. We also examine whether interdependency is captured by the newly proposed method by comparing it to the sum of uni-dimensional alignments. Finally, we examine which cluster solution better discriminates between the cross-sectional characteristics of activity-travel patterns and stronger correlates with individuals' socio-demographic status.

The following set of hypotheses represent our a priori expectations:

HYPOTHESIS 1:   *The distances measured by the proposed multidimensional sequence alignment will differ from those measured by other methods.*

HYPOTHESIS 2:   *The sequential information embedded in activity-travel patterns will lead to differences in distance measures between Euclidean and uni-dimensional sequence alignment methods.*

HYPOTHESIS 3:   *The interdependency embedded in activity-travel patterns will lead to differences in distance measures between the sum of uni-dimensional sequence alignments and the proposed multidimensional sequence alignment.*

HYPOTHESIS 4:   *The proposed multidimensional sequence alignment's cluster solutions will be better discriminating cross-sectional characteristics of activity-travel patterns.*

HYPOTHESIS 5:   *The proposed multidimensional sequence alignment's cluster solutions will be stronger correlated with individuals' socio-demographic status.*

As said, although similar analyses with hypotheses 2 and 3 were already conducted in Section 3.4.1 and Section 4.5.1, respectively, we repeat these but in the context of comparison of the proposed method with other existing methods in activity analysis.

Data

The same activity diary data collected in 1997 in Hendrik-Ido-Ambacht and Zwijndrecht is used as in Sections 3.4.2 and 4.5.2. The empirical analysis of this section used only a sub-set consisting of 999 activity-travel patterns that were randomly selected from the full data set consisting of a total of 2974 activity-travel patterns. The selection involved 498,501 pairwise

comparisons. Each of these activity-travel patterns is described in terms of four attributes: (1) activity-type, (2) travel-mode, (3) accompanying-person, and (4) location. The activity classification used included 12 activity categories (bring/get person or goods, daily shopping, non-daily shopping, service, medical, eat/drink, leisure, non-leisure, social visit, work/school, other, and in-home activity), 6 locations, 5 travel modes (no travel, car driver, slow (walk and bike), public transport mode, car passenger), and 4 accompanying-person situations (alone, with others inside the household, with others outside the household, and with others inside and outside the household). Consecutive episodes of in-home activities were amalgamated into a single episode. The accompanying person dimension was identified according to the first of these in-home activities. An extra code (unknown) was included to represent the attribute elements that were not identified. The average length of these 999 activity-travel patterns was 5.54 with a maximum of 19 and a minimum of 3 activities. The ratio of in-home activities to out-of-home activities was .516 on average.

Analysis scheme

The empirical analysis involved four different distance measures: Cosine Index, Feature Extraction, the sum of Uni-Dimensional sequence alignments (UDsum), and the proposed DOT-MDSAM. The analyzed activity-travel patterns were four-dimensional: activity-type, location, travel-mode and accompanying-person. Thus, in the present analysis we concerned ourselves with qualitative attributes only. It should be noted therefore that our analysis differs from the application of the feature extraction methods by Recker, *et al*. (1985, 1986a, 1986b) and Golob & Recker (1987) in two respects. First, we used a nominal scale for the location attribute instead of distance from home. Second, they used duration data because of their time-slice scheme of activity encoding. In the Feature Extraction method that we illustrate in this chapter, we employed a total of 128 time slices that covers an entire day. Each of the time slices involves 11.25 minutes. Recker, *et al*. (1986a, 1986b) employed an 8.9-minute scheme of 128 slices from 5.5 a.m. to 12.5 a.m. They used the first 50 coefficients in each of transformed feature vectors, while we used here all 128 coefficients. These differences should be kept in mind when interpreting the results of this study.

The following parameter values were selected: $\alpha = \beta = 0.5$, $W_1 = 0.4$ for activity type, $W_2 = W_3 = W_4 = 0.2$ for location, travel mode and accompanying person (Cosine Index); $w_d = w_i = 1$, $\beta_1 = 2$ for activity type, $\beta_2 = \beta_3 = \beta_4 = 1$ for location, travel mode and accompanying person (UDsum and DP-MDSAM). Unlike other measures, Feature Extraction did not differentiate the weight between attributes nor included the 'unknown' level.

Results

Hypothesis 1: The distances measured by the proposed multidimensional sequence alignment will differ from those measured by other methods.

The first hypothesis states that the distances measured by the proposed multidimensional sequence alignment will differ from those measured by other methods. This might be evident a priori, but this analysis was felt important to better understand to what extent the various measures are (linearly) related.

Table 4.6: Pearson correlation coefficient

	Cosine Index	Feature Extraction	Udsum
Feature Extraction	0.427		
UDsum	0.685	0.617	
DP-MDSAM	0.601	0.643	0.963

Note: All are significant at the 0.01 level.

We therefore conducted a correlation analysis between the distances generated by the four measures. A high correlation between the proposed method (DP-MDSAM) and the other methods would lead us to rejecting hypothesis 1. In that case, the rather complex new method would not add much to the conventional methods.

As said, the comparison of the 999 activity-travel patterns yielded 498,501 pairwise distances for each method in multidimensional space. Pearson correlation coefficients were calculated for these distances. The results are shown in Table 4.6. The positive, significant correlations between DP-MDSAM and the other methods suggest the following.

First, DP-MDSAM shares the property of measuring the degree of difference in element composition between activity-travel patterns with all other methods. Secondly, DP-MDSAM shares the property of interdependency with the cosine index method. Finally, DP-MDSAM shares the property of sequential information with feature extraction and UDsum. However, these correlations are far from perfect. Thus, these results support hypothesis 1.

Hypothesis 2: The sequential information embedded in activity-travel patterns will lead to differences in distance measures between Euclidean and uni-dimensional sequence alignment methods.

We hypothesized that the sequential information embedded in activity-travel patterns will lead to differences between Euclidean distance and uni-dimensional sequence alignment methods. The Euclidean distance employed here is defined as the Hamming distance between strings of information as given by equations (3.15), (3.16) and (3.17) in Section 3.2. This hypothesis was tested by calculating the correlation between these measures. A high correlation would contradict the hypothesis. It turned out that the correlation between the two measures for activity-type, location, travel-mode and accompanying-person attributes was 0.700, 0.709, 0.524 and 0.578, respectively. Thus, the two measures are only modestly correlated, providing support for hypothesis 2.

The correlation between these measures computed on the store choice sequences of shopping activity was reported as 0.853 in Section 3.4.1, whereas the correlation computed on the activity sequences in the current section is 0.7. The fact that the sequences included more diverse activity categories lowers the correlation in the current section, while the results are consistent in the sense that both show high, but imperfect correlations.

Hypothesis 3: The interdependency embedded in activity-travel patterns will lead to differences in distance measures between the sum of uni-dimensional sequence alignments and the proposed multidimensional sequence alignment.

The outcomes of the previous two tests suggest that sequence alignment methods may capture different aspects of activity-travel patterns. Hypothesis 3 relates to the question whether a multi-dimensional extension is valuable or whether the sum of uni-dimensional sequence alignments would give similar results. If interdependency in activity-travel patterns is insignificant, the two methods would produce identical results. We assume however that interdependency is embedded in activity-travel patterns, and that it will therefore lead to differences in distance measures between the sum of uni-dimensional sequence alignments and the proposed multidimensional sequence alignment.

To test this hypothesis, we calculated the differences in the mean values of UDsum and DP-MDSAM and performed a correlation analysis. A small difference in mean value would reject the hypothesis. Table 4.6 reports the results of this analysis. It shows that indeed the correlation was relatively high (0.963). This high correlation occurs either when there is almost no integration of operations or when the integration of operations happens very often due to the strong interdependency. The average distance of UDsum and DP-MDSAM is 26.3748 and 14.4333 respectively. The difference between the two means is 11.9415, which is very high. This result suggests that the high correlation can be explained by very frequent operation integration, resulting in a substantial portion of collective deletion and insertion. The results therefore support hypothesis 3.

The correlation between these measures computed on the three dimensional activity-travel patterns including activity type, location and transport mode was reported as 0.951 in Section 4.5.1, which is almost identical with the result of the current analysis although this section's patterns are four dimensional including accompanying person too. The results are consistent in the sense that both show high, but imperfect correlations, which gives the evidence of the interdependency between attributes.

Hypothesis 4: The proposed multidimensional sequence alignment's cluster solutions will be better discriminating cross-sectional characteristics of activity-travel patterns.

We now come to a more critical phase of the analysis. The results of the previous analysis indicate that some degree of interdependency is embedded in activity-travel patterns. We designed the proposed multidimensional sequence alignment method to better capture such interdependency. If it does this successfully, then the cluster solution based on the proposed multidimensional sequence alignment method will better discriminate between activity-travel patterns in terms of their cross-sectional characteristics.

The proportion of the cases, whose cluster memberships are in common between the classification based on a particular distance measure and the classification based on the cross-sectional characteristics of the activity-travel patterns, was used as an indicator for that distance measure's goodness-of-measurement. This proportion is in general called 'the correctly classified proportion'. A low proportion with the multidimensional sequence alignment method than with other methods would reject the hypothesis.

The cluster solutions for each of the four methods were obtained by inputting the corresponding pairwise distance matrix into Ward's clustering algorithm. CHAID (CHi-squared Automatic Interaction Detector) analysis (Kass, 1980; Magidson, 1994) was then used to partition the data based on the cross-sectional characteristics of activity-travel patterns (predictor variables) into mutually exclusive and exhaustive subsets that best

describe the cluster memberships (dependent variables). We assume that more homogeneous clusters are associated with a higher proportion of correctly classified activity-travel patterns. The CHAID classification was based on the following characteristics of activity-travel patterns: the presence and absence of (1) in-home work, (2) bring/get person or goods, (3) grocery shopping, (4) non-grocery shopping, (5) service activity, (6) out-of-home leisure, (7) out-of-home non-leisure, (8) out-of-home social visit, and (9) out-of-home work.

For each measure, a classification model with cluster membership as dependent variable and nine predictor variables was generated from the analysis sample (70 % of 999 activity-travel patterns), and its generalization was tested on the holdout sample (30 % of 999 activity-travel patterns) as denoted. The analysis set returns the result of the CHAID model on the current data, whereas the holdout set shows the generalization power of the model. If there is no big difference or downfall in the correct proportion with the holdout set results, compared with the analysis set results, we could regard the results from the analysis set as being a general conclusion. Several solutions of different numbers of clusters were examined for a minimum of two and maximum of seven clusters.

The proportions of correctly classified activity-travel patterns are shown in Table 4.7. The table shows that the cluster solutions based on DP-MDSAM discriminate considerably better between cross-sectional variables than the solutions based on other measures. Thus, the results of the cluster analysis support hypothesis 4.

Hypothesis 5: The proposed multidimensional sequence alignment's cluster solutions will be stronger correlated with individuals' socio-demographic status.

Although it is fair to say that discrimination between the cross-sectional characteristics of activity-travel patterns is the more fundamental test, we repeated the CHAID analysis with the following variables, representing individuals' situational and socio-demographic status: (1) day of the week, (2) socio-economic class of the household, (3) age of the oldest person in the household, (4) household composition and work status, (5) presence of children in the household, (6) number of cars, (7) gender of the person, (8) official work hours of the person per week, and the travel time to the nearest center for grocery shopping by (9) bike, (10) car, (11) public transport mode, the travel time to the nearest center for service activity by (12) bike, (13) car, (14) public transport mode, the travel time to the nearest center for non-grocery shopping by (15) bike, (16) car, (17) public transport mode, and the travel time to the nearest center for leisure activity by (18) bike, (19) car, (20) public transport mode.

Table 4.7: % correctly classified patterns in terms of cross-sectional variables

	# clusters	Cosine Index	Feature Extraction	UDsum	DP-MDSAM
3	Analysis	74.6	74.5	71.3	82.3
	Holdout	71.6	72.7	69.1	85.7
4	Analysis	69.1	70.0	65.0	77.8
	Holdout	62.0	67.6	58.0	82.0
5	Analysis	60.9	64.5	51.7	71.5
	Holdout	51.0	59.8	51.3	73.1
6	Analysis	57.2	59.1	50.7	67.4
	Holdout	51.2	52.8	48.0	70.2

Table 4.8: % correctly classified patterns regarding situational, socio-demographic variables

# clusters		Cosine Index	Feature Extraction	UDsum	DP-MDSAM
3	Analysis	47.6	70.7	53.9	75.3
	Holdout	38.8	62.4	49.9	76.1
4	Analysis	47.3	66.5	47.9	63.2
	Holdout	38.4	58.7	47.3	60.2
5	Analysis	32.9	61.6	40.0	48.5
	Holdout	32.2	52.1	33.6	39.5
6	Analysis	31.6	52.4	39.5	45.5
	Holdout	28.1	40.6	33.3	36.2

The proportion of correctly classified activity-travel patterns is shown in Table 4.8. The predictors are the twenty variables as described above. It shows that the cluster solutions based on feature extraction and DP-MDSAM are more or less equally correlated with an individual's socio-demographic status. Thus, because we do not find evidence of the superiority of the multidimensional sequence alignment method, we reject hypothesis 5. It is not readily evident why the two measures behave this way. One possible explanation is that the information utilized by the feature extraction method that works on time sliced activity patterns is richer, implying that it may correspond better with socio-demographic variables.

4.6.3 Conclusions

Empirical analysis compared the performance of the proposed multidimensional sequence alignment method for classifying activity-travel patterns with Euclidean distance and signal processing approaches. Previous efforts in activity-travel pattern classification were reviewed, and the principles underlying this new method were discussed. The methods were compared, using Dutch activity diary data as an example.

The analyses resulted in several observations. First, the pairwise comparison showed differences between the newly proposed measure (DP-MDSAM) and more conventional distance measures. Secondly, the sequence alignment method captures sequential information that is not accounted for by conventional Euclidean distance measures. Thirdly, the interdependency between attribute dimensions in activity-travel patterns is not sufficiently captured by uni-dimensional sequence alignment methods, emphasizing the need for the suggested multidimensional extension, which is consistent with the results in the previous illustration sections. Fourthly, the cluster solutions based on the proposed DP-MDSAM better discriminate between activity-travel patterns in terms of their basic characteristics than the cluster solutions based on conventional similarity measures. Finally, the cluster solutions based on the proposed DP-MDSAM do not outperform the cluster solutions based on the feature extraction method of signal processing theory in terms of the correlation with individuals' socio-demographic variables. However, it does provide better results in this regard compared to the solutions based on the cosine index and the sum of UDSAM.

4.7   Conclusions and discussion

This chapter developed a new measure of similarity between activity patterns that accounts for both sequential information and attribute interdependencies in activity-travel patterns. The proposed method is appropriate as a similarity measure in classificatory studies of activity-travel patterns and as a goodness-of-fit measure in activity-based modeling studies. In particular, we have proposed a method that can handle the multidimensional comparison of activity-travel patterns. The method can be considered as an extension of the uni-dimensional sequence alignment method, recently introduced in the transportation and time use literature. The quintessence of the new method is that, while maintaining the central property of the alignment methods of capturing sequential information, the method treats multiple operations for aligning attributes belonging to the same activity as a single operation, reflecting the notion of linkages between attribute dimensions in schedule decision making.

The problem with this conceptualization is that it results in a combinatorial explosion. We therefore developed a heuristic method to find the solution. This heuristic involves segment alignment by first aligning each attribute sequence separately using a conventional sequence alignment method, then integrating the operations that can be applied simultaneously, and finally assigning a single weighting value to the integrated operations unit as if it were a single operation.

Alternative algorithms are developed for the implementation of the suggested method in real time because the basic heuristic algorithm might still be too time-consuming if the number of optimal uni-dimensional trajectories for an attribute is large. Particularly, this problem occurs when an activity-travel pattern consists of many identical elements. Extensions of the basic algorithm were therefore developed to further economize the method for such cases. The suggested alternative algorithms are based on genetic algorithms (GA), a dynamic programming technique (DP) and a hybridization of these two (Hy). The major difference between the DP-based and GA-based approaches is that the GA-based heuristic repeatedly seeks better solutions using a general-purpose search engine, while the DP-based heuristic tests only trajectories closest to the diagonal being the most promising candidate for a solution. The hybridization was initiated to combine the DP-MDSAM as an initialization tool and the GA-MDSAM's multiple-neighbors search as a solution improvement tool for a genetic algorithm.

An empirical application to an activity-diary data set provided evidence for the claim that attribute interdependencies should be incorporated in measuring similarities among activity-travel patterns. Moreover, it was shown that the inclusion of interdependencies changes the similarity measurement results among activity-travel patterns.

A comparative study of alternative algorithms suggests that the DP-based heuristic clearly outperforms the genetic algorithms in terms of computing time, while the genetic algorithms with multiple neighbors improve the solution accuracy significantly. The results strongly suggest that most trajectories belonging to the multidimensional optimum trajectory set are the optimum trajectories, yet there are quite a few uni-dimensional non-optimum trajectories resulting in a multidimensional optimum. This can explain the success of the hybrid algorithm that combined the two algorithms, which sharply improved the solution accuracy while only moderately increasing computing time.

Furthermore, a comparative study of the new measure and existing measures suggests that the proposed multidimensional sequence alignment method constitutes a valuable and potentially more sensitive method for classification analysis in activity-travel behavior research, especially when sequential information and the interdependency between attributes are of great importance. Based on these findings, further research efforts should seek to explore the application of the method in a policy context, such as for example identifying different clusters with varying sensitivity to policy initiatives. For the current research in particular, the proposed method will be used to classify activity schedule data for subsequent analyses of segment-level estimation of activity utility functions.

Overall, the newly developed multidimensional sequence alignment method represents a useful extension of the methodological tools of the transportation analyst, interested in examining sequential information and attribute interdependencies in activity-travel patterns. The recent (re-)interest in the structure of activity and trip sequences in the identification and description of inter-related choices in the organization of activities in time and space and in developing a multi-faceted model of activity-travel patterns demonstrates the potential value of the proposed method. For the present study in particular, the method will be applied to classify the activity schedules for a subsequent segment-level estimation of activity utility functions.

Appendix 4.1: An efficient algorithm for trajectory search and proof of its optimality

An efficient algorithm for searching the optimum trajectories employed by the OT-MDSAM (Section 4.2.3) ignores the order of the applied operations by assuming that deletion and insertion weights are the same and that the substitution weight is the sum of deletion and insertion weights. As a result, the uni-dimensional operation sets of an attribute are identical. The algorithm involves four procedures, applied in the following order.

① Uni-dimensional comparison table of each attribute sequence pair
② Number of identity coordinates of a least-cost trajectory of each attribute sequence pair
③ Upper-most identity trajectory of each attribute sequence pair
④ Remaining identity trajectories of each attribute sequence pair

Procedure 1 provides the basic information of the step-by-step alignment costs represented in the comparison table by which procedures 2, 3 and 4 can trace the history of optimum alignments of the concerned attribute. All least-cost, or optimum, trajectories of a comparison table have the same number of identities (see the proof below), and other operations are appearing in between two adjacent identity operations. Because different orders of other operations in between these identity operations do not affect the optimality of the alignment (see proof below), the algorithm traces only the identified number of identity operations for each optimum trajectory and will later recover other operations based on the identified operations. Procedure 2 provides the number of identities, which procedures 3 and 4 have to consider. Once the identity trajectory running in the upper most of the comparison table is identified by procedure 3. Procedure 4 searches the remainders by using a tree-search algorithm that tries all possibilities of a new branch at each node. Searching in procedure 4 starts with the upper-most trajectory and ends with the lower most. As a result, the algorithm identifies exhaustively the operation sets of optimum trajectories for each attribute dimension.

Theorem 1. *Let $o=\{p_1,\ldots,p_d,\ldots,p_D, q_1,\ldots,q_i,\ldots,q_I, h_1,\ldots,h_z,\ldots,h_Z\}$ be an arbitrary alignment for any pair of sequences, consisting of D deletions, I insertions and Z identities ($D \le m$; $I \le n$; $Z \le \min[m,n]$ where m and n are the length of the source and the target sequences, respectively). Let Z_1^* and Z_2^* respectively be the number of identities of two optimum alignments of different trajectories. Let $(D+I)_1^*$ and $(D+I)_2^*$ be the number of deletions and insertions of two optimum alignments of different trajectories. Let $w_o = w_d = w_i > 0$. Let $d(\mathbf{s},\mathbf{g})$ be the alignment cost as defined in equations (3.1) to (3.6) of Section 3.2. Then,*

$$Z_1^* = Z_2^* \tag{4A1-1}$$

In words, all optimum trajectories have the same number of identity coordinates.

Proof. Given $o=\{p_1,\ldots,p_d,\ldots,p_D, q_1,\ldots,q_i,\ldots,q_I, h_1,\ldots,h_z,\ldots,h_Z\}$, then

$$d(\mathbf{s},\mathbf{g}) = (D + I)_1^* w_o + Z_1^* w_e \le (D + I)w_o + Zw_e$$

$$\forall\ (D\text{+}I),\ Z\ ;\ (D\text{+}I)_1^* \in \{(D\text{+}I)\},\ Z_1^* \in \{Z\} \qquad\qquad (4\text{A}1\text{-}2)$$

or

$$d(\boldsymbol{s}, \boldsymbol{g}) = (D+I)_1^* w_o \le (D+I)w_o \qquad\qquad \text{since } w_e = 0 \qquad\qquad (4\text{A}1\text{-}3)$$

or

$$(D+I)_1^* \le (D+I) \qquad\qquad (4\text{A}1\text{-}4)$$

Hence,

$$(D+I)_1^* = \min(D+I) \qquad\qquad (4\text{A}1\text{-}5)$$

Similarly,

$$d(\boldsymbol{s}, \boldsymbol{g}) = (D+I)_2^* w_o + Z_2^* w_e \le (D+I)w_o + Zw_e$$
$$\forall\ (D\text{+}I),\ Z\ ;\ (D\text{+}I)_2^* \in \{(D\text{+}I)\},\ Z_2^* \in \{Z\} \qquad\qquad (4\text{A}1\text{-}6)$$

or

$$d(\boldsymbol{s}, \boldsymbol{g}) = (D+I)_2^* w_o \le (D+I)w_o \qquad\qquad \text{since } w_e = 0 \qquad\qquad (4\text{A}1\text{-}7)$$

or

$$(D+I)_2^* \le (D+I) \qquad\qquad (4\text{A}1\text{-}8)$$

Hence,

$$(D+I)_2^* = \min(D+I) \qquad\qquad (4\text{A}1\text{-}9)$$

By equations (4A5) and (4A9),

$$(D+I)_1^* = (D+I)_2^* \qquad\qquad (4\text{A}1\text{-}10)$$

Since,

$$n(o) = D\text{+}I\text{+}Z \qquad\qquad \text{given } o=\{p_1,\ldots,p_D,\ q_1,\ldots,q_I,\ h_1,\ldots,h_Z\} \qquad (4\text{A}1\text{-}11)$$

we have

$$(D+I)_1^* + Z_1^* = (D+I)_2^* + Z_2^* \qquad\qquad (4\text{A}1\text{-}12)$$

Therefore, by equations (4A10) and (4A12),

$$Z_1^* = Z_2^*$$

Theorem 2. The operation sets of any two possible paths between two adjacent identity operations in a comparison table are identical. To define this formally, let (k_1,l_1) and (k_2,l_2) be two identity coordinates in an optimum trajectory. Let $o_s=\{\{\text{d}i\},\{\text{i}j\}\}$ be the deletion-insertion operation subset that contains the deletion and insertion operations in-between (k_1,l_1) and (k_2,l_2). Let $o_{s'}=\{\{\text{d}i\}',\{\text{i}j\}'\}$ be an arbitrary deletion-insertion operation subset. Then, the theorem states,

$$O_{s'} = O_s \tag{4A1-13}$$

if

$$k_1 < i < k_2 \; \forall \; \text{d}i \in \{\text{d}i\}' \text{ and } l_1 < j < l_2 \; \forall \; \text{i}j \in \{\text{i}j\}' \tag{4A1-14}$$

In words, there can be no other insertion-deletion operation sets between two adjacent identity coordinates.

Proof. We establish the proof by assuming the negation of the above theorem, i.e.:

$$O_{s'} \neq O_s \tag{4A1-15}$$

Then,

$$\text{d}i \in \{\text{d}i\}' \qquad\qquad \exists \; \text{d}i \notin \{\text{d}i\} \tag{4A1-16}$$

or

$$\text{i}j \ni \{\text{i}j\}' \qquad\qquad \exists \; \text{i}j \notin \{\text{i}j\} \tag{4A1-17}$$

Because

$$k_1 < i < k_2 \qquad\qquad \forall \; \text{d}i \in \{\text{d}i\} \tag{4A1-18}$$

and

$$l_1 < j < l_2 \qquad\qquad \forall \; \text{i}j \in \{\text{i}j\} \tag{4A1-19}$$

we have

$$i \leq k_1, \text{ or } i \geq k_2 \qquad\qquad \exists \; \text{d}i \notin \{\text{d}i\} \tag{4A1-20}$$

or

$$j \leq l_1, \text{ or } j \geq l_2 \qquad\qquad \exists\ \mathtt{i}j \notin \{\mathtt{i}j\} \qquad\qquad\qquad (4A1\text{-}21)$$

Both equations (4A1-20) and (4A1-21) contradict equation (4A1-14), which is the condition of the theorem, and hence, the negation expressed by equation (4A1-15) is false.

Therefore,

$$O_{s'} = O_s$$

**Appendix 4.2: Multiple alignments and a multidimensional alignment**

This appendix explains the difference between multidimensional sequence alignment and the method of multiple sequence alignments developed in molecular biology. Multidimensional sequence alignment refers to the pairwise alignment of multidimensional patterns consisting of multiple sequences, whereas multiple sequence alignment concerns the multiple alignments of uni-dimensional sequences. The two approaches have in common that both are calculating the minimum operational-efforts to equalize sequential information, and that the solutions do not necessarily result in the optimum pairwise alignments of uni-dimensional sequences (see, Murata, *et al*., 1985; Carrillo & Lipman, 1988; Schuler, *et al*., 1991; Thompson, *et al*., 1994; McClure, *et al*., 1994; Gusfield, 1997b) They differ however in terms of application and methodological principle.

      First, multidimensional alignment seeks the pairwise distance between multidimensional patterns that can be used for the subsequent classification of observed patterns or as a goodness-of-fit measure between observed and predicted patterns. The alignment does not attempt to compare three or more patterns at a time. Multiple alignments, on the other hand, identify the set of elements that are identical or similar between two, three or more sequences and distinguish groups of sequences in this regard. The alignment result provides a measure of the largest similarity calculated on a set of sequences as a whole. It also provides information about which set of elements of sequences of a group involves the biological information that distinguishes the sequences from those of other groups. Hence, the alignment in general attempts to compare three or more sequences to compare.

      Secondly, the methodological principle differs between the two measures. Multidimensional alignment that compares two *K*-dimensional patterns aligns each dimension between patterns independently and then integrates the uni-dimensional alignments. The integration is achieved by identifying the deletion and insertion operations applied to the elements of the same position in the sequences across different attribute dimensions, which defines a multidimensional alignment. The alignment does *not* attempt the comparison on different dimensions between the patterns. (For example, an activity type sequence of an activity-travel pattern is not comparable with a location sequence of the other.) Multiple alignments that compare *K* uni-dimensional sequences, on the other hand, align one sequence or alignment against another and find the globally best alignments, providing that the similarity is measured on all the sequences compared. Unlike the multidimensional alignment, each sequence included in this multiple applications of uni-dimensional pairwise alignment is comparable with all other sequences. (They are all for example DNA sequences.) In principle, the pairwise trajectories included in the final solution of the multiple alignments are near to the optimum pairwise trajectories because all sequences are comparable to each other and seek the largest common structure. On the other hand, the pairwise trajectories included in the final solution of the multidimensional alignment can be quite different from the optimum pairwise trajectories because the multidimensional optimum integration of uni-dimensional operation sets may not necessarily be the integration of uni-dimensional optimum operation sets. The difference between the two measures is illustrated in Figure 4.13.
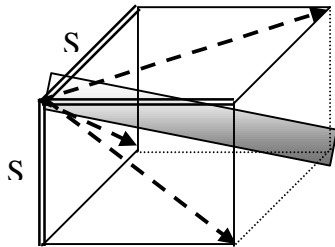
Set of pairwise alignments (dashed arrows) and the resultant multiple alignment solution (shadowed area): S1, S2 and S3 represent for example DNA sequences.
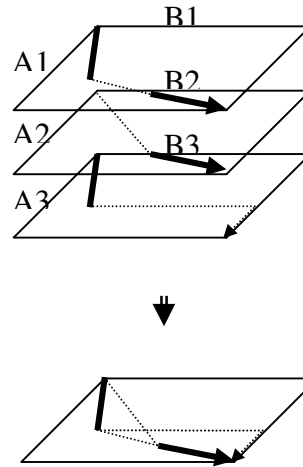
Set of uni-dimensional alignments and the resultant multidimensional alignment solution: In the upper figure, A1-B1, A2-B2 and A3-B3 are the pairs of sequences of for example activity-type, location and travel mode dimensions of activity-travel pattern A and B, respectively. The alignment paths denoted by bold lines, unlike the dotted paths are integrated across dimensions in the bottom figure.

Figure 4.13: Multiple alignments and a multidimensional alignment

Part II: Predicting Activity Rescheduling Behavior

5 A Model of Activity Rescheduling – Aurora

5.1 Introduction

Part-I has developed a comprehensive theory, method and implementation model of measuring activity-rescheduling behavior. While this concerns a descriptive analysis of activity-travel behavior, Part-II will develop a model of predicting such activity-travel behavior. Measurement and prediction of activity-travel behavior are complementary to each other. The model of measurement developed in Part-I provides natural definitions and descriptions of activity-travel behavior to be predicted by the model of prediction that will be developed in Part-II. In particular, the measurement model of Part-I will serve as a tool for the classification of activity-travel patterns on which the prediction model of Part-II estimates the model parameters that are specific to each group of homogeneous activity-travel behavior.

A theory and model of predicting activity-travel behavior of Part-II will be developed in the context of the activity-based approach. The theory and model will consider travel as a derived demand and activity-travel behavior as a result of a dynamic decision-making process of short-term schedule adjustments that an individual makes on the basis of his/her evaluation on such rescheduling decisions. This contrasts most of the existing activity-based travel behavior models, which focus on the *structure* of activity-travel patterns. Activity-travel patterns are typically predicted as a function of their structural characteristics and socio-demographic variables (Bhat & Koppelman, 1999; Timmermans, *et al.*, 2002a). To date, only few scholars have explicitly addressed the problem of *dynamics* of activity scheduling decisions. Computational processes models such as Scheduler (Gärling, *et al.*, 1989), Smash (Ettema, *et al.*, 2000), AMOS (Kitamura, *et al.*, 1995) and Albatross (Arentze, *et al.*, 2000) involve dynamics, but only in the sense that these models have derived rules or mechanisms of activity scheduling behavior. Except for AMOS, these models do not explicitly consider adaptation processes. Timmermans, *et al.* (2000) address learning and long-term dynamics. They showed that their learning model was capable of representing various typical behaviors, including habit formation and chaotic behavior. Their main focus is however a long-term mechanism of learning processes.

From an applied perspective, the problem of how individuals adjust their planned activity-travel schedules as a function of time pressure and unexpected results is even more relevant. Congestion, for example, may require people to reschedule their activities, implying that the distribution of traffic over time and space may change. The only publication that we found on this topic is that from Gärling, *et al.* (1999), who suggested an appealing framework to address this problem. They assumed that when faced with time pressure, individuals first try to compress the duration of activities, or try to reschedule them. If this is not sufficient, individuals are assumed to prioritize activities and eliminate the one with the lowest priority. This process is assumed to continue until the total duration is below

some threshold. Despite its appeal, however, this conceptual framework only addresses some aspects of the effects of time pressure on the execution of activity programs. The theoretical underpinnings of the framework are not fully elaborated, rescheduling decisions are not examined in much detail, and the framework does not allow for any substitution of activities.

In this chapter, we develop a more 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.

The chapter is organized as follows. Section 5.2 conceptualizes the problem of activity rescheduling as a function of unexpected events. The section includes the conceptual framework of schedule adaptation, given the utility, constraints and behavioral rules that control the internal and external components, and formalizes the definition of the rescheduling problem. Utility is modeled as a function of the duration of activities. Having discussed the background, Section 5.3 develops a utility function on which the evaluation of the schedule adaptation is based. The description of the basic form of activity utility is followed by an extension of the functional form to incorporate other than duration facets as well, including location, transport mode, etc. Next, it will be shown how utilities across activities produce the schedule utility as a whole. The chapter also discusses how adaptation styles can be incorporated in the model that an individual may choose to cope with uncertainty. Having explained the activity-specific utility functions, Section 5.4 introduces a model of decision heuristics. The model implements the schedule adjustment based on the individual activity utilities by applying a set of schedule adjustment operators. A theory and assumptions are discussed and the model is detailed. It includes the overall structure of the heuristics, the individual operators and the details of the application procedure. Section 5.5 then discusses the results of numerical simulations that were conducted to test the face validity of the model using a simulated transportation environment. The chapter will end with some conclusions and discussion.

5.2   Conceptualization

Our theory of individuals' scheduling and rescheduling behavior involves the following conceptual considerations. First, individuals execute activities to meet a variety of needs. Fulfilling activities returns satisfaction or utility as a reward for meeting the needs. The list of activities to conduct is determined by an individual's personal desires, responsibility for family and work contract (Damm & Lerman, 1981; Bhat & Koppelman, 1993).

Secondly, a set of circumstantial conditions limits the extent to which individuals can increase the utility. These conditions include individuals' physical condition, their role in society and the physical environment surrounding them. These conditions guide individuals and society to available means of fulfilling activities. Activities of particular purposes are then organized in space and time (Pred, 1981a; Thrift, 1983).

Thirdly, uncertainty should also be taken into account. Given the needs and conditions, individuals identify and evaluate activities in terms of their anticipated utilities for possible implementation. Uncertainty, however, affects the evaluation due to the fact that the activities in the later positions of the planned schedule may involve a larger amount of uncertainty. The evaluation results differ between individuals faced with uncertainty, dependent on their personalities or decision styles in dealing with uncertainty, which in turn affect the schedule.

Fourthly, individuals are assumed to use heuristics in looking for alternatives instead of becoming involved in an exhaustive search, due to the fact that their rationality is bounded. Individuals usually have numerous alternative ways of planning a schedule given a time horizon, each of which may result in a different level of utility. Cognitive constraints however prevent individuals from identifying and evaluating every single alternative in the universe of alternatives. Individuals therefore use a set of heuristics to reduce the burden of search and to pursue cost effectiveness. A typical example is habitual behavior (Gärling, *et al.*, 1998), which is concerned only with routinized alternatives, and hence is far from optimizing behavior. Heuristic behavior may result in sub-optimal, satisfying choices.

Finally, an activity schedule is tentative and may be changed at any time. Every moment in time, there may be the need for changing the schedule of remaining not-yet-completed activities. An individual may be forced to change the schedule due to time pressure or may actively decide to change and improve the existing schedule. Any (sub-optimal) decision is enforced until a further need to reschedule the activities arises.

Based on the above discussion, we formulate a conceptual framework of individuals' scheduling and rescheduling behavior as illustrated in Figure 5.1. Initially, a tentative schedule is given. The set of activities included in the current schedule is a subset of the activity program. The individual evaluates the utility of activities for possible implementation as well as non-implementation. When an individual with a certain decision style evaluates the utility of alternative activities under a set of constraints, he/she examines whether some change of the schedule is necessary.

More specifically, the individual examines whether there is any time pressure or any increase in utility possible by changing the existing schedule. Because it is impossible to identify and evaluate all possible alternatives due to cognitive constraints, individuals adopt certain heuristic strategies to effectively and efficiently reduce the search space to reach reasonably good solutions in real time. The adjusted activity schedule is then implemented.
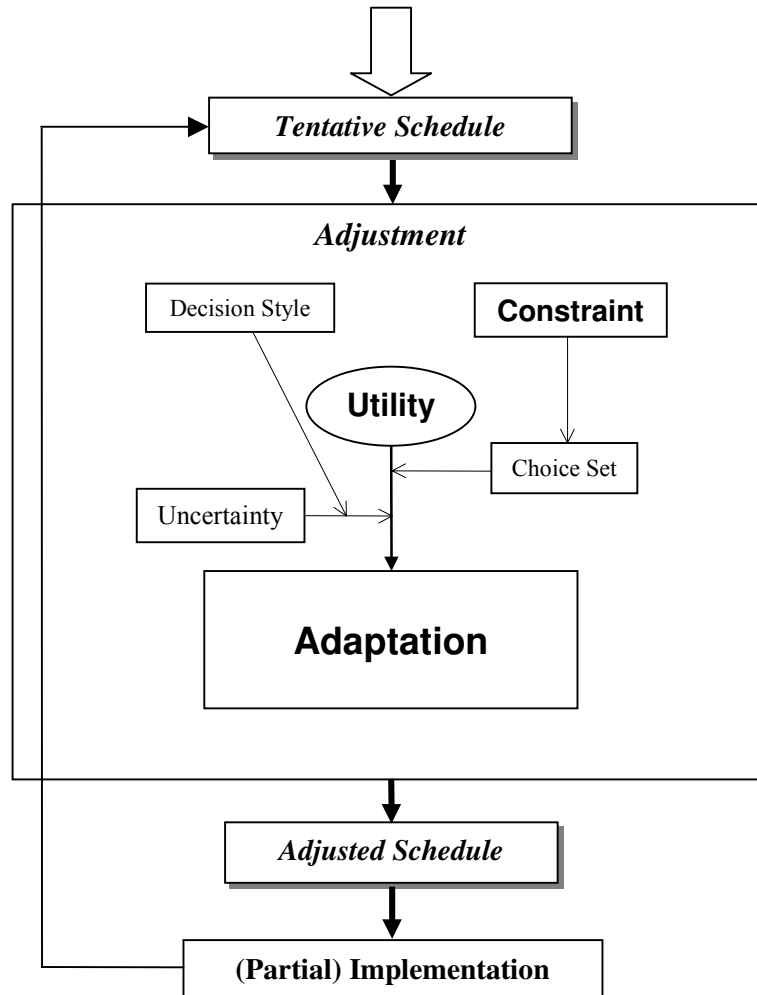
Figure 5.1: Conceptual framework

The utility of the remaining schedule is again subject to unexpected events, such as traffic congestion, cancellation of a business meeting, etc., causing increased or reduced time pressure. Therefore, the schedule will often be only partially implemented, and the adjusted schedule remains tentative.

To develop our scheduling theory, we use the following notation. $AP = \{1, \ldots, a, \ldots, A\}$ represents an activity program, where a is an index for activities. S represents a set of scheduled activities. R represents the complementary set of activities that are not scheduled at the current stage of scheduling. U represents the *total utility* of rescheduling that consists of the utility $U(S)$ and the utility $U(R)$. Although being assigned zero duration, the activities included in set R also contribute to the total utility U because that non-performance of an activity also returns positive, zero or negative utility. An activity schedule is a sequence of activities $[a_1, \ldots, a_k, \ldots, a_K]$, where $a_k \in S$, and k is an index for positions in the current schedule. Each activity includes a variety of schedule resources such as duration v ($v > 0$),

clock time of a day t ($t \in \{0, 1, \ldots, T\}$), location l ($l \in \{1, \ldots, L\}$), accompanying person w ($w \in \{1, \ldots, W\}$), transport mode b ($b \in \{1, \ldots, M\}$), and travel time Λ ($\Lambda \geq 0$).

The nature of each activity and institutional and situational constraints limit these schedule resources. Activities can be conducted only with a particular set of locations $\{l\}$ and accompanying persons $\{w\}$. Institutional constraints confine the start and end times of an activity. The start time t_a^s should be in-between the earliest and latest possible start times t^{s-} and t^{s+}. Likewise, the end time t_a^f should be in-between the earliest and latest possible end times t^{f-} and t^{f+} (e.g., opening hours or work contract). Situational constraints limit the temporal availability of particular schedule resources such as the transport modes available at time t in the current schedule $\{b\}_t$. While institutional contexts are static, situational constraints are changing dynamically dependent on the context of the activity schedule. For example, the car is not available as an alternative transfer mode after a train trip to an out-of-home location even if one has a car at home and a driving license.

The problem of rescheduling under time pressure then is to find the activity schedule at a particular point in time on a particular day by which an individual achieves the following objective.

$$\max_{\{S,R\}} U = U(S) + U(R) \tag{5.1}$$

subject to:

$$S \cup R = AP \tag{5.2}$$

$$S \cap R = \phi \tag{5.3}$$

$$t_a^s + v_a = t_a^f \qquad \forall\, a \tag{5.4}$$

$$t_a^s + v_a = t_{a+1}^s \qquad \forall\, a \tag{5.5}$$

$$\sum_{a=1}^{A} v_a = B \tag{5.6}$$

$$l_a \in \{l\}_a \qquad \forall\, a \tag{5.7}$$

$$w_a \in \{w\}_a \qquad \forall\, a \tag{5.8}$$

$$\Lambda_a \leq v_a \qquad \forall\, a \tag{5.9}$$

$$t_a^{s-} \leq t_a^s \leq t_a^{s+} \qquad \forall\, a \tag{5.10}$$

$$t_a^{f-} \leq t_a^f \leq t_a^{f+} \qquad\qquad \forall\, a \qquad\qquad\qquad (5.11)$$

$$b_{at} \in \left\{ \overleftrightarrow{b} \right\}_t \qquad\qquad \forall\, a \qquad\qquad\qquad (5.12)$$

where,

a^{+1} is the activity scheduled next to a;
B is the time budget of the day, which normally stands for 24 hours, as we consider the case of daily scheduling;
other symbols are defined as before.

Equations (5.2) and (5.3) state that the list of activities to be scheduled should be a subset of a given activity program. Equations (5.4) to (5.6) show that the sum of durations across activities equals the total duration of the schedule, and hence, satisfies the time budget constraints in all situations. Equations (5.7) and (5.8) mean that the location and accompanying person of a scheduled activity a belong to the location and accompanying person choice sets, respectively. Particularly important regarding equation (5.9) is that we treat travel as part of an activity as opposed to an independent activity. This means that the duration of an activity includes the duration of conducting the activity *and* the time for traveling from the previous location to the location of the current activity. Equation (5.9) hence dictates that the duration of conducting activity a should at least be equal to the duration required to travel to the location of activity a. Equations (5.10) and (5.11) dictate that the start and end time of activity a should meet the time constraints set by the institutional context. Finally, equation (5.12) implies that the transport mode chosen for activity a at time t should be available at that time in the current schedule S. Note that, related to the issue of day-to-day variability in activity performance, the particular values of most constraint variables are dependent on the day of the week.

Given the objective of maximizing the utility of (re)scheduling decisions, subject to these constraints, an individual is assumed to try and optimize his/her schedule in a situation of time lack, time surplus or any other event. Unlike the existing utility maximization models, however, we assume bounded rationality as a result of incomplete information and imperfect choice behavior. An individual is limited in his/her cognitive capacity to identify and optimize a complex decision problem. In particular, the cognitive constraints induce the following heuristic search strategy for schedule adaptation.

① Identify the problem
② Identify alternative courses of actions to change the schedule
③ Evaluate these actions in terms of the total utility of rescheduling
④ Implement the action maximizing the total utility of rescheduling
⑤ Repeat

Identifying alternative courses of action implies possible changes in the choice facets to solve the emergent problem of time lack, time surplus, etc. These actions include the application of a variety of rescheduling operators such as changes in the duration of particular activities, the list of activities, the sequence of activities, and the location,

accompanying person and travel mode of activities. Clearly, the assumption of bounded rationality implies that the model does not consider such changes simultaneously. Rather, an iterative procedure in which one operation at a time is evaluated and implemented is adopted. In the following, we provide a formal description of two major components of the suggested model, the utility functions and the heuristic solution methods, to operationalize the conceptualization. In particular, we shall call the proposed model of rescheduling behavior Aurora (Agent for Utility-driven Rescheduling Of Routinized Activities).

5.3   Utility function

Individuals derive a certain level of utility directly or indirectly from participating in activities. The utility function associates some selected characteristics of activities with particular numeric values that are assumed to correspond to particular utility levels. The utility also varies with characteristics of individuals and households. We assume that the utility of an activity is a function of the amount of time spent on the activity, where longer duration provides a higher level of utility.

Existing theories on time allocation in transportation and economics generally assume that utility is a monotonically increasing function of duration. Regarding the rate of increase, however, different assumptions have been made. Microeconomic theory assumes an increasing utility function with a diminishing marginal utility over the entire range of input variable values. The utility functions of activities used in activity-based approaches adopting time-use microeconomic theory (Becker, 1965) almost invariably rely on the same assumption of a logarithmic, ever-diminishing marginal utility over the entire range of activity duration (Kitamura, *et al.*, 1996b; Bhat, 1999).

In contrast, Supernak (1988) argued for different, more complicated, functions, dependent on the characteristics of the given activity. It is important to note that the utility function of the present study does not pursue the classical economic question of long-term decisions such as how people allocate their time between work and leisure. Rather, the focus here is on individuals' schedule adaptation decisions in the course of a day. Several long-term decisions affect or constraint such short-term decisions. For example, the choice of the duration of a work activity is an issue here only when working time is flexible in the short term. Given this difference in focus there is a need to reconsider earlier concepts and develop new theory. The present study therefore developed such an alternative utility function as discussed in the following.

5.3.1   Basic form of the activity utility function

The functional form of utility is derived from particular theoretical assumptions on the nature of the activity implementation over time. It may not be unrealistic to assume that the

implementation of activities describes a certain general form of change in utility over time, although the particular functional form may not be following the ever-diminishing marginality.

Assuming a constant increase in utility for additional units of available time would imply the functional form of a straight line. Alternatively, one might assume diminishing returns over the entire time range or first increasing returns and then diminishing returns (i.e., an S-shape). To identify characteristics of activities that relate to particular forms, several cases are instructive. First, consider an activity that consists of completing a list of items. Assume furthermore that each item or task element yields a partial result that is positively evaluated and requires an equal amount of time. An example is a shopping activity involving a list of items to buy in the same store. If time is limited, only part of the list can be completed. Assume that the utility attached to each item is the same. Then, clearly, the function would describe a constant increase in utility. Now, assume that different utilities are attached to the items, for example, because the need or urgency of obtaining the item differs. Then, if time were limited, a rational individual would choose the highest prioritized items. When time is extended, increasingly less prioritized items would be added. The result is a diminishing return over the entire range of time. This is a logarithmic utility function that most time use research derives from the assumption of a saturation effect, where marginal returns generally diminish over time. As one spends more time on an activity, the marginal increase in utility decreases whereas the overall utility increases.

The above-mentioned constant or diminishing returns may however hold only for ideal type of activities. In reality, circumstances may be less perfect. Consider the case where the condition of equal time for the task elements does not hold in the sense that spending more time yields a better result for each item. This is a realistic assumption in cases where information is incomplete and searching increases the chances of obtaining a better result. For example, in the case of a shopping activity, an individual could use time for searching and finding a lower-priced item or one of higher perceived quality. If information is complete, the assumption is also realistic in cases where different locations yield different results. To stick to the example, changing stores to buy different items yields better outcomes if (the disutility of) additional travel is outweighed by (the utility of) a better quality or lower prices. In such cases where the utility depends on search or travel time, marginal utilities may first be increasing and then decreasing, resulting in an S-shape form of the utility function.

The discussion so far implicitly assumed that utility depends exclusively on the outcome of the activity (e.g., the items bought-indirect utility: consuming the items-direct utility). In general, however, individuals will derive, at least to some extent, also a direct utility from the activity. That is, utility is derived from the process of performing an activity. This is obvious in the case of discretionary activities such as for example leisure or social activities. But also mandatory activities may have intrinsic value. For example, one may derive direct satisfaction from working or studying. In the case of mandatory activities, the direct component does not need to be positive. If efforts required to complete a task are negatively valued, the component will be negative. Furthermore, the weight of the direct component relative to the indirect component may vary from activity to activity. Lying on the beach, for example, may be an extreme case where utility consists almost entirely of direct satisfaction (unless a tan is the envisioned result).

With respect to the direct utility component, we assume that marginal utilities of successively added time units decrease when a saturation effect is dominant. The more time spent in the activity, the lower the value assigned to an extra time unit. Although diminishing returns are obvious, it is not so obvious what happens when the initial duration is still short. The direct relation between time spent in the activity and utility derived from it implies that there is no minimum duration for the direct component. We assume, however, 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. The implication of this reasoning is that the utility function follows an S-shape also for the direct component, which dominates in discretionary type of activities.

Activities generally yield a mixture of direct and indirect satisfaction implying that the actual functional form is determined by the sum of its constituents. Because the direct and indirect utility functions are not necessarily aligned with respect to the reflection point, i.e. the duration where marginal utilities start to decrease, the overall utility may be a more complicated function of duration. If the inflection points occur at different moments, the overall utility no longer follows an S-shape, but rather a more complicated form with two reflection points, etc. In the following, we will conveniently assume that either the direct component is small in comparison to the indirect component or is perfectly aligned with the indirect component so that the S shape is maintained in the overall function.

The following equation is proposed to define the general form of the relationship between utility and duration of an activity.

$$U_a = U_a^{\min} + \frac{U_a^{\max} - U_a^{\min}}{\left(1 + \gamma_a \exp[\beta_a(\alpha_a - v_a)]\right)^{1/\gamma_a}} \qquad (5.13)$$

where,

a is an index of activities; v is the 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.

The general form of the activity utility function of equation (5.13) is an asymmetric S-shaped curve with an inflection point. This functional form was originally developed in biological science, called a generalized logistic curve or growth curve (Richards, 1959). A typical example of the use of this form can be found in the prediction of the animal weights over time elapsed since the birth. In that field, the functional value U denotes for example a prediction of the weight of a cow at the moment in time v elapsed since its birth, given the maximum possible weight of a cow $U^{\max}$. The parameters are obtained by a curve fitting procedure using a non-linear regression analysis. Alhough the original application of the function far differs from the present research, we employ the functional form because it suites the description of our theory of activity utility, which will be detailed below.

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. This utility might be zero

or negative, but is never positive. In most cases, the minimum utility is zero because not conducting the activity often merely means the absence of benefits. This might, however, not be true for biological needs, such as sleeping, eating, leisure, etc. where delaying satisfaction might produce negative effects (hunger, lack of sleep, loss of concentration, etc.). The minimum might also be negative in the case of maintenance activities that cannot be delayed (e.g., shopping when stocks are empty).

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 utility and zero. When the value approximates 0, the utility at the inflection level is also close to zero, implying that marginal utility is diminishing at virtually all levels of duration.

Figure 5.2 shows various forms of the activity utility function that illustrate the impacts of coefficients determining the level of utility over duration. In the figure, the X-axis represents activity duration v, while the Y-axis represents utility of activity.

Change in α (100 for A $\rightarrow$ 150 for B)   Change in β (0.05 for A $\rightarrow$ 0.1 for B)

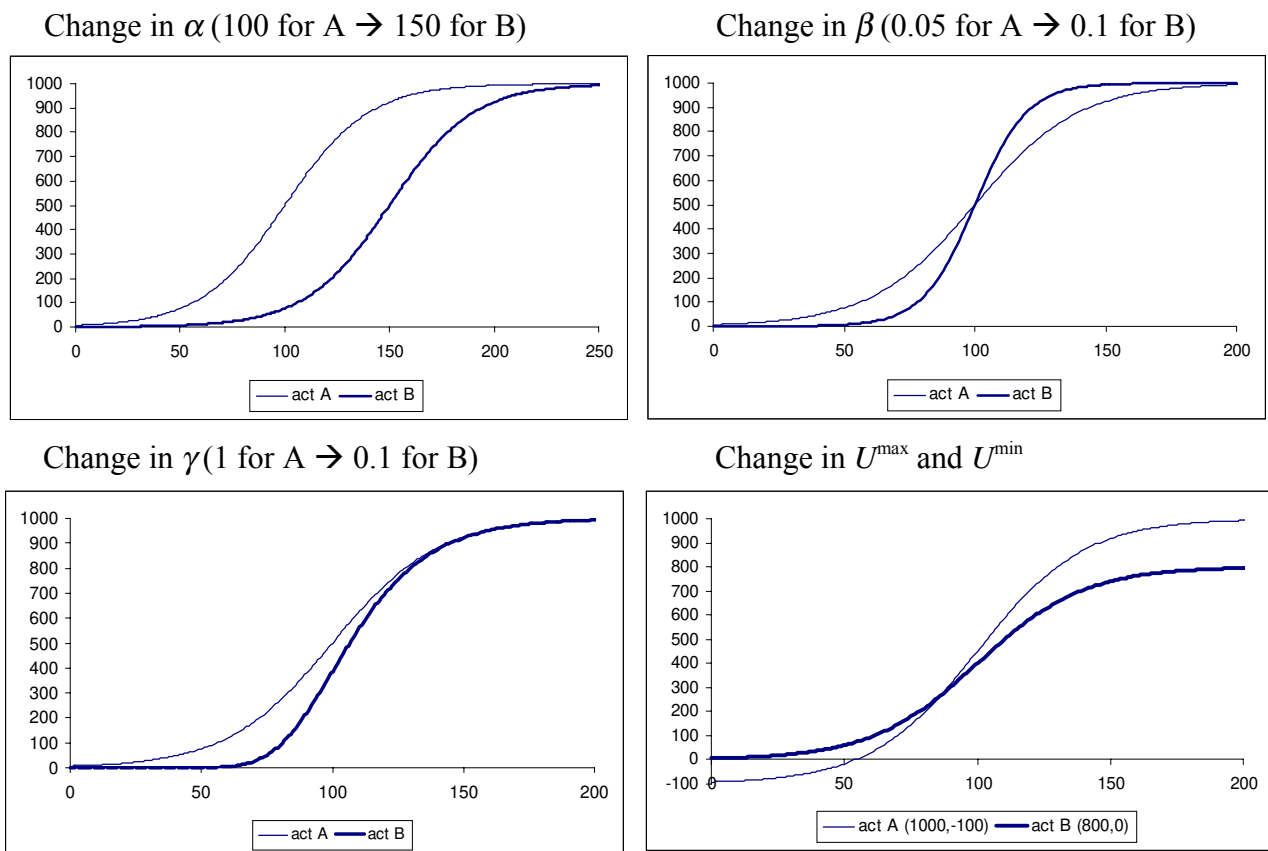Change in γ (1 for A $\rightarrow$ 0.1 for B)   Change in $U^{\max}$ and $U^{\min}$

Figure 5.2: Impacts of utility parameters

Note that the meaning of the X- and Y-axes differs from conventional concepts in economic theory of time use, where the X-axis usually represents clock time and the Y-axis a cumulative utility (Winston, 1982). Thus, each point in the curve describes an individual's utility of the anticipated value of the activity under that duration choice.

The upper left figure of Figure 5.2 illustrates two activities having the same utility parameter values, except for the α values, which are 100 and 150 for utility curves of activities A and B, respectively. The utility curve of activity B is more to the right than activity A by 50 units. As a result, the level of utility curve of activity B is much lower than activity A's for the same duration. In other words, activity B requires much more duration to reach the same level of utility than activity A. The figure also illustrates the importance of the location of the utility curve along the X-axis, regarding the impact of travel time on the level of utility. Assume that the two curves refer to the same activity, instead of two different activities, whereby the locations where the activity is conducted are different. The curve denoted by A represents that the activity is conducted at the same location as in the previous activity's, while the curve denoted by B represents that the activity location is 50 minutes away from the location of the previous activity. The curve A therefore is the utility of the activity duration per se, while the curve B is the utility of the activity duration plus the effect of the 50-minutes travel time from the previous activity location. This clearly shows that, with other things being equal, the nearer activity location of shorter travel time must be preferred to reach the desired level of utility, given the limited time budget.

The upper right graph of Figure 5.2 illustrates two activities with different β values of 0.5 and 1.0, respectively. The utility curve of activity B is steeper and shows more rapid changes of utility levels around the inflection point. Before the inflection point, the utility level is higher in the flatter curve denoted by activity A, while the level becomes higher in the steeper curve denoted by activity B afterwards. The implication of the bigger size of β is that the activity has smaller interval of durations between very low (near zero) and very high (near maximum) utilities and therefore is less flexible in duration adjustment.

The bottom left figure of Figure 5.2 illustrates two activities of different γ values of 1 and 0.1 for utility curves of activities A and B, respectively. The curve of activity A shows a symmetric S shape with minimum level of utility of zero, maximum of 1000 and inflection level of utility of 500 at the duration of 100, while the curve of activity B is asymmetric with inflection level of utility of 400 at the duration of 100. Activity B has a bigger proportion of the diminishing marginal utility, and the level of utilities before inflection point is quite small compared with activity A. The implication of the bigger size of γ is that the activity would more likely have the duration of either bigger than inflection point or rather zero, and therefore, the actual schedule data would show the activity of saturated duration more often.

The bottom right figure of Figure 5.2 shows two activities of different U^{max} values of 1000 and 800 and U^{min} values of 0 and -100 for their utility curves, respectively. The higher level of U^{max} offers a higher level of utility for the same amount of activity duration. The minimum utility level is also associated with the minimum duration of the activity. The minimum duration represents the duration in which the activity starts producing positive outcomes when time is added. In the range of duration with positive utility, the individual would choose to conduct that activity unless a competing activity would have higher returns. Some 'skeleton' activities of the schedule are expected to have negative U^{min} values.

Having identified the generic form and parameters of the function, the next question is how to set the parameters for a given activity. Schedule context may be a moderator in the sense that the maximum of a utility may depend on the time of day and interactions with other activities (preferred combinations of activities). History may be a moderator in the sense that the time passed since performing the activity last may influence utility. We assume that parameters α, β and γ exclusively depend on the nature of the activity. The underlying notion is that these parameters relate to technical aspects of the activity related to *the productivity of time units (indirect utility) or strength of the saturation effect (direct utility)*. In contrast, we assume that the minimum and maximum utility, $U^{\min}$ and $U^{\max}$, are moderated by context and history factors. The activity's nature – i.e. the invariant property of the activity across instances of the activity – determines a base line, which is moderated in upward or downward direction by context and history effects. The more urgent the activity (given its history) the bigger $U^{\max}$ will be. In addition, $U^{\max}$ will increase when the activity can be conducted at the preferred time of day while negative carrying-over effects from previous activities are absent.

5.3.2 An extension of the activity utility function

The utility function of equation (5.13) includes only duration as a facet of activity choice for adjusting the activity-travel schedule. We should however also be able to consider other key choice facets such as activity location, accompanying person, activity timing, travel time, and transport mode. As pointed out earlier, $U^{\max}$ and $U^{\min}$ in equation (5.13) are moderated by the schedule context. In particular, the utility function assumes that, with other things being equal, the activity with higher (lower) $U^{\max}$ provides higher (lower) utility than other activities over the entire range of duration. Thus, the $U^{\max}$ term captures the impacts of all choice facets other than duration. We suggest the following general form of the $U_a^{\max}$ function.

$$U_a^{\max} = f\left(U_{x_a}, \tau_a, w_a, l_a, T_a, A_{bla}, \kappa_{ba}, \Psi_a\right) \tag{5.14}$$

where,

U_{x_a} is the intrinsic level of maximum utility of activity a;

τ, w and l are respectively an index for episodes of a day, accompanying persons and locations;

T_a is the time elapsed since the last implementation of activity a;

A_{bla} is the total time required for the completion of the travel from the previous location to the current location l of activity a;

$\Lambda_{b_y la}$ is the time required for mode b chosen to travel the yth stage in between the previous location to the current location l of activity a ($\Lambda_{bla} = \sum_y^Y \Lambda_{b_y la}$, where $Y > 1$ implies a multi-modal trip.);

$\lambda_b \Lambda_{bla}$ is the total cost for the completion of the travel from the previous location to the current location l of activity a; λ_{b_y} is the generalized marginal cost for travel by mode b chosen for the yth stage in between the previous location and the current activity location l ($\lambda_b \Lambda_{bla} = \sum_y^Y \lambda_{b_y} \Lambda_{b_y la}$);

κ_{ba} is the activity-specific level of preference for traveling by mode b;

Ψ_a represents the level of preference for the chain relationship between previous, current and next activities.

The first term in the parenthesis of the right hand side of equation (5.14) implies that the U_a^{max} level is primarily determined by a certain level of intrinsic maximum utility of activity a. The rest of the terms indicate that the U_a^{max} level is also dependent on many other choice facets and aspects of the schedule context. Different locations (i.e., city center vs. local center, or floor space of the facilities), accompanying persons (i.e., alone vs. with friends), and activity timings (i.e., afternoon vs. evening) attributes will adjust the level of intrinsic maximum utility. T_a, the history of the implementation of activity a, will also greatly affect the level of U_a^{max}. As the history becomes longer, the urgency for conducting the activity grows, and the U_a^{max} will increase. This is important in the sense that if the functional relationship of history with the maximum utility is known, the frequency of the activity could also be predicted by a schedule model.

Travel time Λ from the previous location to the current location l of activity a by mode b, Λ_{bla}, also contributes to the level of maximum utility. The contribution will be negative with longer travel time. Travel time has another, more significant effect on the overall utility, which is concerned with the activity duration. Longer travel time more reduces actual duration of the activity. This effect shifts the overall utility curve to the right along the X-axis, implying that the utility of the same activity duration becomes lower with longer travel time. This will be detailed later in this section. κ_{ba} term implies that particular transport modes are likely preferred for particular activity types (i.e., car for shopping), which have constant impacts on U_a^{max}, regardless of the travel distance. Finally, the term Ψ_a represents possible cross-effects between activities with respect to their order of the implementation sequence. For some people, for example, the sports activity would be preferred *before* dinner instead of *after* dinner. Although it is not explicitly represented here, the choice of particular trip chains will also be realized through the schedule-reschedule process. Chaining trips for a certain set of out-of-home activities would improve the schedule by saving travel time. The transport mode also accounts for possible positive or negative associations between activities within chains. The importance of the interactions between activities in the schedule has been a critical issue in transportation research, and in

particular, evidence of chain relationships between successive activities can be found in Kitamura (1984a) and Arentze, *et al*. (1993).

The impacts of travel time also concern the actually dispensable amount of duration for an activity because it reduces the available time for the activity. The total time budget at any moment is limited. A particular amount of duration assigned to an activity is not used only for that activity itself but also for the travel time to reach the location of that activity. As said, the utility of an activity is an increasing function of duration spent on that activity. Shorter duration corresponds to lower utility. Longer travel time makes the actually dispensable activity duration shorter and therefore lowers the utility. This notion can be reflected by revising equation (5.13) into equation (5.15).

$$U_a = U_a^{\min} + \frac{U_a^{\max} - U_a^{\min}}{\left(1 + \gamma_a \exp[\beta_a(\alpha_a - (v_a - \Lambda))]\right)^{1/\gamma_a}} \tag{5.15}$$

Figure 5.3 illustrates the travel time effect where the utility curve of an activity is differentiated between different locations. It is clear from the figure that the travel time greatly affects the utility level. It shifts the functional curve of the activity utility horizontally to the right by the amount of travel time, and subsequently, lowers the level of the utility of a given activity duration. When the activity is implemented at the same location as the previous activity location and has no travel involved the amount of duration assigned can be used entirely for that activity. With other things being equal, the activity with no travel time achieves higher utility than others for the same amount of duration. For example, the implementation of this activity without travel obtains utility level of 500 from duration of 100 while others require durations of 125 and 150 for the same level of utility.

However, the impacts of the choice facets are often mixed, which complicates the effect on the utility level. Figure 5.4 shows combined impacts of different travel time and attractiveness between locations, as an example of the complexity of the impacts of various combinations of choice facets on the utility level. The location associated with the bold line is more attractive than the other for this activity, and therefore the bold line's $U^{\max}$ is higher than the other's according to equation (5.14).
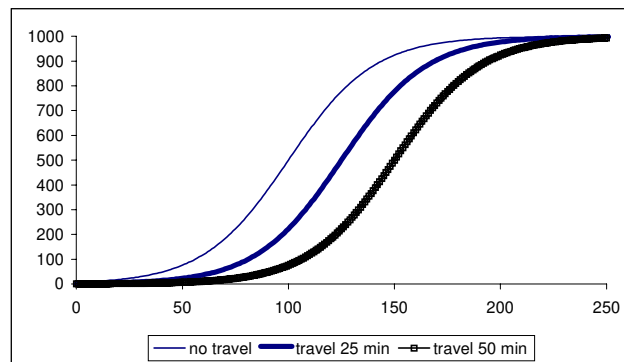

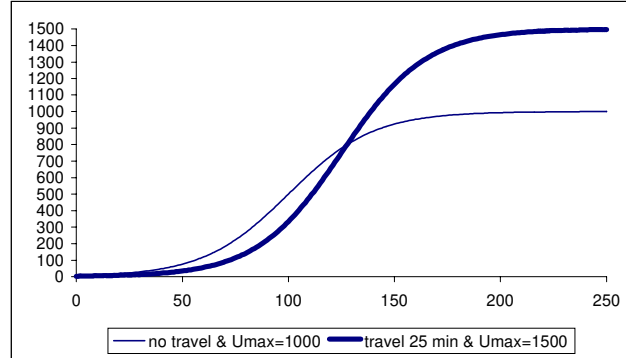Figure 5.3: Impact of travel time on activity utility

Figure 5.4: Combined impact of travel time and location choice

Although it is more attractive, the location of the bold line requires travel time of 25 minutes from the previous activity location in the current schedule context, whereas the less attractive location requires no travel. This combined effect of the travel time and location attractiveness results in the interception of the utility functions. The less attractive location with no travel has higher utility from the beginning up to the duration of 130, and thereafter the other more attractive location overcomes the disadvantage of the travel time and returns a higher utility.

5.3.3 Total utility of rescheduling

Given the utility function for individual activities, the total function for an entire schedule should aggregate the utilities across activities of S and R. The aggregation equation can be manifold, and some multiplicative form may be desirable to reflect the mutual relationships between activities. Obviously, certain activities have complementary or substitution relationships. A business meeting, for example, has a complementary relationship with a follow-up social event. In-home and out-of-home leisure activities likely have a substitution relationship due to the fixed amount of time in the evening after work. To cope with these activity-specific relationships, the constituent activities should be grouped in a multiplicative term of an additive aggregate function. In the present study however we simplify the problem and assume a simple additive aggregate utility function as:

$$U = \sum_{a=1}^{A} U_a \tag{5.16}$$

with

$$U_a = U_a^{\min} + \frac{U_a^{\max} - U_a^{\min}}{\left(1 + \gamma_a \exp[\beta_a(\alpha_a - (v_a - \Lambda))]\right)^{1/\gamma_a}} \tag{5.17}$$

and

$$\sum_{a=1}^{A} v_a = B \qquad\qquad (5.18)$$

where, 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.

The equations show that the basic functional structure of the utility remains the same. The summation in equation (5.16) re-states that the total utility includes the utilities not only of the scheduled activities of S but also of the currently non-scheduled activities of R as the non-performance of an activity may return a zero or negative utility. In particular, the additive form with the time budget constraint implies that activities have a general relationship with all others regarding their duration in the schedule. Increasing the duration of an activity means that the duration of other activities is decreased, depending on their utility function. To increase total utility, therefore, utility increase of the increased activities must exceed utility decrease of the decreased activities, and no change is induced otherwise. Thus, while the marginal utility of duration of an activity is positive, it may not always be positive for the entire schedule due to the budget constraint. More specifically, while the increase of v_a increases the utility U_a, it may sometimes decrease the *total* utility U because of the bigger amount of decrease in the utilities of other $U_{a'}$s where $a' \neq a$. However, an activity does not have any activity-specific relationship with other activities.

5.3.4 Adaptation styles under uncertainty

The utility function introduced above would be sufficient to develop a model of schedule adaptation based on utility maximization if we assume unbounded rationality. As we argued in earlier sections, *bounded* rationality relates to *problem solving*, which will be discussed in the next section, and *incomplete information*. Incomplete information implies that the exact values of the function parameters are uncertain. Furthermore, individuals rather clearly know the details and circumstances of an activity to be implemented right now, whereas they may not have a concrete idea about an activity later in the schedule.

Consider, for example, a person who has a schedule involving a sequence of ten activities for the day and has already conducted the first two activities. Now, the person is faced with a time lack situation and is going to reschedule the remaining eight activities. The person probably has a concrete idea about the details of the activity that is to be conducted next at the third position of the schedule, whereas the person might have a less clear idea about the tenth activity at the last position in the schedule. We assume that the amount of uncertainty is an exponentially increasing function of time elapsed since the current stage of implementing the rescheduling:

$$\xi_{k'}^{upper} = (1 + \xi)^{k'-1} \qquad\qquad (5.19)$$

$$\xi_{k'}^{lower} = (1-\xi)^{k'-1} \tag{5.20}$$

where,

k' is an index for the position of an activity in the schedule still to conduct ($k' = 1, \ldots$);

ξ is a parameter of uncertainty ($0 \le \xi < 1$);

$\xi_{k'}^{upper}$ and $\xi_{k'}^{lower}$ define the amount of uncertainty for the utility function of activity $a_{k'}$.

We distinguish three different decision styles, *rational*, *conservative* and *opportunistic*, regarding the behavior under uncertainty. Under the situation of time lack, the individual must reduce the total duration of the activities in *S*. A *conservative* person, as opposed to an opportunistic person, would perceive the decrease in utility by reduction in duration more seriously than what it really is. The perceived functional slope and maximum utility of an activity at the kth position in the remaining schedule can be defined as $\beta_{a_{k'}} = \beta_a \xi_{k'}^{upper}$ and $U_{a_{k'}}^{max} = U_a^{max} \xi_{k'}^{upper}$ for a conservative person, and $\beta_{a_{k'}} = \beta_a \xi_{k'}^{lower}$ and $U_{a_{k'}}^{max} = U_a^{max} \xi_{k'}^{lower}$ for an opportunistic person.

As illustrated in Figure 5.5, a conservative person tends to perceive the functional curve of each activity steeper (LHS) or the maximum utility bigger (RHS) than their reality, whereas an opportunistic person tends to perceive the functional curve flatter (LHS) or the maximum utility smaller (RHS) than what they are. Because uncertainty increases with time elapsed from the current stage of rescheduling, the difference between these two decision styles also grows and is biggest for the last activity in the schedule. The perceived slopes and U^{max} of the activities later in the schedule become very steep and big for a conservative person. Consequently, when a need for adjustment arises due to time pressure, a conservative person focuses on the adjustments of the emergent activities to perform right now because he/she is very reluctant to make any change in the later activities. Overall, due to the overly perceived slopes and U^{max} across activities, a conservative person's adjustment would be smaller than what it might be.
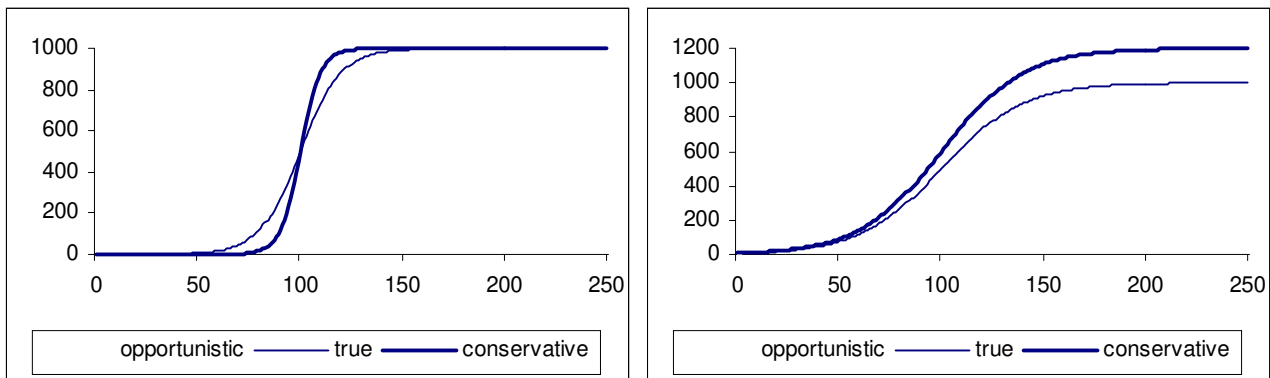

Figure 5.5: Perceived functional slope (LHS) and U^{max} (RHS)

On the other hand, the perceived slopes and U^{max} of the activities later in the schedule become very flat and small for an opportunistic person. Consequently, he/she will perform the emergent activities as scheduled without adjustment, while trying to adjust the later activities. Overall, due to under-perceived slopes and U^{max} across activities, an opportunistic person's adjustment would be bigger than what it might be.

5.4   Search tree

The fundamental heuristic will embed the bounded rationality into our operational model of schedule adaptation, given a utility function for each activity in S and R, and relevant institutional and situational constraints. In the following, we first discuss the theory and assumptions necessary for the model development and then provide the details of the operational heuristic scheduling model.

5.4.1   Theory and assumptions

Assume an individual who has formulated an initial schedule of activities and related travel for a given day. The initial schedule describes which activities are to be conducted and for each activity how it is to be implemented in terms of a start time, duration, location and, if travel is involved, transport mode. 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.

The fourth assumption means that a general tendency to reschedule activities and travel will vary between individuals, and the fifth assumption implies that preferred ways of rescheduling will vary between individuals as well.

5.4.2 Model

Based on these conceptual considerations, this subsection develops a model of rescheduling behavior, the heuristic search component of Aurora. As said, the model outlined here assumes functions for evaluating the feasibility and utility of a schedule as given. We emphasize that the model proposed here does not depend on a specific implementation of the utility model. This section first outlines the structure of the model. Next, we focus on each of the operators. Finally, we describe the calculation procedure.

Overall structure

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 5.6) uses a tree structure to arrange options for rescheduling and control the search process.

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 resultant mental adjustment processes is therefore flexible enough such that the application order of the operators could be anything like [sequence → location → activity insertion], [duration → transport mode → accompanying person → location], or whatever.

The model therefore is expected to successfully advance at each rescheduling step to the better parts of the solution space by this choice facet-by-choice facet, recursive and non-hierarchical search process, based on the expected utility of rescheduling.
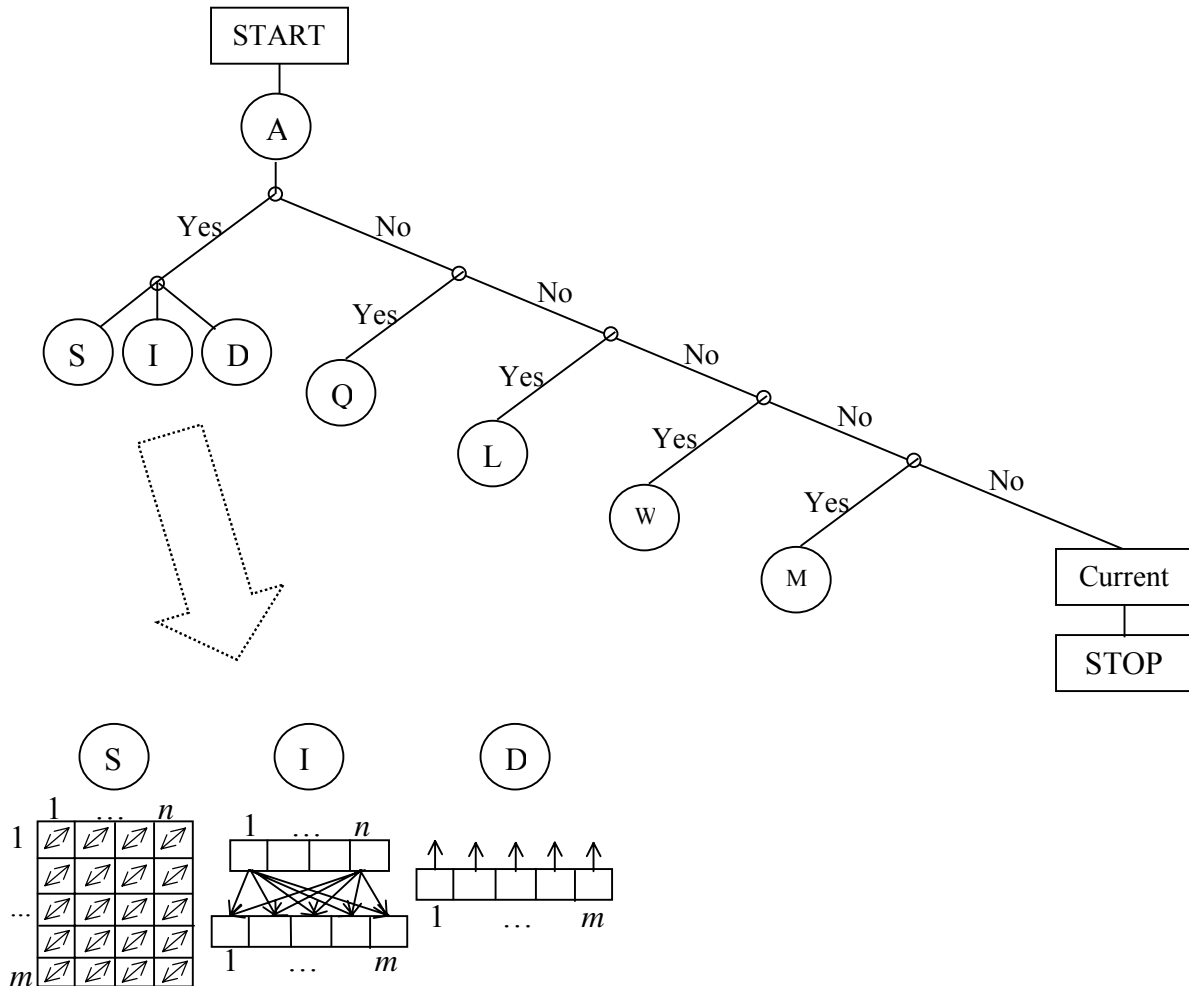
Figure 5.6: Search tree

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.

The overall scheme of the proposed search model in Figure 5.6 depicts in detail the following control mechanism.

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.

Operators

This section provides a detailed description of the operators employed in the proposed search model. As before, the set notations *AP*, *S* and *R* are used to respectively denote an activity program, a set of scheduled activities and a complementary set of activities that are not scheduled at the current stage of rescheduling, where $S \cup R = AP$, and $S \cap R = \phi$.

Duration adjustments: The *duration operator* considers exchanges of duration units between activities. To evaluate an exchange, the operator compares the marginal utility of one unit of duration to be exchanged between two activities. The operator (mentally) increases the duration for the activity offering the biggest marginal utility increase and decreases for the activity having the smallest marginal utility decrease in the current distribution of durations across activities of *S*. This adjustment continues until the biggest utility increase becomes equal to or smaller than the smallest utility decrease. The result would then be accepted if the total net utility increase exceeds a predetermined threshold, and the scheduling efforts do not exceed a given tolerance level. When the duration of an activity is reduced to zero as a result of the duration adjustments, the activity moves from *S* to *R*.

The duration-units exchange between two activities can be implemented in one of two directions. Consider an exchange of one unit of duration as shown in Figure 5.7. Currently, activities A and B have durations as in the top of the figure. Assume that the exchange is taking place such that activity A gains one unit of duration from activity B. Exchange case I of the figure shows the exchange taking place inner direction between the two activities, whereas Exchange case II represents an outer-direction exchange. By examining the possible ways of duration unit exchanges in this way, the system is able to incorporate the timing preference of activities and, more importantly, the scheduling constraints in the resultant rescheduling actions. The system tries both directions and chooses the best one regarding the resulting utility of the possible adjustment.
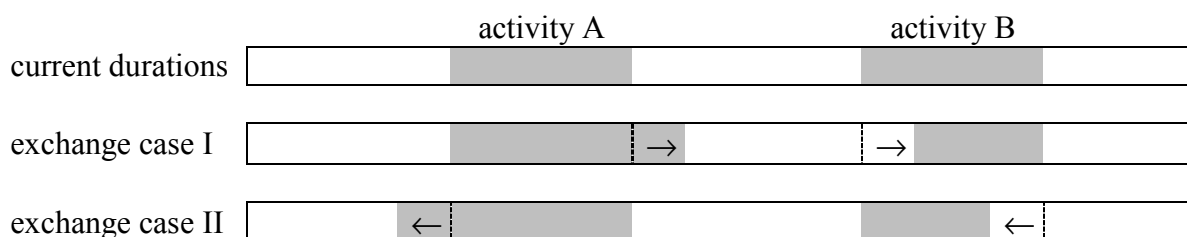

Figure 5.7: Duration exchanges (An example)

Composition adjustments: Composition adjustment may include *substitution*, *insertion* and *deletion* of activities. These operators change the compositions of sets *S* and *R*, the operations of which are obvious from their names. The following details of deletion and insertion however need to be mentioned. The *deletion* operator replaces a candidate activity for deletion with a 'do-nothing' (d-n) activity that is assumed to have zero utility over the entire range of duration. The operator then adjusts the durations of other activities of *S*. Due to possible time constraints limiting the range of BT and ET of each activity, the duration adjustment does not guarantee a complete re-distribution of the duration of the d-n activity to other activities, and the d-n activity may sometimes not completely be removed from *S*.

The *insertion* operator adds a new activity from *R* to *S*, whose schedule position, accompanying-person, location and transport-mode and duration are yet to be defined. To determine the schedule position, the operator tries all the positions one at a time for each new activity. To determine the other facets, on the other hand, the operator employs certain 'default' values. Accompanying person is assumed to be the same as that of the previous activity. (The same holds for a substitution.) The location is chosen among the available locations such that the sum of travel distances between the previous activity, new activity and next activity is minimized. (The same holds for a substitution.) When the inserted activity's location differs from that of the existing previous activity, the most preferred transport mode for the inserted activity is chosen. (The same holds for substitution, deletion, and sequence and location changes.) As for duration, an average duration is initially assumed for an activity insertion from *R*. Furthermore, an insertion of a new activity from *R* requires a reduction in the duration of another activity of *S*. This reduction is tried in two directions for each existing activity of *S*, this corresponds to the adjustment directions as explained in duration adjustment.

Adjustments of other choice facets: Individuals may also change other choice facets such as the sequence of activities, location, accompanying person, and transport mode. Each of the suggested *sequencing, location* and *accompanying-person* operators tries different values of the concerned facet one at a time, and then (mentally) implements the best one. The *transport-mode* operator, on the other hand, is applied to optimize a mode pattern at the tour level. (A tour is a series of trips included in a home-to-home journey.) More precisely, the tour-optimization operator works according to the following procedure. (1) The operator identifies all the tours appearing in *S*, (2) enumerates all possible sequences of the transport-modes for each tour, (3) examines the constraints for each mode sequence of a tour, (4) evaluates the utilities of rescheduling based on the mode sequences across tours, and finally, (5) (mentally) implements the best mode sequence across tours, which offers the highest increase in utility of rescheduling. Note that the tour-based optimization of transportation modes takes into account interdependencies of choices for the trips belonging to the same tour. Importantly, the system allows tour optimization involving multi-modal trips that connect two locations by a combination of public and other transport modes when there is no direct public transport line available.

Note that at each time of rescheduling, individuals (mentally) implement the adjustments using the operators described in this section and finally determine the actual implementation of an operator that offers the maximum increase across operators in the anticipated utility of scheduling. In addition to evaluating the utility of rescheduling,

individuals also examine the feasibility of the resulting schedule. They remove from their consideration the alternatives that violate at least one of the following constraints; (1) The begin time (BT) and end time (ET) of an activity resulted from the adjustment should meet timing constraints such as for example defined by opening hours of required facilities and work contract. For example, one cannot buy goods at a supermarket after closing hour. (2) The use of public transport mode should meet the earliest and latest possible BTs of public transport lines. (3) The use of a transport mode should meet the temporal availability of the concerned mode given previous mode uses. For example, one cannot ride a car when the car is not available at a particular location at a particular moment (even if having a car at home and a driving license).

Calculation procedure

Given the overall structure of the search tree depicted in Figure 5.6 and the details of the operators, the calculation of the total rescheduling utility proceeds as follows. First, the model calculates the utility of each leaf node representing a particular operator. Secondly, the utility of each parent node is determined as the maximum utility among child nodes. Finally, the node representing the overall maximum is chosen, and the concerned operator is implemented at the concerned rescheduling step. As mentioned earlier, the mental effort is cumulated as the rescheduling process goes on, and the level of resistance to change may vary between operators.

In the proposed model, the utility of rescheduling using a particular operator is defined as:

$$U_t^o = U_{t-1} + \Delta U_t^o \tag{5.21}$$

with

$$\Delta U_t^o = \begin{cases} \widetilde{U}_t^o - U_{t-1} & \text{if } \Delta U_t^o > \theta_o + h(t) \\ 0 & \text{otherwise} \end{cases} \tag{5.22}$$

$$h(t) = (\Omega)^{t-1} - 1 \tag{5.23}$$

$$\widetilde{U}_t^o = \max_y [\widetilde{U}_t^{o_y}] \qquad \text{where } y \in \{1, \ldots, Y_o\} \text{ if } o \neq A, \text{ and } y = Y_A \text{ otherwise} \tag{5.24}$$

where,

t represents the rescheduling step ($t \geq 1$; Going back to START in Figure 5.6 increases t by 1);
o is an index for operators;
U_t^o is the utility of the schedule after rescheduling when operator o is applied at t;

U_{t-1} is the utility of the schedule at $t-1$ (U_0 is the initial utility of the schedule);

ΔU_t^o is the utility increase achieved by rescheduling when operator o is applied at t, where resistance and mental fatigue are taken into account;

$\widetilde{U}_t^o$ is the maximum utility from rescheduling that the application of operator o can achieve at t, without considering resistance and mental fatigue;

Y_o is the number of computations of operator o at the current step of rescheduling ($Y_o \geq 0$);

θ_o is the amount of utility decrease induced by resistance to change when operator o is applied ($\theta_o \geq 0$);

$h(t)$ is the amount of utility decrease induced by mental fatigue, defined as an exponentially increasing function of t ($h(t) \geq 0$);

Ω is a parameter of mental fatigue of rescheduling, defined as a base of the exponential function ($\Omega \geq 1$).

Equation (5.21) implies that the utility of rescheduling by operator o is determined by the amount of improvement in utility. Equation (5.22) states that the utility increase should exceed the chosen operator-specific resistance to change and the mental fatigue. Equation (5.24) implies that the model chooses the best one of many possible ways to apply operator o, i.e. the application that offers the highest utility for the concerned rescheduling step. Furthermore, equation (5.24) treats the duration adjustment as a special case of rescheduling as follows.

$$\widetilde{U}_t^A = U_t^{A_{Y_A}} \tag{5.25}$$

or

$$\widetilde{U}_t^A = U_{t-1} + (U_t^{A_1} - U_{t-1}) + (U_t^{A_2} - U_t^{A_1}) + \ldots + (U_t^{A_{Y_A}} - U_t^{A_{Y_A-1}}). \tag{5.26}$$

This says that the schedule improvement by the duration operator is the sum of marginal (1-unit) duration adjustments, each of which is applied to the current schedule, and continues until the equilibrium is achieved at step Y_A.

The utility after each rescheduling step is finally determined as:

$$U_t = \max_o [U_t^o] \tag{5.27}$$

where, $o \in \{S, I, D, Q, L, W, M\}$ or $o = A$. Equation (5.27) defines U_t as the outcome of the competition between operators and its adjustment of duration at step t.

Given the number of activities of S and R, m and n, the required number of computations for the different operators at each step of the search tree is defined as:

$$Y_S = m \times n \tag{5.28}$$

$$Y_I = m \times n \tag{5.29}$$

$$Y_D = m \tag{5.30}$$

$$Y_Q = m! \tag{5.31}$$

$$Y_L = \prod_a^m l_a \tag{5.32}$$

$$Y_W = \prod_a^m w_a \tag{5.33}$$

where,

Y_S, Y_I, Y_D, Y_Q, Y_L and Y_W respectively denote the required number of computations of substitution, insertion, deletion, sequencing, location and accompanying-person operators for each rescheduling step;
l_a and w_a are respectively the number of available locations and accompanying-person options of activity a.

Unlike other operators, the numbers of steps, Y_A and Y_M, required in duration adjustments and tour optimization vary with the schedule specifications. Note that m and n may change over rescheduling steps, while $m+n$ stays the same.

Equations (5.31) to (5.33) express an exhaustive search for sequence, location and accompanying-person facets, respectively, which require an unrealistically complex and high computing effort. The model thus assumes the following simplification.

$$Y_Q = m(m-1)/2 \tag{5.34}$$

$$Y_L = \sum_a^m (l_a - 1) \tag{5.35}$$

$$Y_W = \sum_a^m (w_a - 1) \tag{5.36}$$

Compared to equations (5.31) to (5.33), equations (5.34) to (5.36) state that each step computes only part of what is necessary for an exhaustive combinatorial search. In other words, the choice facet-by-choice facet search is simplified again to be an activity-by-activity search for each choice facet. We argue that this simplified heuristic is behaviorally more likely, while at the same time, the power of the search is maintained by the recursive and non-hierarchical characteristics that allow further improvements at later steps of rescheduling. This again reflects that the overall mechanism of the heuristics should make only a small adjustment at each step to reach the final adjusted schedule.

In sum, due to the overall structure of the choice facet-by-choice facet search as shown in Figure 1, the size of computation for each rescheduling step (the adjustment of S, I, D, Q, L, W or M and the fine-tuning of A) is thus:

$$Y = Y_S + Y_I + Y_D + Y_Q + Y_L + Y_W + Y_M + Y_A \tag{5.37}$$

instead of

$$Y = Y_S \times Y_I \times Y_D \times Y_Q \times Y_L \times Y_W \times Y_M + Y_A \qquad (5.38)$$

where, Y denotes the total number of computations for a rescheduling step.

5.5   Numerical Simulations

In this chapter, we have proposed a model of activity rescheduling behavior, which consists of two complementary sub-models: i.e. the activity utility functions on which the scheduling decisions are evaluated as developed in Section 5.3, and the search tree that searches the (sub-)optimal alternative scheduling decisions in the solution space that is reduced in a way that mimics human search behavior as suggested in Section 5.4. In this section, we examine the proposed model on the basis of the following research questions.

• Related to the search tree:

Sensitivity of rescheduling choice to parameter settings: When employing different sets of values of the search-tree parameters, does the model produce courses of rescheduling actions that are distinguishable in the end result?

Face validity: If the above is the case, are the different results interpretable in behavioral terms?

• Related to the transportation environment:

Accessibility: Does the model illustrate more restricted rescheduling actions when a poorer transportation connection is provided?

To study the first questions of search tree, different sets of values of the search-tree parameters were assumed in simulations. As a case, the simulations considered a hypothetical set of activities and occurrence of an unexpected time lack situation at some moment in time. It is to note that we do not concern ourselves with different adaptation styles discussed in Section 5.3.4 because the primary purpose of this section is to capture the mainline property of the proposed model, and to this end, we decided to assume that individuals perceive the true utility functions. The second question of transportation environment is particularly relevant to the study of multi-modal mode use. A better transport connection likely offers more diverse, flexible ways of organizing the trips throughout the schedule, and possibly improves the 'quality' of the schedule. As a case, the simulations study the difference in the rescheduling actions when the public transport lines are disconnected in a given transportation environment.

Simulation settings

Utility parameters: The decision regarding a choice facet is made on the basis of activity utilities that are defined according to the following functional specifications:

$$U = \sum_{a=1}^{A} U_a \tag{5.39}$$

$$U_a = U_a^{\min} + \frac{U_a^{\max} - U_a^{\min}}{\left(1 + \exp[-\beta_a(v_a - \alpha_a - \Lambda_m)]\right)^{\gamma_a}} \tag{5.40}$$

$$U_a^{\max} = U_{wl\tau a}^{\max} - \lambda_m \Lambda_m + \kappa_{ma} \tag{5.41}$$

subject to: $\sum_{a=1}^{A} v_a = B$ (5.42)

where,

U is the total utility of the activities across S and R;
U_a is the utility of activity a; A is the number of activities across S and R;
B is the time budget; v_a is the duration of activity a;
$U_a^{\min}$ is the lower asymptote of U_a;
$U_{wl\tau a}^{\max}$ is the maximum utility of activity a for the combination of particular w, l and τ, α, β and γ are activity-specific parameters;
Λ_b is the travel time by transport mode b from the previous to the current activity;
λ_b is marginal cost of transport mode b;

Table 5.1: Average activity durations and utility parameters of activities and transport modes

Activity in AP	$\overline{ND}$	$U^{\min}$	α	β	γ	Mode Preference (κ)		
						Car	Public	Slow
Sleep	480	-5	465	0.16	5	5	0	10
Pcare	60	0	55	0.10	1	5	0	10
Work1	180	-5	150	0.15	5	5	10	0
Lunch	60	0	35	0.15	1	0	5	10
Work2	300	-5	250	0.15	5	0	5	10
Dinner	60	0	55	0.10	1	0	5	10
Leis_I	360	0	100	0.10	1	5	0	10
Leis_O	180	0	200	0.10	1	0	10	5
Mcare	30	0	65	0.425	5	10	5	0
Dshop	10	0	35	0.30	1	10	5	0

Note: Pcare, Work1, Work2, Leis_I, Leis_O, Mcare, Dshop respectively denote personal care, work in the morning, work in the afternoon, in-home leisure, out-of-home leisure, medical care and grocery shopping. $\overline{ND}$ is the average duration of an activity that is assumed fixed in the short run.

Table 5.2: Maximum utility ($U_{wl\tau}^{\max}$) varying with timing, location and accompanying-person

Combination			Sleep	Pcare	Work1	Lunch	Work2	Dinner	Leis_I	Leis_O	Mcare	Dshop
T1	L1	a	100	100	300	0	0	0	100	0	0	0
		w	100	100	300	0	0	0	100	0	0	0
	L2	a	-	-	-	0	-	0	-	0	-	0
		w	-	-	-	0	-	0	-	0	-	0
T2	L1	a	0	0	0	100	200	0	100	0	100	100
		w	0	0	0	100	200	0	100	0	100	100
	L2	a	-	-	-	100	-	0	-	0	-	80
		w	-	-	-	100	-	0	-	0	-	80
T3	L1	a	100	0	0	0	0	100	80	140	100	140
		w	100	0	0	0	0	120	80	140	100	140
	L2	a	-	-	-	0	-	60	-	100	-	120
		w	-	-	-	0	-	80	-	100	-	120
T4	L1	a	100	0	0	0	0	0	80	140	0	0
		w	100	0	0	0	0	0	80	140	0	0
	L2	a	-	-	-	0	-	0	-	100	-	0
		w	-	-	-	0	-	0	-	100	-	0

Note: T1, T2, T3 and T4 indicate morning, afternoon, evening and night timings, respectively. L1 and L2 imply location 1 and 2, respectively. 'a' and 'w' denote 'alone' and 'with someone', respectively. These parameters of maximum utility represent the effects of different choice facets as follows.
- Accompanying person effect: Dinner = Higher with someone than alone
- Location effect: Leis_O = Higher at the center than in the neighborhood
- Timing effect: Leis_I = Higher in the evening than in the afternoon
- Location-Timing effect: Dshop = Higher at the center in the evening than in the neighborhood in the afternoon

κ_{ba} is level of preference for transport mode b for activity a.

The functional specification of $U_a^{\max}$ in equation (5.41) is suggested only for the simulation. The decision heuristic is however not dependent on any particular form of the utility function. Given the utility functions, the set of utility parameters used is:

Table 5.3: Transportation environment

Available activities at the location	Sleep, Pcare, Leis_I,Lunch, Dinner	Work1, Work2, Lunch	Dshop, Dinner, Leis_O	Dshop	Leis_O
location	Home	Work	Center	Neighbor1	Neighbor2
Work	12*				
Center	11*	5*			
Neighbor1	5	15	13		
Neighbor2	4	12	9	4	
Medical	5*	17*	16*	4	7

Note: The numeral denotes the travel time by car between the two locations of the concerned cell. The speeds of the transport modes are assumed as car : public : slow = 1 : 2 : 4. The marginal cost (λ) is set as 4, 0.5 and 0.25 for car, public (such as bus, tram and metro) and slow modes (such as walk, bike, scooter, etc.), respectively. The asterisk indicates that the public transport mode is available between the two locations.

Table 5.4: Institutional constraints

Constraints		t^{s-}	t^{s+}	t^{f-}	t^{f+}
opening hours/work contract	Work1	-	09:30	11:30	12:30
	Work2	12:30	13:30	17:30	-
	Mcare	10:00	-	-	18:00
	Dshop	08:00	-	-	20:00
public mode operating hours		08:00	24:00	-	-

Note: t^{s-}, t^{s+}, t^{f-} and t^{f+} denote the earliest and latest possible begin times and the earliest and latest possible end times, respectively.

$$UF = \{\{\alpha, \beta, \gamma, U^{min}, U^{max}_{wl\tau}, \kappa_b\}_a, \lambda_b\} \tag{5.43}$$

We assume a hypothetical specification of activities and transportation environment as indicated in Tables 5.1 to 5.4, and a pictorial image is presented in Figure 5.8. The total utility after rescheduling is the sum of utilities across all activities in the activity program. As discussed in Section 5.1.1, the baseline shape of an activity's S-shaped utility function is determined by the parameters α (the location of the functional curve along the X-axis), β (the slope of the functional curve) and γ (the position of the inflection point on the functional curve), which are dependent on the nature of the activity.
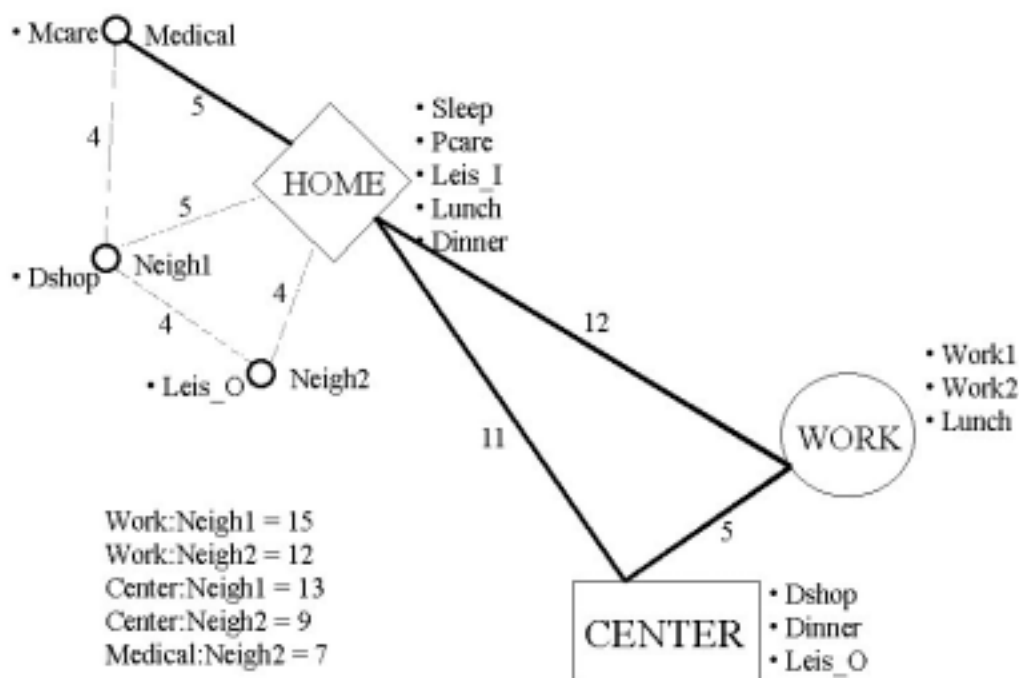

Figure 5.8: Pictorial image of a hypothetical transportation environment

Note: The listed activities are available at the concerned locations. The bold lines represent public transport connection.

For example, compared to the 'grocery shopping' activity (Dshop) in Table 5.1, the 'work in the morning' activity (Work1) has a functional curve located much to the right (α), flatter (β) and a much lower position of the inflection point (γ).

Search tree parameters: As Figure 5.6 indicates, the following parameters of the search tree need to be specified.

$$ST = \{\theta_A, \theta_S, \theta_I, \theta_D, \theta_Q, \theta_L, \theta_W, \theta_M, \Omega\} \tag{5.44}$$

where,

θ_A, θ_S, θ_I, θ_D, θ_Q, θ_L, θ_W and θ_M are the resistance-to-change parameters when applying the duration-Adjustment, Substitution, Insertion, Deletion, seQuence change, Location change, accompanying-person (With-whom) change and transport-Mode operators, respectively;
Ω is explained in equation (5.23).

The simulation will vary the set of search tree parameter values to address our research questions as shown in Table 5.5. In the table, Set 1 implies that all operators except duration have an extremely high level of resistance-to-change (Case 1). Set 2 implies that all operators can be freely applied (Case 2). Set 3 implies that all operators differ in resistance level (Case 3). In Set 4, mental fatigue has a higher marginal value, compared to Set 3 (Case 4). Finally, Set 5 implies that the sequence, location, accompanying-person and transport-mode operators have a combination of resistance levels, different from Set 3 (Case 5).

Results of the simulations for search tree study

The initial schedule assumed in the simulation is shown in Table 5.6. The schedule after Work2 includes Dinner and Leis_I at home. The transport modes used are the car for all trips of home-to-work for Work1, work-to-home for Lunch, home-to-work for Work2, and work-to-home for Dinner in turn.

Now, the simulation first lets the hypothetical person optimize the initial schedule and then describes how the person adjusts the optimized schedule when it is informed by the ratio broadcast before the departure for Work1 that travel to work in the morning takes half-an-hour longer than expected due to congestion.

Table 5.5: Testing sets of values of search-tree parameters

Operator	Set 1	Set 2	Set 3	Set 4	Set 5
Duration (θ_A)	0	0	10	10	10
Substitution (θ_S)	1000	0	30	30	30
Insertion (θ_I)	1000	0	5	5	5
Deletion (θ_D)	1000	0	50	50	50
Sequence (θ_Q)	1000	0	10	10	**5**
Location (θ_L)	1000	0	40	40	**2**
With-Whom (θ_W)	1000	0	10	10	**25**
Mode (θ_M)	1000	0	2	2	**50**
(Fatigue: Ω)	1.05	1.05	1.05	**7**	1.05

Table 5.6: Initial schedule (Total utility = 588.4)

Activity	Duration	Location	With Whom	Travel Mode	Begin Time	End Time	Travel Time
Sleep	480	H	a	-	0: 0	8:00	
Pcare	60	H	a	-	8:00	9:00	0
Work1	180	Wrk	a	car	9:00	12:00	12
Lunch	60	H	a	car	12:00	13:00	12
Work2	300	Wrk	a	car	13:00	18:00	12
Dinner	60	H	a	car	18:00	19:00	12
Leis_I	300	H	a	-	19:00	24:00	0
Lesi_O	0	-	-	-	-	-	-
Mcare	0	-	-	-	-	-	-
Dshop	0	-	-	-	-	-	-

Note: In the location column, H and Wrk denote home and work place, respectively.

Because Sleep and Pcare were already implemented before the congestion, they were *not* candidate activities for rescheduling. Note that even if the initial schedule is the same across hypothetical persons, the resulting optimized schedule before the event likely differs between persons. Indeed, Tables 5.7 to 5.10 show the difference in the initially optimized schedule between hypothetical persons. Rescheduling as a response to congestion was implemented on those different optimized schedules.

Case 1 - Extremely high resistance-to-change except duration adjustment: Table 5.7 shows the result of the applications of Parameter Set 1 before and after the congestion. First, the initial optimization of the schedule improved the total utility from 588.4 to 747.3. Due to the congestion, the utility of the schedule was reduced from 747.3 to 698.3. The schedule adjustments after the congestion improved the total utility to 737.1. Secondly, due to the very high level of resistance to change across all operators except the duration operator, the system, as expected, applied the duration operator only. Finally, many activities underwent big changes in the duration in the initial optimization before the congestion, while only few activities were subject to adjustments after the congestion occurred.

Table 5.7: Extremely high resistance-to-change except duration adjustment (Parameter Set 1)

Before congestion							→	After congestion						
Dura	Loc	WW	Mod	BT	ET	TT		Dura	Loc	WW	Mod	BT	ET	TT
507	H	a	-	22:21	6:48		Sleep		H	a	-	22:21	6:48	
101	H	a	-	6:48	8:29	0	P_care		H	a	-	6:48	8:29	0
								Congestion						*30*
213	Wrk	a	car	8:29	12:02	12	Work1	198	Wrk	a	car	8:59	12:17	12
76	H	a	car	12:02	13:18	12	Lunch	61	H	a	car	12:17	13:18	12
309	Wrk	a	car	13:18	18:27	12	Work2	309	Wrk	a	car	13:18	18:27	12
90	H	a	car	18:27	19:57	12	Dinner	90	H	a	car	18:27	19:57	12
144	H	a	-	19:57	22:21	0	Leis_I	144	H	a	-	19:57	22:21	0

Note: The before-congestion schedule of the left hand side represents the one optimized from the initial schedule, while the after-congestion schedule is the one optimized from the before-congestion schedule due to the congestion. In the column labels, Dura, Loc, WW, Mod, BT, ET, and TT respectively represent duation, location, accompanying-person, transport-mode, begin time, end time, and travel time (included in the duration).
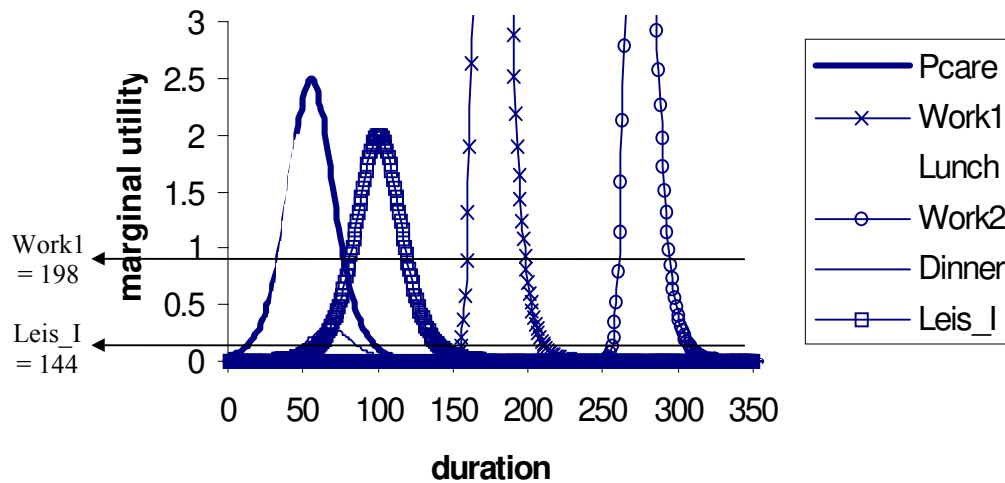
Figure 5.9: Marginal utilities of activities

As Table 5.7 further shows in the before-congestion schedule, all seven activities underwent the duration adjustments. Leis_I's duration was reduced by 156 units (from 300 to 144) and redistributed to other six activities. The amount of the redistribution differed between activities. On the other hand, the after-congestion schedule shows that only two activities Work1 and Lunch underwent the duration adjustments. Schedule adjustment choices take into account the marginal changes in the activity utility and the schedule constraints.

Figure 5.9 shows the marginal utility as a function of duration for each activity. First, given the duration of each activity of the initial schedule, the marginal utility of Leis_I was much smaller than that of all other activities. After a series of reductions of Leis_I's duration and corresponding increases of other activities' durations, the system reached a state of equal marginal utility across activities when the Leis_I's duration was reduced to 144. Next, when Work1's duration was reduced from 213 to 183 due to the half-an-hour congestion, Work1's marginal utility was sharply increased. This situation disturbed the equilibrium state and called for new adjustments by increasing Work1's duration and correspondingly decreasing the duration of all other activities. However, the institutional constraints in Table 5.4 and the before-congestion schedule in Table 5.7 shows that no more delay of the begin time of Work2 is possible, and hence, the only reduction in duration can be made with Lunch. Equal marginal utility between Work1 and Lunch was achieved by increasing Work1's duration by 15 units (from 183 to 198) and decreasing Lunch's duration from 76 to 61.

Case 2 - No resistance-to-change: When the resistance level was set to zero for all operators, the system applied a variety of operators to improve the schedule. After evaluating the initial schedule, the system first adjusted the duration of activities, and then implemented a series of rescheduling choices; location → duration → transport mode → duration → accompanying person → location → duration operators, which resulted in the before-congestion schedule shown in Table 5.8. The adjustments in response to the congestion

consist of transport mode → duration → insertion operators. The locations were optimized to reduce the total travel time and increase the utility (work place for Lunch; center for Dinner). For Dinner, an accompanying person was chosen to increase the utility. The optimized transport modes public-slow-slow for the before-congestion schedule were changed back to car to reduce the travel time for Work1. Insertion of Dshop before Dinner at the center increased the total utility. To lessen the reduction in total utility due to the congestion, Leis_I's duration was much reduced, and Work1's duration was recovered. The total utility changed from 588.4 for the initial schedule to 982.2 for the before-congestion schedule, which is much bigger than that in Parameter Set 1. The utility was reduced to 837.4 due to the congestion, but again increased to 906.1 for the after-congestion schedule, which is also much bigger than that in Parameter Set 1.

Case 3 - Resistance-to-change differs across operators I: The zero value of resistance-to-change parameters for Parameter Set 2 implies a very active rescheduling process without operational costs. In reality, however, resistance likely limits further improvement that may potentially be possible. The system applying Parameter Set 3 reflects this notion and resulted in a rescheduled activity pattern that one would expect. Going again through the initial duration adjustment, the rescheduling involved a smaller number of adjustments compared to Set 2, viz. location → transport mode → duration → accompanying person, which resulted in the before-congestion schedule. Table 5.9 shows that the high resistance level for the location operator affected the adjustment choice. That is, as in the initial schedule, the location for Dinner stayed the same in the before-congestion schedule and even in the after-congestion schedule. Because of the higher resistance level for the insertion operator, the insertion of Dshop did not occur either. After all, no operator was applied in the after-congestion schedule, which would have been too expensive compared to the schedule improvement. The total utility was also affected by this fact. It changed from 588.4 for the initial schedule to 941.9 for the before-congestion schedule, which is in-between those in Parameter Set 1 and 2. The utility was reduced to 868.6 due to the congestion. The level of utility stayed equal to 868.6 for the after-congestion schedule because there was no improvement by rescheduling.

Table 5.8: No resistance-to-change (Parameter Set 2)

Before congestion							→	After congestion						
Dura	Loc	WW	Mod	BT	ET	TT		Dura	Loc	WW	Mod	BT	ET	TT
499	H	a	-	22:21	6:40		Sleep		H	a	-	22:21	6:40	
88	H	a	-	6:40	8:08	0	P_care		H	a	-	6:40	8:08	0
								Congestion						*30*
217	Wrk	a	pub	8:08	11:45	24	Work1	210	Wrk	a	car	8:38	12:08	12
60	Wrk	a	-	11:45	12:45	0	Lunch	66	Wrk	a	-	12:17	13:14	0
291	Wrk	a	-	12:45	17:36	0	Work2	296	Wrk	a	-	13:18	18:10	0
							Dshop	10	Centr	a	car	18:10	18:20	5
110	Centr	w	slow	17:36	19:26	20	Dinner	92	Centr	w	-	18:20	19:52	0
175	H	a	slow	19:26	22:21	44	Leis_I	143	H	a	car	19:52	22:15	11

Table 5.9: Resistance-to-change different across operators I (Parameter Set 3)

Before congestion							→	After congestion						
Dura	Loc	WW	Mod	BT	ET	TT		Dura	Loc	WW	Mod	BT	ET	TT
505	H	a	-	22:21	6:46		Sleep		H	a	-	22:21	6:48	
97	H	a	-	6:46	8:23	0	P_care		H	a	-	6:48	8:23	0
								Congestion						*30*
223	Wrk	a	pub	8:23	12:06	24	Work1	193	Wrk	a	pub	8:53	12:06	24
66	Wrk	a	-	12:06	13:12	0	Lunch	66	Wrk	a	-	12:06	13:12	0
296	Wrk	a	-	13:12	18:08	0	Work2	296	Wrk	a	-	13:12	18:08	0
114	H	w	pub	18:08	20:02	24	Dinner	114	H	w	pub	18:08	20:02	24
139	H	a	-	20:02	22:21	0	Leis_I	139	H	a	-	20:02	22:21	0

Case 4 - High mental fatigue: A higher marginal level of mental fatigue may prohibit any schedule adjustments if the improvement is not big enough compared to the cumulated level of mental fatigue. The simulation results illustrate this mechanism (Table 5.10). When employing Parameter Set 4 in which the marginal mental fatigue is increased from 5 to 7, the rescheduling process stopped already after three steps in the before-congestion schedule; while maintaining the contents of the rescheduling process up to that step. A premature termination of the adjustment processes was also reflected by the total utility levels. The utility changed from 588.4 to 910.4 for the before-congestion schedule. It was reduced to 707.5 due to the congestion. Rescheduling after congestion increased again the utility to 841.6.

Case 5 - Resistance-to-change differs across operators II: Parameter Set 5 has the same resistance level for the duration operator and the operators of the composition adjustments (substitution, insertion and deletion) as Parameter Set 3. Yet, the resistance levels for the sequence and location operators become much smaller, while those for the accompanying-person and transport-mode operators become bigger. Given these parameter values, the rescheduling choices were duration → location → transport mode → duration → location → duration operators for the before-congestion schedule. The first and second applications of the location operator changed the location for Lunch to work and the location for Dinner to center, respectively.

Table 5.10: High mental fatigues (Parameter Set 4)

Before congestion							→	After congestion						
Dura	Loc	WW	Mod	BT	ET	TT		Dura	Loc	WW	Mod	BT	ET	TT
507	H	a	-	22:21	6:48		Sleep		H	a	-	22:21	6:48	
101	H	a	-	6:48	8:29	0	P_care		H	a	-	6:48	8:29	0
								Congestion						*30*
213	Wrk	a	pub	8:29	12:02	24	Work1	208	Wrk	a	car	8:59	12:27	12
76	Wrk	a	-	12:02	13:18	0	Lunch	63	Wrk	a	-	12:27	13:30	0
309	Wrk	a	-	13:18	18:27	0	Work2	299	Wrk	a	-	13:30	18:29	0
90	H	a	pub	18:27	19:57	24	Dinner	89	H	a	car	18:29	19:58	12
144	H	a	-	19:57	22:21	0	Leis_I	143	H	a	-	19:58	22:21	0

Table 5.11: Resistance-to-change different across operators II (Parameter Set 5)

Before congestion							→	After congestion						
Dura	Loc	WW	Mod	BT	ET	TT		Dura	Loc	WW	Mod	BT	ET	TT
499	H	a	-	22:21	6:40		Sleep		H	a	-	22:21	6:40	
88	H	a	-	6:40	8:08	0	P_care		H	a	-	6:40	8:08	0
								Congestion						*30*
218	Wrk	a	pub	8:08	11:46	24	Work1	188	Wrk	a	pub	8:08	11:46	24
60	Wrk	a	-	11:46	12:46	0	Lunch	60	Wrk	a	-	11:46	12:46	0
291	Wrk	a	-	12:46	17:37	0	Work2	291	Wrk	a	-	12:46	17:37	0
109	Centr	a	slow	17:37	19:26	20	Dinner	109	Centr	a	slow	17:37	19:26	20
175	H	a	slow	19:26	22:21	44	Leis_I	175	H	a	slow	19:26	22:21	44

The system, however, applied no operator in the after-congestion schedule because the operators other than the location operator were too expensive to apply, while all locations of the listed activities were already optimized for the before-congestion schedule, and there was no location improvement left for the after-congestion adjustment.

   As Table 5.11 shows, the location operator was encouraged, while the accompanying-person and transport-mode operators were discouraged, which reflect the disproportional changes in the resistance level. The figure also shows that in spite of a lower resistance level, there was no application of the sequence operator, which might imply that the possibility of a sequence change is more limited than that of other operators due to the constraints. The resulting total utilities of the schedules optimized on this parameter set were independent of those in Parameter Set 3. The utility changed from 588.4 for the initial schedule to 962.8 for the before-congestion schedule. It was reduced to 831.9 due to the congestion. The level of utility stayed equal to 831.9 for the after-congestion schedule because there was no improvement by rescheduling.

   In sum, the results illustrate the following mechanisms. First, in Parameter Set 1 where the resistance levels of all operators, except the duration operator, were extremely high, the schedule was adjusted by only the duration operator, and in such a case, the adjustment results were explained by the marginal utilities of activities of *S*. Secondly, in Parameter Set 2 where the resistance levels of all operators were equal to zero, providing cost-free adjustment operators, the rescheduling process resulted in a diverse application of different operators and a bigger improvement of the schedule in terms of the total utility, compared to Parameter Set 1. Thirdly, given a combination of different levels of resistance across operators, the rescheduling process resulted in an outcome in-between those in Parameter Set 1 and 2. Fourthly, in Parameter Set 4 that has a bigger marginal value of mental fatigue, the rescheduling process resulted in a premature termination and hence a sub-optimal adjustment, compared to Parameter Set 3. Finally, a different combination of resistance levels of operators encourages and discourages particular operators as shown in the results based on Parameter Set 5.

Results of the simulations for transportation environment study

As discussed earlier in the second research question, the rescheduling actions when the public transport service is removed from the originally given transportation environments are

examined. As for the simulation setting, the only difference from Figure 5.8 is that there are no public transport connections denoted by bold lines.

To focus on the effect of the public mode connection on the rescheduling behavior without considering the effect of search tree parameters, we set the resistance-to-change levels to zero for all parameters as of Set 2 in Table 5.5. The hypothetical person of zero resistance-to-change level then optimizes the initial schedule of a day as given in Table 5.6 in the transportation environment of no public mode connection. We compare the rescheduling actions between this and that discussed earlier with the results of the before-congestion scheduling of Case 2 with regard to the number of scheduling steps, the number of alternative mode sequences considered, the resultant choices of transport mode of the day and the utility level of the resultant schedule. The results are shown in Table 5.12.

The simulation results clearly show that the proposed model simulates the likely rescheduling actions as expected. Given the limitation of the mode choice allowed only for car and slow modes, the rescheduling actions become simpler. The number of scheduling steps is reduced from four to two involving only the accompanying person and location changes once, respectively. The total number of alternative mode sequences that have been considered for composing the tours of the day throughout the scheduling steps has also been sharply reduced from 616 to 64. Resultant mode sequence is much simpler as Car-Car instead of the sequence of Public-Slow-Slow. Importantly, the limited availability of the transport mode does not only means the limited choice alternatives of mode sequence but also the limited choice options for activity sequences, which likely leads to the final schedule having lower utility. In this example, the high marginal cost of the car use, as explained in Table 5.3, contributed to the reduction of the utility of the resultant schedule.

5.6   Conclusions and discussion

This chapter proposed a model of activity-travel rescheduling behavior in response to changes in the transportation environment. To this end, the chapter first conceptualized the problem and developed two complementary components of the model: an activity utility function and search tree for decision making related to schedule adjustment. This is followed by a set of numerical simulations to examine the face validity of the model.

Table 5.12: The effect of public mode availability on the rescheduling actions

	Public mode available	Public mode *not* available
# Scheduling steps other than duration adjustment	4: Location-Mode-WithWhom-Location	2: WithWhom-Location
# Alternative mode sequences considered	616	64
Chosen sequence of modes	Public (P_care→Work) Slow (Work→Dinner_Out) Slow (Dinner_Out→Leis_In)	Car (P_care→Work) Car (Work→Dinner_In)
Resultant schedule utility	982.2	944.7

The model is meant to make a contribution to a general theory and model of short-term activity adaptation decisions. It is assumed that such adaptation or adjustment decisions may involve changing the duration of activities, changing the sequence in which the activities are conducted, and adapting the composition of the activity program by inserting or deleting activities. Individuals are assumed to try to maximize the utility of their activity-travel pattern, subject to cognitive constraints. They apply decision strategies and heuristics to reschedule their activities in situations where unexpected events occur. The adaptation processes may vary depending on the strategies adopted.

The utility for the duration of an activity can be represented by an asymmetric logistic equation. The maximum, minimum, slope and inflection point of this equation are assumed not only to depend on the kind of activity, but also on a variety of choice facets and the history of the activity. Thus, the utility is assumed to be context-dependent. The S-shaped function of a particular form also has the potential to cope with several styles of adaptation. In particular, a distinction was made between risk-avoiding and opportunistic styles, and between hedonistic and conservative behavior.

To account for cognitive constraints and cope with unexpected events, decision heuristics were introduced to derive an operational model. These heuristics arranged in a search tree simulate how individuals will adjust the various facets of an activity-travel schedule, such as duration, destination, transport mode and schedule composition, in situations of unexpected events, such as delay, congestion, missed connections, etc. The search tree is complementary to activity-specific utility functions, and takes into account possible resistance-to-change of particular facets of a planned activity-travel schedule and mental fatigue. The search tree is framed in the context of bounded rationality and sub-optimal, satisfying behavior, captured in terms of an iterative, recursive procedure.

The face validity of this extended theory and associated model was examined by performing a set of numerical simulations for a series of typical cases. The results of numerical simulations indicate that the proposed model is capable of representing the assumed behavior. More specifically, the simulations lead to the following conclusions. First, the system simulates many 'invisible mental' adjustments that likely exist before one actually 'observes' the final schedule. Secondly, the system involves a rescheduling process based on the marginal utilities of activities, subject to various constraints. Thirdly, disproportional change in the resistance level across operators affect the adjustment process in general and encourages and discourages the use of particular operators in particular. Finally, and most importantly, the system is sensitive to different sets of parameter values and supports the theory, giving face validity to the suggested model.

The proposed model is a potentially valuable tool to predict changes in planned activity schedules as a function of time pressure and unexpected events in general. As such it could complement the structural models of activity scheduling decisions and activity-travel patterns. To be used for prediction, the parameters of the utility functions as well as the choice heuristics need to be estimated based on observed choices. In the following chapter, we will discuss the problem of estimation of activity utility functions and suggest suitable methods to solve the problem.

6 Estimation Method

6.1 Introduction

In Chapter 5, we have developed a comprehensive theory and model of the process of scheduling and rescheduling activities. The system is comprehensive in that it allows modeling the dynamics of activity scheduling and rescheduling decisions as a function of unexpected events during the execution of activity programs. The model incorporates several behavioral principles and decision styles, including risk-avoiding and opportunistic behavior. The assumed activity utility function incorporates a variety of choice facets and the complementary set of decision heuristics implements various scheduling operators to find the near-best schedule adjustments.

The question considered in this chapter is how the parameters of the utility function can be estimated. This is certainly not a trivial question as we are faced with several problems. First, the model has no algebraic solution. Secondly, the theory underlying the model argues that scheduling decisions are state-dependent. Finally, the model should satisfy several sets of discontinuous constraints. The present chapter is devoted to describe the development and test of such an estimation method. The chapter that follows will describe an application to a (real) activity data set.

We stress that the proposed model of activity rescheduling behavior consists of two complementary sub-models, and therefore there are two sets of parameters to estimate from empirical data. The method described in the chapter concerns the parameter estimation of the activity utility function only. The estimation of search tree parameters is left to future research.

The chapter is organized as follows. Section 6.2 establishes a theory for estimating the activity utility functions. A critical assumption is introduced because of the non-analytical nature of the problem. Furthermore, the detailed description of the theory addresses the issues of non-linearity, illegal solution and dual solution of the problem. Having developed the theory, Section 6.3 develops an implementation algorithm. A tailored genetic algorithm is suggested. In Section 6.4, the developed theory and the implementation algorithm are tested on simulated schedule data to examine whether the proposed estimation approach is indeed able to predict the parameter values with a certain precision. The model first estimates the activity utility functions on the simulated data and compares the predicted parameter values with the 'known' true values. The model is then tested on simulated data with simulated noise of various sizes and of several types. This will show the extent to which the suggested model is robust for noise, which inevitably is involved in real world data. Section 6.5 ends the chapter with some conclusions and discussion.

6.2 Theory

When faced with time pressure or unexpected events, an individual is assumed to mentally adjust the schedule, as described by the search tree model. In the proposed model, various operators are assumed to accomplish schedule adjustments. The schedule composition operator changes the list of activities included in a schedule by deleting, inserting and substituting activities. Sequencing, location, transport mode and accompanying person operators change the means of implementing the concerned activity. The application of the operators leads to incremental mental adjustments of the schedule and continues until no more improvement is possible. The schedule improvement is evaluated based on the utility that is assumed to be the sum of utilities of activities of the schedule, as defined in Section 6.3.3. In the following, we suggest a method to estimate such utility functions.

There are two unique features of our estimation method. First, the activity utility function that we estimate does not describe an association of a set of external variables with the likelihood of an observed behavior. Instead, the utility function represents a simple, intrinsic relation between activity duration of continuous time and the level of utility. At the same time, however, the utility function should be consistent with individual's incremental rescheduling decisions between competing activities, locations, etc., which finally results in the observed schedule. Secondly, in spite of such intermediate rescheduling decisions, however, the utility function will be estimated directly from the activity duration data without consulting such intermediate rescheduling decisions. Having the utility of continuous time function is particularly important in the sense that most available activity diary data only provide the information of the activity durations as the final results of the scheduling/rescheduling processes. The estimation of the model will therefore be specially designed for the duration data.

Assume that we know in advance the maximum level of utility $U^{\max}$ of each activity, and we can observe the level of utility U of each activity over time. We could then linearize the suggested activity utility function and, using the information of duration v of the observed schedule data, directly solve the equation for the parameter values α, β and γ for each activity. This is unfortunately not the case because the utilities of the activities (U and $U^{\max}$) are unobservable and unknown. Furthermore, unlike the logarithmic function of ever-diminishing marginality (e.g., Kitamura, 1984b; Bhat & Misra, 1999), the suggested utility function assumed here does not provide an algebraic solution for the durations that maximize the schedule utility. Therefore, we cannot directly 'solve' the estimates but have to 'find' the estimates that best fit the observed durations by searching iteratively multiple combinations of parameter values. The number of such combinations would however be prohibitively large for an exhaustive search.

For the above reasons, we suggest a heuristic method that searches only part of the entire solution space, but at the same time, provides good, near optimum solutions. The method is based on the critical assumption that the marginal utility of activities in the schedule is the same. If this would not be the case, an individual would further adjust durations to increase the total utility. The duration of the activity of the higher marginal utility will be increased while the duration of the other activity will be decreased.
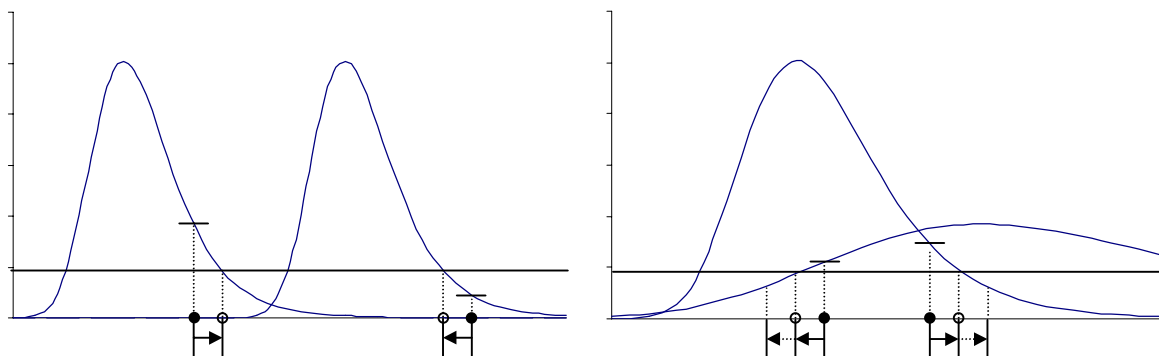
Figure 6.1: Equilibrium with saturated/unsaturated durations

However, given the marginal utility, there are generally two duration points where the marginal utility is reached. Because of this fact, the equal marginal utility that is assumed above indeed corresponds to two duration points that are saturated, where marginal utility is diminishing, and also unsaturated, where marginal utility is increasing. For the sake of argument, we assume for the moment that we know or are able to observe the level of marginal utility of each activity over time. Consider first the activities of saturated durations as in the LHS of Figure 6.1. The figure illustrates two marginal utility curves, which is the derivative of utility function discussed in Chapter 5. The X-axis denotes the duration and Y-axis the level of marginal utility. When there is a difference in marginal utility between activities as denoted by the two black dots in the figure, the adjustment takes place such that the marginal utilities of the activities are equalized to increase the total utility that is the sum of integrals of the marginal utility curves from zero to the current duration points. The result of the adjustment is to reach the equal level of marginal utility by increasing the duration of the activity of the higher marginal utility and decreasing the other activity's duration.

Next, consider two activities, one of which is saturated, and the other unsaturated as in the RHS of Figure 6.1. There is also a difference in marginal utility, and the adjustment results in increasing the duration of the activity of the steeper marginal curve and decreasing the other activity's duration because the increased integral of the activity of the steeper marginal curve is bigger than the decreased integral of the other activity. The two activities are in equilibrium at the durations indicated by the white dots. Obviously, the equilibrium that includes unsaturated activities would be observed much less frequently, but we do not exclude such cases from consideration.

In principle, based on these theoretical decisions, an estimation method could be developed. However, the value of the equal marginal utility of the schedule is unknown in reality, and multiple solutions for the parameter estimates that satisfy the equal marginal utility across activities of the schedule could exist. Therefore, an additional assumption is required. To find a solution, we postulate that the level of equal marginal utility of the schedule is partly reflected by the amount of time pressure of the schedule, measured as the total duration of the *fixed* activities of the schedule, and the number of activities. The level of equal marginal utility can then be approximated as a function of these variables. The rationale behind this assumption is that given the number of activities, higher time pressure

(less available time) would also raise the level of equal marginal utility. On the other hand, given the time pressure, a larger number of activities would raise the marginal utility for each activity. These assumptions seem appropriate given our theory especially for saturated activities. Equation (6.1) expresses this critical assumption.

$$\frac{\beta U^{max} \exp[\beta(\alpha - v)]}{(1 + \gamma \exp[\beta(\alpha - v)])^{1/\gamma + 1}} = \sum_k \delta_k X_k \qquad \forall a \in S \qquad (6.1)$$

where,

X_k is the kth attribute of the equal-marginal-utility function (X_1 = fixed duration, X_2 = number of activities of the schedule);
δ_k is the marginal contribution of the kth attribute X_k to the level of equal marginal utility, which is attribute-specific;
S denotes the current schedule.

By solving equation (6.1) for v, given each of the combinations of possible values of parameters, the overall goodness-of-fit of the predicted set of parameter values can be calculated as in the following, and the set of parameter values that corresponds to the best goodness-of-fit can then be identified.

$$G_l = \sum_a G_{a_l} \qquad (6.2)$$

with

$$G_{a_l} = | v_a^o - v_{a_l}^p | \qquad (6.3)$$

where,

G_l is the goodness-of-fit of the lth predicted combination of parameter estimates, where $l = 1$, …, L, and L is the number of the parameter values combinations to be examined;
G_{a_l} is the goodness-of-fit of the lth predicted combination of parameter estimates for activity a;
v_a^o and $v_{a_l}^p$ are respectively the observed duration of activity a and the duration of activity a predicted by the lth predicted combination of parameter values.

Still, however, some further operational problems need to be solved for obtaining the duration prediction v^p in order to compute the goodness-of-fit of the associated set of predicted parameter estimates. First, there is no direct, algebraic solution for v^p that satisfies equation (6.1), and therefore, we used an algorithm of golden section search to 'find' the duration instead of 'solving' it.

Secondly, the predicted set of parameter values may have no cross points between the equal marginal utility line given by the RHS of equation (6.1) and the marginal utility curve given by the LHS of equation (6.1). That is, it may be the case that the predicted time pressure goes beyond the maximum of the marginal utility. It then has no cross points

needed for the duration prediction. In reality, it may be that when the time pressure is so high, and the schedule requires very high marginal utilities for activities to be included, the activities with a lower maximum marginal utility will not survive, and therefore, we would not observe such activities in the schedule. In our estimation, however, we do observe the activity that was implemented in the schedule, and therefore, if the predicted parameters result in no cross points, that predicted solution would clearly be wrong. The predicted parameters associated with such 'illegality' and their neighbors should not be visited again in the iterative solution search procedure. This can be enforced by assigning an appropriate size of penalty. To this end, the goodness-of-fit of an activity should be revised from equation (6.3) as:

$$
G_{a_l} = \begin{cases} \mid v_a^o - v_{a_l}^p \mid & \text{for a legal solution} \\ \mid v_a^o - 0 \mid + TD + gap_a & \text{for an illegal solution} \end{cases} \tag{6.4}
$$

where,

v_a^o is the observed duration of activity a;

TD is the total sum of duration units of a day, which is computed as 1440 in the current study;

gap_a is the difference between the predicted time pressure and predicted maximum of activity a's marginal utility.

As implied by this equation, the measure of the goodness-of-fit of the illegal solution for an activity is the sum of three sources of differences. The first source of difference is the pure difference between observation and prediction. As discussed above, if the time pressure is much too high compared to the maximum level of an activity's marginal utility, that activity should not be included in the schedule, and therefore, the predicted duration v^p of this activity is zero. The second source of difference is a penalty for being illegal. In the current study, we used 1 minute as the unit of duration. The added number 1440 then means the entire time of a day in minutes. Equation (6.4) distinguishes illegal solutions from legal ones by adding this big number, which makes the resulting measure of goodness-of-fit worse than any possible legal solution. The final source of difference for the illegal solutions is the degree of illegality to make the search sensitive for direction.

Figure 6.2 illustrates three different solutions of an activity, where the predicted parameter values of this activity's marginal utility curve α, β, γ, α_x, β_x and U_x are the same, and only the time pressure parameter values δ are different. The first solution is legal in the sense that the marginal utility curve and the time pressure line (TP$_1$) crosses at least one point. The second and third solutions are however illegal, because the marginal utility curve and time pressure lines do not cross. The lower part of equation (6.4) should be applied. The first two terms of the RHS of the lower part of this equation are the same for the second and third solutions, which makes their goodness-of-fit measure much worse than the first solution. The vertical arrows between the time pressure lines and the maximum of the marginal utility curve makes a further distinction between these illegal solutions, which states that the third solution is even worse than the second.
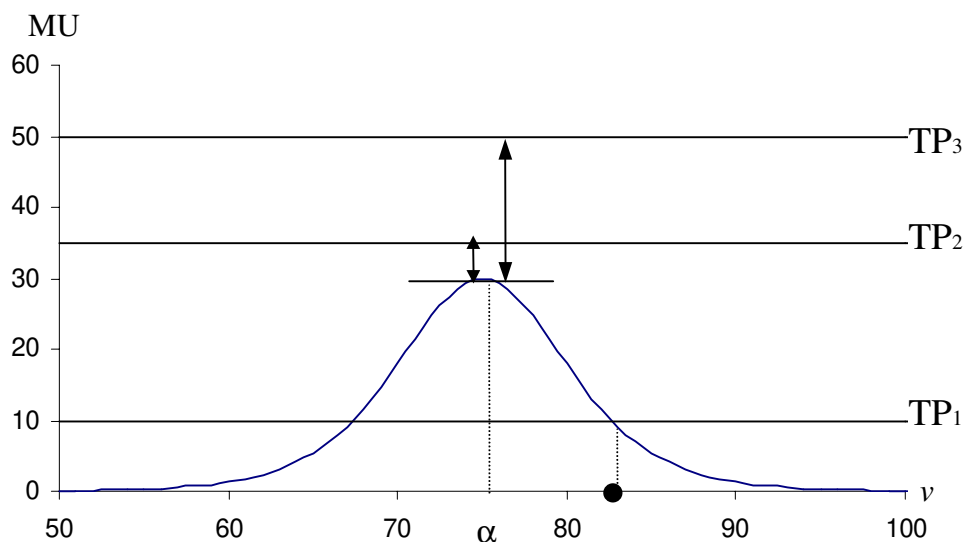
Figure 6.2: Illegality of the solutions

Finally, the existence of the equilibrium durations at both sides of the inflection point raises the question of how to choose the one that is used for prediction. We let the method choose the one that gives the better match. This can be illustrated by the graph in Figure 6.3. In the figure, the black dots are the predicted durations v^p corresponding to the cross points of the observed level of equal marginal utility and the marginal utility curve. The white dot is the observed duration v^o of this activity. The black dot on the RHS is chosen in this illustration because it is closer to the observation than the other black dot. Accordingly, the goodness-of-fit of an activity is again revised from equation (6.4) as:
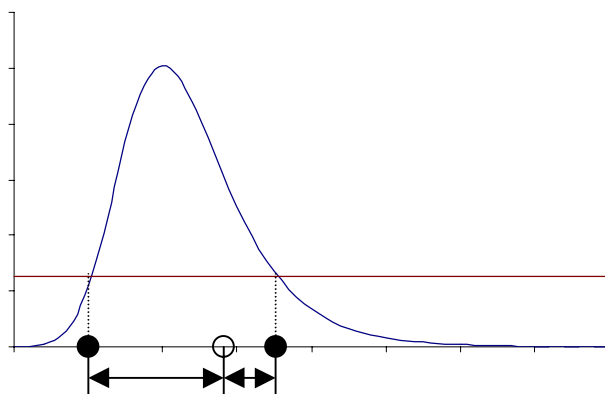
Figure 6.3: Decision of predicted duration

$$G_a = \begin{cases} \min(|\, v_a^o - v_a^{p^{\text{LHS}}} \,|, |\, v_a^o - v_a^{p^{\text{RHS}}} \,|) & \text{for a legal solution} \\ |\, v_a^o - 0 \,| + TD + gap_a & \text{for an illegal solution} \end{cases} \qquad (6.5)$$

where, $v_a^{p^{\text{LHS}}}$ and $v_a^{p^{\text{RHS}}}$ are the predicted durations of activity a that are respectively on the LHS and the RHS of the inflection point.

The problem addresses in the proposed estimation method can therefore be summarized as:

Minimize: $G = \sum_s \left(\sum_a G_a \right)_s$ $\qquad\qquad\qquad\qquad\qquad\qquad (6.6)$

with

$$\left(\sum_s \left(\sum_a G_a \right)_s \right)^* \in \left\{ \left(\sum_s \left(\sum_a G_a \right)_s \right)_l \right\} \qquad (6.7)$$

and

$$G_a = \begin{cases} \min(|\, v_a^o - v_a^{p^{\text{LHS}}} \,|, |\, v_a^o - v_a^{p^{\text{RHS}}} \,|) & \text{for a legal solution} \\ |\, v_a^o - 0 \,| + TD + gap_a & \text{for an illegal solution} \end{cases} \qquad (6.5)$$

subject to: $\left((MU_a)_s = TP_s \right)_l \quad \forall s \in \Gamma$ $\qquad\qquad\qquad (6.8)$

with

$$MU_a = \frac{U_a^{\max} \beta_a \exp[\beta_a (\alpha_a - (v_a)_s)]}{\left(1 + \gamma_a \exp[\beta_a (\alpha_a - (v_a)_s)]\right)^{1/\gamma_a + 1}} \qquad (6.9)$$

and

$$U_a^{\max} = \frac{U_{x_a}}{1 + \exp[\beta_{x_a} (\alpha_{x_a} - T_a)]} \qquad (6.10)$$

and

$$TP_s = \sum_k \delta_k (X_k)_s \qquad (6.11)$$

where,

G is the goodness-of-fit of the predicted parameter values combination;

G_a is the goodness-of-fit of the predicted parameter values specifying the utility function of activity a;

$(\Sigma(\Sigma G_a)_s)^*$ denotes the sum of the goodness-of-fit across the best predicted activity utility functions;

s is an index of schedules, where $s \in \Gamma = \{1, \ldots, TS\}$, and TS is the total number of the schedules of the data;

l is an index of the predicted parameter combinations, where $l = 1, \ldots, L$, and L is the total number of the parameter value combinations to be examined;

$(MU_a)_s$ is the marginal utility of activity a, computed for schedule s;

TP_s is the time pressure, computed for schedule s;

$(X_k)_s$ is the values of the kth time pressure attribute of schedule s;

δ_k is the kth time pressure attribute-specific parameters, denoting the marginal contributions of X_k to the time pressure of the schedule, respectively.

Solving equations (6.9) to (6.11) for v across activities of the schedule, such that the equilibrium condition of equation (6.8) is met, provides the prediction of activity duration. For each activity of the schedule, the prediction error then is computed based on equation (6.5), and the overall goodness-of-fit of a current set of parameter estimates is the sum of prediction errors across activities as in the parenthesis of the RHS of equation (6.7). Note that equation (6.10) specifies the U^{max} function assuming an S-shaped curve like the U function and is a function of the activity history. The associated parameters of this U^{max} function are also estimated simultaneously with the parameters of the U function. In this way, the model once estimated is not only able to predict activity durations (based on the U function), but also activity frequencies (based on the U^{max} function).

6.3   Algorithm

Our problem thus is to estimate from schedule data the activity-specific parameters α, β, γ, α_x, β_x and U_x, given the information of duration v, history T and time pressure attribute X. A genetic algorithm was applied to solve equations (6.6) and (6.8). The following operational decisions were made.

6.3.1   Representation of the solution candidates

We employed a real coding scheme to represent the solution candidates of the real parameter values. The real-coding genetic algorithm (RCGA) does not binary-digitalize the real number information but uses real numbers directly representing the solutions with minimum and maximum possible values (Wright, 1991). Given m parameters to estimate for each of n activities and p time-pressure parameters, a solution candidate is represented as an array of

$mn+p$ elements of real numbers, and an element of a real number represents a corresponding parameter. In a preliminary study, this RCGA representation scheme outperformed the ordinary binary representation scheme in terms of precision and speed. In particular, the increased speed was obtained by the RCGA representation scheme, where the encoded information (genotype) for genetic modification and the real form (phenotype) for candidate evaluation are the same, and hence, a decoding process that transforms the genotype information into the phenotype is not required.

6.3.2   Genetic operators

Our RCGA also employed crossover and mutation operators for genetic modification of the solution candidates like any other GA. The details of the operators of the RCGA are however different from ordinary binary GAs. After a series of preliminary studies, we chose the BLX-0.5 crossover and Mühlenbein mutation (Herrera, *et al.*, 1998). As for crossover, assume two solution candidate arrays $C_1 = [c_1^1,..,c_{mn+p}^1]$ and $C_2 = [c_1^2,..,c_{mn+p}^2]$ that are selected from the current pool of solution candidates to be modified for the next pool. The h_i of the offspring $H = [h_1,..,h_{mn+p}]$ is determined such that the value randomly lies in-between $c_{\min} - I \cdot \omega$ and $c_{\max} + I \cdot \omega$, where $1 \leq i \leq mn+p$, $c_{\min} = \min[c_i^1, c_i^2]$, $c_{\max} = \max[c_i^1, c_i^2]$ and $I = \left|c_i^1 - c_i^2\right|$. We chose 0.5 for ω. As for mutation, assume a randomly selected solution candidate $C = [c_1,..,c_{mn+p}]$. The c_i' of the offspring $C' = [c_1',..,c_{mn+p}']$ is determined such that

$$c_i' = c_i \pm 0.1 \cdot (b_i - a_i) \cdot \sum_{k=0}^{15} \eta_k 2^{-k}$$, where a_i and b_i are the minimum and maximum values that

the ith parameter can take, η_k is randomly determined to be 1 with a probability of 1/16 and 0 with a probability of 15/16, and the + or – sign is chosen with a probability of 0.5.

6.3.3   Genetic parameters

After an extensive study, we chose the following operational parameter values for the genetic procedure.

- Size of the pool or Number of solution candidates for an iteration = 100
- Stop condition = 10000 iterations after the initialization
- Probability of choosing crossover instead of mutation for the current round iteration = 70 %
- Number of solution candidates selected for crossover from the previous pool = 50
- Number of solution candidates selected for mutation from the previous pool = 90
- Selection of solution candidates for modification = Random selection with replacement
- Probability of mutating a parameter of the solution candidate selected for mutation = 10 %

6.3.4 Overall procedure

Overall, our RCGA works as follows. ① The RCGA randomly initializes 100 solution candidates, each of which is an array of $mn+p$ real numbers that represent m parameters of n activities and p time pressure parameters. ② It then evaluates each candidate, which is a rather complex procedure. Each solution candidate is a prediction of parameter values of the activity utility function at the current step of iteration. Given these values and the time pressure information of the observed schedules, the system finds the predicted duration of each activity included in the observed schedule. More specifically, this is done by using the relation of equality between the marginal utilities mathematically derived from the utility function and the marginal utility predicted based on the time pressure attributes X. The absolute difference between predicted and observed durations of that activity is then computed, and these differences are summed across activities of the schedule, and finally across schedules of the entire data to produce a measure of goodness-of-fit of the solution candidate. ③ The RCGA selects solution candidates, and the selection probability is proportional to the goodness-of-fit. Better goodness-of-fit increases the chance for a candidate to be selected. The following probabilistic roulette wheel is used at each time of a selection.

$$P_l = \frac{\sum_{l'} G_{l'}}{G_l} \bigg/ \sum_{l'} \frac{\sum_{l'} G_{l'}}{G_{l'}} \tag{6.12}$$

where, P_l and G_l are the selection probability and the goodness-of-fit measure of the lth solution candidate ($l = 1, \ldots, 100$).

Note that the goodness-of-fit of a candidate is the sum of prediction errors across schedules, and hence, a smaller value means a better fit. The selection is repeated 100 times with replacement. ④ Among the selected candidates, the RCGA modifies randomly selected 50 (for crossover) or 90 (for mutation) candidates. ⑤ The RCGA again evaluates the new pool of genetically modified solution candidates. An iteration consists of the steps ③-④-⑤ and is repeated 10000 times to complete a run.

6.4 Model test

Before an application to an empirical data, we examined the properties of the suggested estimation method on simulated data. The purpose of this study was to investigate whether the suggested method produced the correct results using a set of simulated schedule data. Furthermore, we wanted to better understand the performance of the suggested approach for noisy data. To this end, we prepared a set of simulated activity schedule data, which assumed no noise for activity duration and time pressure attributes, and another set of activity schedule data, using the same value with some added amount of noise. In the

following, we first examine whether the suggested estimation method is capable of reproducing the parameters, and then further examine the robustness of the suggested method for various sources of noise in the simulated data.

6.4.1   Estimation results for simulated activity schedules using exact data

The specification of the model used for the current simulations is the same as the one expressed in equations (6.6) and (6.8), except that we simulated five time pressure attributes, instead of two, and hence we have five time pressure parameters, δ_1 to δ_5, for the purpose of testing the method.

We assumed two types of activities, which entails a total of seventeen activity utility parameters (= 2×6+5) to estimate. The simulated data consists of fifty simulated schedules of these two types of activities. A schedule provides information about the duration v and history T of each activity and the values of five time pressure attributes X of that schedule. The observed history is simulated in the range from 1 to 30 integer values, and the observed time pressure attributes are varied in the range from 0 to 100 real values across cases. The 'true' values for parameters were prescribed arbitrarily but reasonably representing assumed activities. Given these simulated observations and the true values of the activity utility function parameters (the column of 'true value' in Table 6.1), the simulated duration observations for the activities of each schedule can be obtained from equation (6.8).

Table 6.1: Estimation results with exact data

parameter		true value	estimated
α	activity 1	75	75.31
	activity 2	420	421.39
β	activity 1	0.15	0.15
	activity 2	0.10	0.11
γ	activity 1	0.8	0.58
	activity 2	0.1	0.27
α_x	activity 1	7	7.64
	activity 2	3	3.06
β_x	activity 1	0.15	0.14
	activity 2	0.20	0.19
U_x	activity 1	250	307.20
	activity 2	150	173.02
δ_1		0.0125	0.01587
δ_2		0.0500	0.06253
δ_3		0.0240	0.02952
δ_4		0.0800	0.09671
δ_5		0.0100	0.01213
GOF		-	0.09946

As mentioned in Section 6.3.1, the RCGA needs predefined minimum and maximum parameter values. The following ranges for the parameter values were used: $\alpha = 10 \sim 300$; $\beta = 0.01 \sim 1$; $\gamma = 0.1 \sim 1$; $\alpha_x = 1 \sim 30$; $\beta_x = 0.01 \sim 1$; $U_x = 50 \sim 500$.

The proposed estimation method was run 30 times on the same data. Each run was terminated after 10000 iterations. The total of 30 runs took approximately 22 hours to complete, indicating the complexity of the problem. Table 6.1 shows the estimation results averaged across the 30 runs. The results suggest that the parameter estimates are close to the true parameter values that were used for generating the simulated schedule data. This means that if our assumption that individual activity-rescheduling behavior is based on equalizing marginal utilities is true and the assumed form of utility functions is adequate, and data do not exhibit any noise, then the suggested estimation method will produce fairly exact estimates of activity utility parameters.

A more detailed inspection of the results suggest that the α, β, α_x and β_x values are estimated more precisely than γ and U_x. This can be explained by examining Figure 6.4 which portrays the marginal impacts of the parameters and shows that the impact of γ and U_x is relatively small. In case of γ, it is difficult to recognize the difference in the curve between different γ's under a certain level of time pressure. In case of U_x, unless the difference is very large (500 and 100), the curves show little difference between U_x's (500 and 450). The GA is therefore less sensitive to these two parameters in the estimation. In contrast, changes in duration are most sensitive to the α parameter, which is consistent with the estimation results where the α value has the highest accuracy.

An additional concern when estimating these types of functions is the possible linear correlation between parameter estimates.

Table 6.2: Correlations between parameter estimates

	Activity 1					
	α	β	γ	α_x	β_x	U_x
α	1	-.616**	-.842**	-.415*	.493*	-.567**
β	-.616**	1	.698**	.935**	-.943**	.899**
γ	-.842**	.698**	1	.410	-.453*	.654**
α_x	-.415*	.935**	.410*	1	-.990**	.839**
β_x	.493*	-.943**	-.453*	-.990**	1	-.842**
U_x	-.567**	.899**	.654**	.839**	-.842**	1

	Activity 2					
	α	β	γ	α_x	β_x	U_x
α	1	.610**	-.551**	-.201	.200	-.871**
β	.610**	1	.322	.106	-.097	-.258
γ	-.551**	.322	1	.340	-.341	.769**
α_x	-.201	.106	.340	1	-.921**	.402
β_x	.200	-.097	-.341	-.921**	1	-.424*
U_x	-.871**	-.258	.769**	.402	-.424*	1

Note: * and ** denotes that the correlation is significant at the 0.05 and 0.01 levels, respectively.

Table 6.2 shows the correlation between parameter estimates over 30 runs of estimation. There exist significant linear correlations between parameter estimates. These results suggest that when dealing with the empirical data, a sequential estimation strategy may be preferable if we face substantial interaction between parameter estimates, resulting in unstable parameter estimates over runs. As shown in Figure 6.4, the α parameter is most sensitive to the change in the duration and is thus expected to be most accurate and stable in predictions, which is proven in Table 6.1. The sequential estimation may therefore begin with the estimation of α given other parameter values of averages of the initial simultaneous estimations.

Change in α (60 → 75 → 90: to right)   Change in β (0.5 → 0.3 → 0.1: to bottom)

Change in α_x (10 → 20 → 25: to bottom) Change in β_x (0.05 → 0.1 → 0.15: to bottom)

Change in γ (0.2 → 0.5 → 1: to bottom)   Change in U_x (500 → 450 → 100: to bottom)
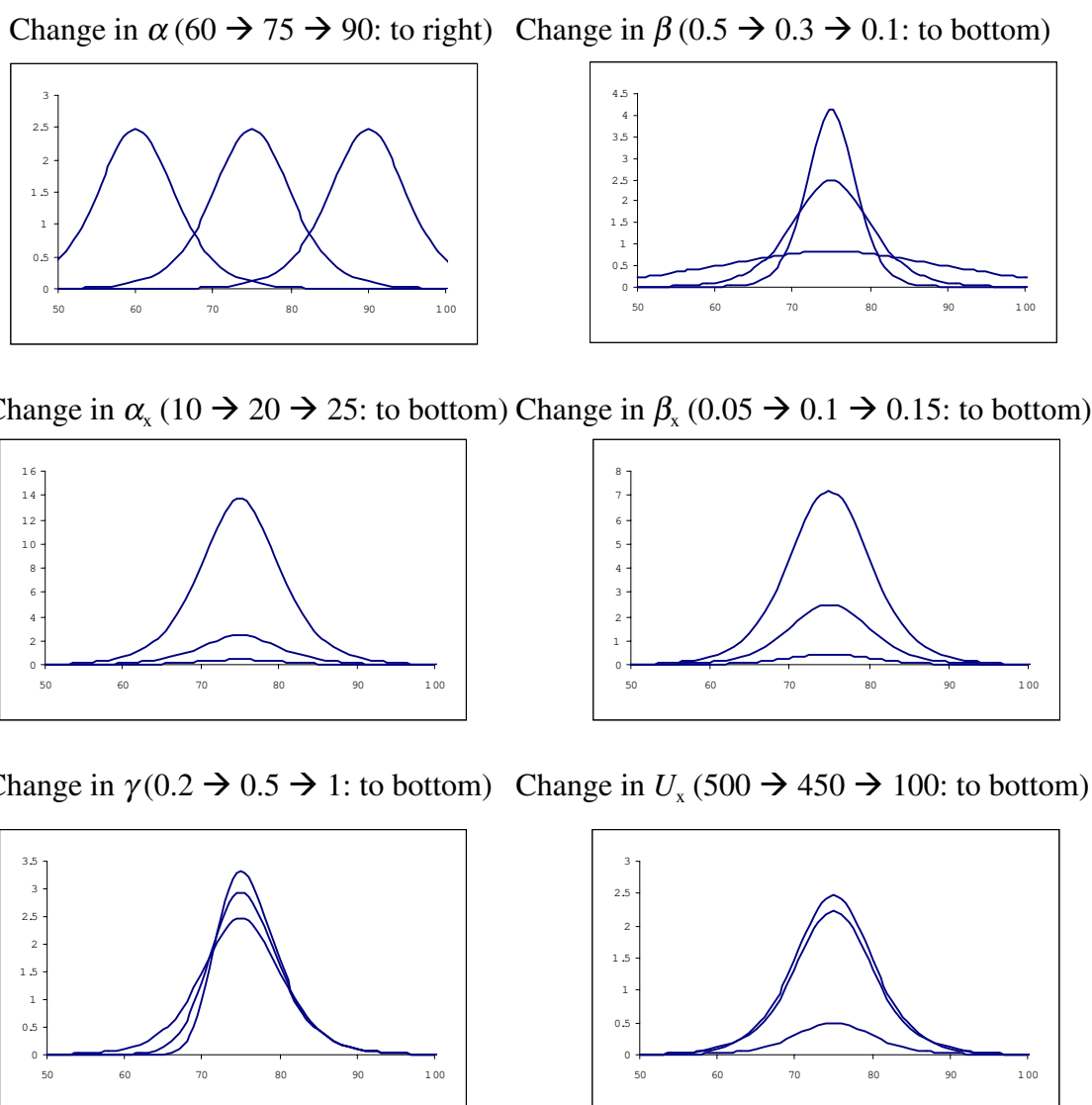
Figure 6.4: Impacts of parameter values on the marginal utility curve

6.4.2 Estimation results for simulated activity schedules using noisy data

Three types of noise were considered: (i) rounding of reported activity duration, (ii) inexact observation of the time pressure attributes and (iii) inexact observation of activity duration. These sources of noise can be expressed in a single equation as:

$$\frac{\beta U_x \exp[-\exp[\beta_x(\alpha_x - T)]]\exp[\beta(\alpha - (\hat{v} + e_{vn}))]}{(1 + \gamma \exp[\beta(\alpha - (\hat{v} + e_{vn}))])^{1/\gamma + 1}} = \sum \delta X + e_n \qquad (6.13)$$

where, $\hat{v}$ is the duration rounded by respondents; e_n is the error term of the time pressure for the nth observed schedule; e_{vn} is the error term of the duration observation.

The goal of the analysis here was to examine the robustness of the suggested estimation method in the presence of such noise for each source separately, one at a time.

Rounding noise

The original simulated data represent activity duration to the precision of three digits after decimal points. Given the simulated observed T and X, a search algorithm finds the value of v based on equation (6.8) at this level of precision.

Table 6.3: Estimation results with rounded data

parameter		true value	no rounding	1 minute rounding	10 minutes rounding
α	activity 1	75	75.31	75.89	80.11
	activity 2	420	421.39	421.80	422.92
β	activity 1	0.15	0.15	0.14	0.18
	activity 2	0.10	0.11	0.11	0.13
γ	activity 1	0.8	0.58	0.27	0.76
	activity 2	0.1	0.27	0.48	0.87
α_x	activity 1	7	7.64	6.61	9.14
	activity 2	3	3.06	3.02	3.18
β_x	activity 1	0.15	0.14	0.15	0.13
	activity 2	0.20	0.19	0.20	0.19
U_x	activity 1	250	307.20	248.52	171.89
	activity 2	150	173.02	176.77	142.70
δ_1		0.0125	0.01587	0.01603	0.00979
δ_2		0.0500	0.06253	0.06445	0.04069
δ_3		0.0240	0.02952	0.03003	0.02402
δ_4		0.0800	0.09671	0.09735	0.07987
δ_5		0.0100	0.01213	0.01211	0.01197
GOF		-	0.09946	0.34374	11.81063

However, the respondents likely round the numbers in reporting the start and end time of activities, and therefore, the estimation model should be prepared with this inaccuracy. The assumed rounding noise is simulated,[1] and Table 6.3 presents the results of the estimation for different degrees of rounding error. As expected, more rounding error results in less accurate estimates, in particular the estimates of γ and U_x as discussed in Figure 6.4. Considering the homogeneous activity durations resulting from the rounding, however, the results are still rather accurate and promising.

Time pressure attribute observation noise

To study this effect, two scales of the error e_n were introduced in the RHS of equation (6.13) in terms of standard deviation of an assumed normal distribution N $(0,\sigma^2)$. One has a standard deviation size of 10 % of the average time pressure level 2.7, and the other the standard normal distribution. That is, $e_n \sim N$ $(0,0.27^2)$ and $e_n \sim N(0,1)$. The results shown in Table 6.4 state that the estimates appear to be relatively robust for this type of noise, except for some scale. If the estimation method is perfect, the introduction of a random error term e_n in the RHS of equation (6.13) should not affect the results. Given the limited number of simulated observations and the small size of time pressure, however, the result is not very disappointing. The random error of scale, STD = 1, seems to confuse the GA too much, considering the small size of time pressure.

Table 6.4: Estimation results with noisy time-pressure data

parameter		true value	no noise	STD = 0.27	STD = 1
α	activity 1	75	75.31	77.93	80.37
	activity 2	420	421.39	424.66	426.76
β	activity 1	0.15	0.15	0.17	0.19
	activity 2	0.10	0.11	0.13	0.13
γ	activity 1	0.8	0.58	0.58	0.16
	activity 2	0.1	0.27	0.19	0.18
α_x	activity 1	7	7.64	6.93	11.16
	activity 2	3	3.06	3.42	3.71
β_x	activity 1	0.15	0.14	0.16	0.12
	activity 2	0.20	0.19	0.16	0.27
U_x	activity 1	250	307.20	211.23	361.45
	activity 2	150	173.02	126.98	178.28
δ_1		0.0125	0.01587	0.01767	0.03461
δ_2		0.0500	0.06253	0.06288	0.09891
δ_3		0.0240	0.02952	0.03223	0.07479
δ_4		0.0800	0.09671	0.09972	0.09974
δ_5		0.0100	0.01213	0.00759	0.02435
GOF		-	0.09946	4.59547	11.60373

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[1] Appendix 6.1 presents an example of the simulated data.

Increasing the number of observations should improve the estimation results.

Optionally, the time pressure parameters would improve their accuracy by a sequential estimation, instead of the current simultaneous approach. More specifically, we may estimate the time pressure parameters of the RHS of equation (6.13) by taking an ordinary linear regression analysis where the independent variables are the time pressure attributes X, and the dependent variable is computed on the LHS of the equation having the estimated values of the parameters.

Duration measurement noise

Measurement error e_{vn} is added to the duration both in the numerator and denominator of the LHS of equation (6.13) as $v + e_{vn}$. The errors were drawn at random from a normal distribution $N(0, \sigma^2)$. The average simulated duration of activity 1 and activity 2 is 86 and 429 minutes, respectively. Hence the "STD 10%" condition includes the error $e_{vn} \sim N(0, 8.6^2)$ for activity 1 and $e_{vn} \sim N(0, 42.9^2)$ for activity 2 added to the duration v in both the numerator and the denominator of the LHS of equation. The "STD 5%" condition results in $e_{vn} \sim N(0, 4.3^2)$ for activity 1 and $e_{vn} \sim N(0, 21.45^2)$ for activity 2.[2]

Table 6.5: Estimation results with measurement noise on the data of different sizes

parameter		true value		no error	STD = 10%	STD = 5%
			50-cases data			
α	activity 1	75		75.31	83.20	82.74
	activity 2	420		421.39	410.46	418.40
β	activity 1	0.15		0.15	0.47	0.24
	activity 2	0.10		0.11	0.04	0.08
γ	activity 1	0.8		0.58	0.64	0.64
	activity 2	0.1		0.27	0.53	0.62
α_x	activity 1	7		7.64	17.38	11.09
	activity 2	3		3.06	6.47	6.45
β_x	activity 1	0.15		0.14	0.22	0.32
	activity 2	0.20		0.19	0.34	0.33
U_x	activity 1	250		307.20	207.95	166.70
	activity 2	150		173.02	430.42	390.40
δ_1			0.0125	0.01587	0.04447	0.04911
δ_2			0.0500	0.06253	0.01751	0.04327
δ_3			0.0240	0.02952	0.05218	0.06489
δ_4			0.0800	0.09671	0.05001	0.05607
δ_5			0.0100	0.01213	0.00807	0.01505
GOF			-	0.09946	44.00144	22.10836
to be continued						

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[2] The simulated duration and measurement error are illustrated in Appendix 6.2.

200-cases data					
parameter	true value		no error	STD = 10%	STD = 5%
α	activity 1	75	75.57	79.03	78.58
	activity 2	420	421.31	421.55	423.48
β	activity 1	0.15	0.15	0.18	0.17
	activity 2	0.10	0.11	0.05	0.06
γ	activity 1	0.8	0.51	0.70	0.63
	activity 2	0.1	0.44	0.55	0.62
α_x	activity 1	7	7.65	8.91	7.42
	activity 2	3	3.02	6.13	6.05
β_x	activity 1	0.15	0.14	0.14	0.15
	activity 2	0.20	0.19	0.30	0.29
U_x	activity 1	250	288.17	288.00	279.12
	activity 2	150	174.95	326.01	271.48
δ_1		0.0125	0.01522	0.02678	0.02406
δ_2		0.0500	0.06057	0.06283	0.07522
δ_3		0.0240	0.02835	0.03579	0.04032
δ_4		0.0800	0.09343	0.09786	0.09879
δ_5		0.0100	0.01176	0.01231	0.01332
GOF		-	0.17417	36.42288	18.13449

To investigate the effect of the duration measurement noise, we tested two sets of simulated schedule data of different sizes. The estimation results are shown in Table 6.5. The following observations can be made. As for the sample size, the bigger sample (n=200) returns a better result than the smaller sample (n=50). As for the goodness-of-fit, the size of the GOF of the estimated model is almost the same across the sizes of the error, and the estimates are converged.

The figures of Table 6.6 show the results averaged across n cases. As for the accuracy of the estimates, the estimates are not very accurate for some parameters. Moreover, the inaccuracy is amplified with the size of the introduced error across parameters of both activities in both data sets. The reason may be the following. When measurement error e_{vn} is introduced from a normal distribution, duration for the actual estimation is changed to $v + e_{vn}$. If the estimation method is insensitive to the introduced random duration error, the marginal utility (the LHS of equation) should be averaged to the true values. In other words, given the marginal utility $MU = f(v)$, $f(v) \approx \left(f(v + e) + f(v - e) \right)/2$.

Table 6.6: Goodness-of-fit across error sizes

sample size	error size	GOF	error sum
$n = 50$	STD=10%	44.00	47.97
	STD=5%	22.11	23.98
$n = 200$	STD=10%	36.42	37.41
	STD=5%	18.13	18.70

Note: The introduced error sum = $|e_{1n}| + |e_{2n}|$.
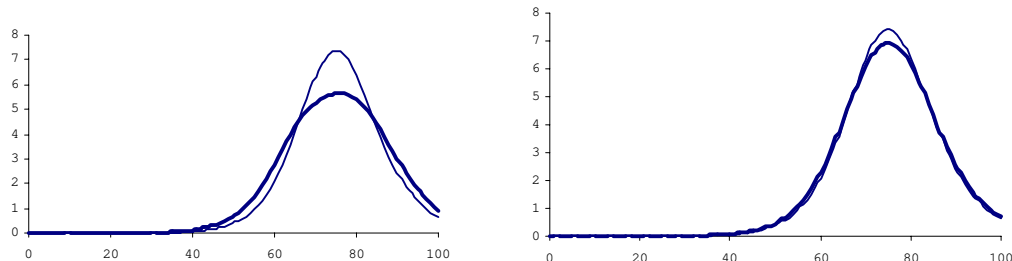
Figure 6.5: Average marginal utility curve with exact measurement and with measurement error of 10% (LHS) and 5% (RHS) of average duration

For example, the marginal utility of the true duration 440 should (more or less) be the same as the average of two marginal utilities of duration 440+40 and duration 440-40.

Assume that α, β, γ, α_x, β_x and U_x are 75, 0.15, 0.8, 7, 0.15 and 250, respectively, T is 15, and the average duration v is 86. Then, the STD of the random error is 8.6 and 4.3, which are 10 % and 5 % of the average duration, respectively. The average of the absolute values of the error randomly drawn from these sizes then was 6.7 and 3.3, respectively.

Figure 6.5 shows the error-size impacts in terms of the difference between $f(v)$ and $\left(f(v+6.7)+f(v-6.7)\right)/2$ for error size of 10% and the difference between $f(v)$ and $\left(f(v+3.3)+f(v-3.3)\right)/2$ for error size of 5%. The error-averaged marginal utility is drawn as bold lines.

The difference between the two is explained in Figure 6.6. In both figures, the thin, dotted and bold lines denote the true value, the value with negative error, and the value with the positive error, respectively. The introduction of a single measurement error changes the α value, and hence, the inflection point of the critical point of the function. As long as the introduced measurement error is from a symmetrical normal distribution, however, the averaged marginal curve maintains the inflection point as before, which also keeps the predicted α values as before.
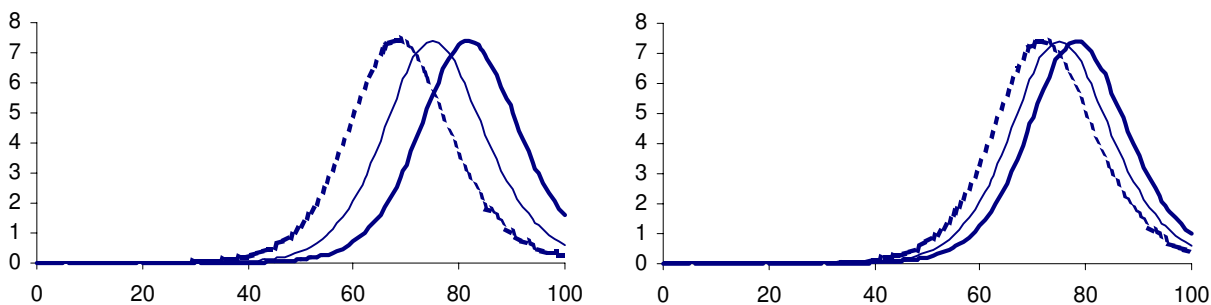
Figure 6.6: Marginal utility curve with exact measurement and with measurement error of ±10% (LHS) and ±5% (RHS) of average duration

Meanwhile, all other aspects of the functional curve changes as can be seen in Figure 6.4. As a result, the error introduction from a symmetric (normal) distribution implies the disruption of estimates of β, α_x and β_x to some extent, but not α. In fact, throughout the estimation simulation, the α estimate was relatively irrelevant to the measurement error size.

6.5   Conclusions and discussion

In this chapter a method of estimating utility parameters of the Aurora model based on activity duration data was introduced and tested. Unlike other utility models of time use, Aurora is based on a complex asymmetric S-shaped utility function. While we argue that this specification has some clear theoretical advantages, the estimation of the model becomes highly complex. Before applying a method to real empirical data, we felt it was important to first study the performance of the suggested approach on simulated data.

The suggested estimation uses a combination of searching the solution space, using a tailored genetic algorithm, and some theoretical concepts. In particular, a key assumption is that an activity schedule is the result of equalizing the marginal utilities of activities subject to time pressure. The method was specifically developed for the case where duration (time use) data are available.

The results of the simulations suggest that the proposed estimation method performs well on the exact data, and reasonably good on noisy data but with some exceptions of particular parameters. The simulated noises that the method was tested on include time pressure, duration rounding and the overall measurement error in duration. Among the simulated errors, the overall measurement error in duration has the biggest impact on the accuracy of the parameter estimation, bigger than the error in measuring the time pressure variables and the systematic rounding in reporting the duration. This suggests the need to increase the quality of duration data to the extent possible. It also shows the typical problems of non-linear models, especially the interaction between parameter estimates. The latter suggests using a sequential estimation strategy where each parameter is estimated in turn. In a preliminary study, it did provide the most stable results for the present model, and these results can probably be generalized to similar models.

Having developed this estimation model, we will apply and test the estimation model to real, empirical data. The results of this effort will be discussed in Chapter 7.

Appendix 6.1: Example of the simulated schedule data (no rounding, 1-minute and 5-minutes rounding)

| no rounding | | | | | | | | |
case	v1	v2	T1	T2	X1	X2	X3	X4	X5
1	85.616	422.797	24	25	2.62	29.41	59.2	23.3	23.68
2	96.986	421.676	22	1	9.40	5.72	14.58	2.44	21.95
3	88.115	421.881	17	7	44.35	0.35	45.41	12.54	63.88
4	89.351	427.553	18	8	11.11	32.59	0.34	12.14	19.60
5	83.345	427.412	12	23	40.48	9.26	50.68	14.46	86.35
6	92.574	436.768	26	22	8.27	10.79	22.74	4.25	70.86
7	93.965	438.813	23	16	1.80	5.78	39.95	3.80	22.22
8	75.334	444.023	2	22	21.04	7.56	9.96	0.91	24.98
9	91.649	434.218	27	15	4.65	4.73	34.40	6.20	92.67
10	82.997	425.829	12	17	53.92	17.02	11.46	24.87	54.58
…	…	…	…	…	…	…	…	…	…

| 1-minute rounding | | | | | | | | |
case	v1	v2	T1	T2	X1	X2	X3	X4	X5
1	86	423	24	25	2.62	29.41	59.2	23.3	23.68
2	97	422	22	1	9.4	5.72	14.58	2.44	21.95
3	88	422	17	7	44.35	0.35	45.41	12.54	63.88
4	89	428	18	8	11.11	32.59	0.34	12.14	19.6
5	83	427	12	23	40.48	9.26	50.68	14.46	86.35
6	93	437	26	22	8.27	10.79	22.74	4.25	70.86
7	94	439	23	16	1.8	5.78	39.95	3.8	22.22
8	75	444	2	22	21.04	7.56	9.96	0.91	24.98
9	92	434	27	15	4.65	4.73	34.4	6.2	92.67
10	83	426	12	17	53.92	17.02	11.46	24.87	54.58
…	…	…	…	…	…	…	…	…	…

| 10-minutes rounding | | | | | | | | |
case	v1	v2	T1	T2	X1	X2	X3	X4	X5
1	90	420	24	25	2.62	29.41	59.2	23.3	23.68
2	100	420	22	1	9.4	5.72	14.58	2.44	21.95
3	90	420	17	7	44.35	0.35	45.41	12.54	63.88
4	90	430	18	8	11.11	32.59	0.34	12.14	19.6
5	80	430	12	23	40.48	9.26	50.68	14.46	86.35
6	90	440	26	22	8.27	10.79	22.74	4.25	70.86
7	90	440	23	16	1.8	5.78	39.95	3.8	22.22
8	80	440	2	22	21.04	7.56	9.96	0.91	24.98
9	90	430	27	15	4.65	4.73	34.4	6.2	92.67
10	80	430	12	17	53.92	17.02	11.46	24.87	54.58
…	…	…	…	…	…	…	…	…	…

Note: v1 and T1 denote the duration and history of activity 1, and X1 denotes the time pressure attribute 1.

Appendix 6.2: Data with measurement error of different sizes

	error size of 10% of average duration					
case	original duration		introduced error		duration with error	
	activity 1	activity 2	std10% act1	std10% act2	activity 1	activity 2
1	83.720	442.837	-16.19	-13.34	67.530	429.497
2	84.856	423.586	-2.76	-76.64	82.096	346.946
3	93.901	436.775	-20.59	31.91	73.311	468.685
4	85.396	431.398	-6.86	-19.63	78.536	411.768
5	91.466	434.846	2.93	-10.68	94.396	424.166
6	90.889	430.142	10.94	-58.65	101.829	371.492
7	87.401	427.610	4.53	39.37	91.931	466.980
8	92.693	422.688	8.47	-41.10	101.163	381.588
9	90.541	430.078	4.88	28.22	95.421	458.298
10	89.534	431.238	-4.73	-1.59	84.804	429.648
…	…	…	…	…	…	…

	error size of 5% of average duration					
case	original duration		introduced error		duration with error	
	activity 1	activity 2	std5% act1	std5% act2	activity 1	activity 2
1	83.720	442.837	-8.09	-6.67	75.630	436.167
2	84.856	423.586	-1.38	-38.32	83.476	385.266
3	93.901	436.775	-10.3	15.95	83.601	452.725
4	85.396	431.398	-3.43	-9.82	81.966	421.578
5	91.466	434.846	1.47	-5.34	92.936	429.506
6	90.889	430.142	5.47	-29.32	96.359	400.822
7	87.401	427.610	2.27	19.68	89.671	447.290
8	92.693	422.688	4.23	-20.55	96.923	402.138
9	90.541	430.078	2.44	14.11	92.981	444.188
10	89.534	431.238	-2.37	-0.79	87.164	430.448
…	…	…	…	…	…	…

Note: For example, 'std10% act1' means that the error is randomly drawn from a normal distribution of size σ, which is 10 % of the average duration of activity 1 in the data.

7 Estimation of Aurora using Activity-Diary Data

7.1 Introduction

In the last chapter we have developed a method for estimating the activity utility functions of the Aurora model. In particular, the method was designed to estimate the model from activity duration data, which can relatively easily be collected in an activity diary survey. The proposed method employs a genetic algorithm that seeks the solution in a wide and discontinuous search space. The promising results made us decide to use this method to estimate the utility function using real world activity travel diary data.

This chapter describes the results of this estimation, using activity diary data collected in the Amsterdam-Utrecht corridor in the context of the Amadeus research program (Timmermans, *et al*., 2002b). Two estimations are conducted. The first estimation is based on the entire activity pattern data, ignoring possible differences between groups. Next, we investigate whether there are significant differences between groups. To that effect, the activity patterns are segmented into a limited number of groups of more homogeneous patterns, using the multi-dimensional sequence alignment method developed in Chapter 4, and the estimation procedure is repeated for each of the resulting segments.

This chapter is organized as follows. Section 7.2 briefly introduces the sample selection scheme, followed by Section 7.3 that details the Amadeus activity-travel diary data used for the empirical analysis. Section 7.4 then reports the results of the estimated utility functions for the total sample, and the segmented activity patterns respectively. The chapter ends with some conclusions and discussion.

7.2 The 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 7.1. 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. The characteristics considered include size (i.e., hyper, high, medium and low), urban characteristics (i.e., central city, suburban and others) and public transportation-network characteristics (i.e., inter-regional, regional, local and car-dominated).
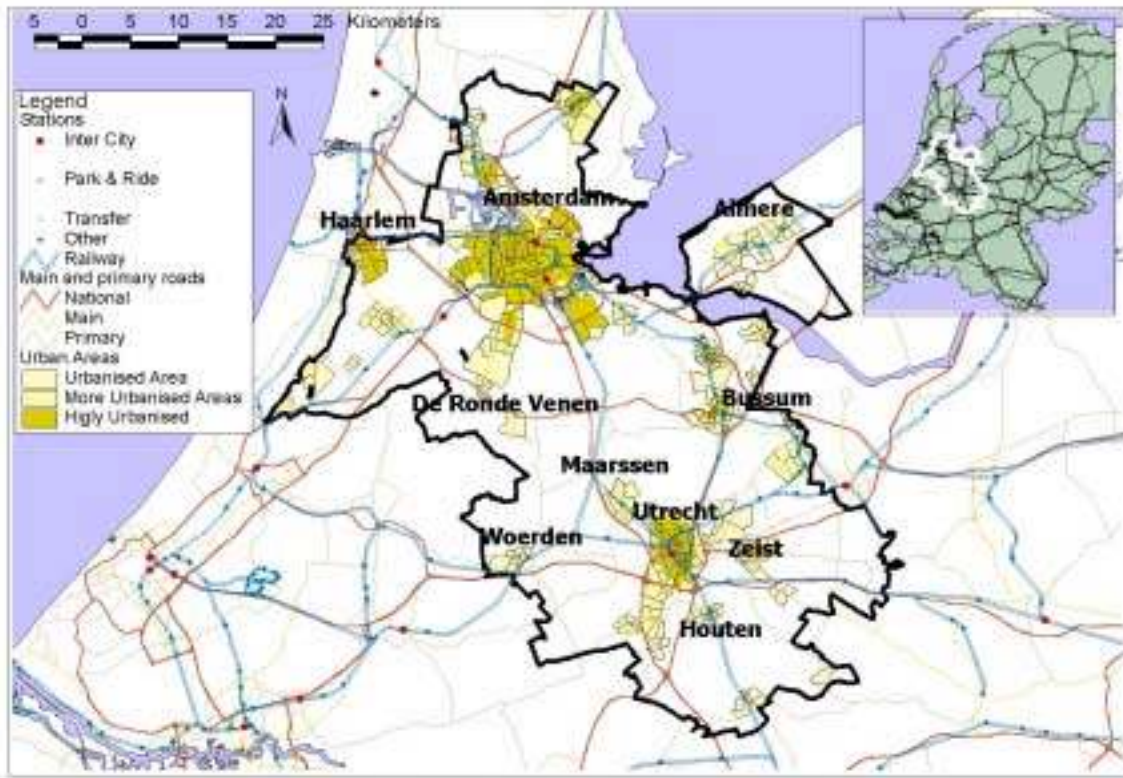
Figure 7.1: *Amadeus* Study area (Graphic source: Krygsman, 2004)

In addition, other characteristics were considered, which included density, facility proximity, park-and-ride availability, travel infrastructure, one- or multiple-center orientation and acceptable representation of households with higher income categories and with children. Figure 7.2 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. Each day started at 3 am and ended at 3 am on the next day. To avoid bias in the frequency of the days of the week, households were distributed across days. Saturdays and Sundays were however deliberately underrepresented in the sample. The diary contained activity-pattern information such as the list of activities, duration, location, transport mode if traveled, accompanying person, etc. In addition, respondents were asked to complete an activity questionnaire, asking details of activities and personal, household and institutional contexts. In particular, it entailed: (1) an extensive list of activities that the respondents may conduct, (2) the temporal and spatial details of crucial activities such as work, school, daily shopping, non-daily shopping, union and sports activities and bringing and getting children, and (3) scheduling details of out-of-home activities reported by the individual in the diary of the two days. Of the 4800 households who were willing to participate in the main survey, 1966 (41.0 %) returned the questionnaires.
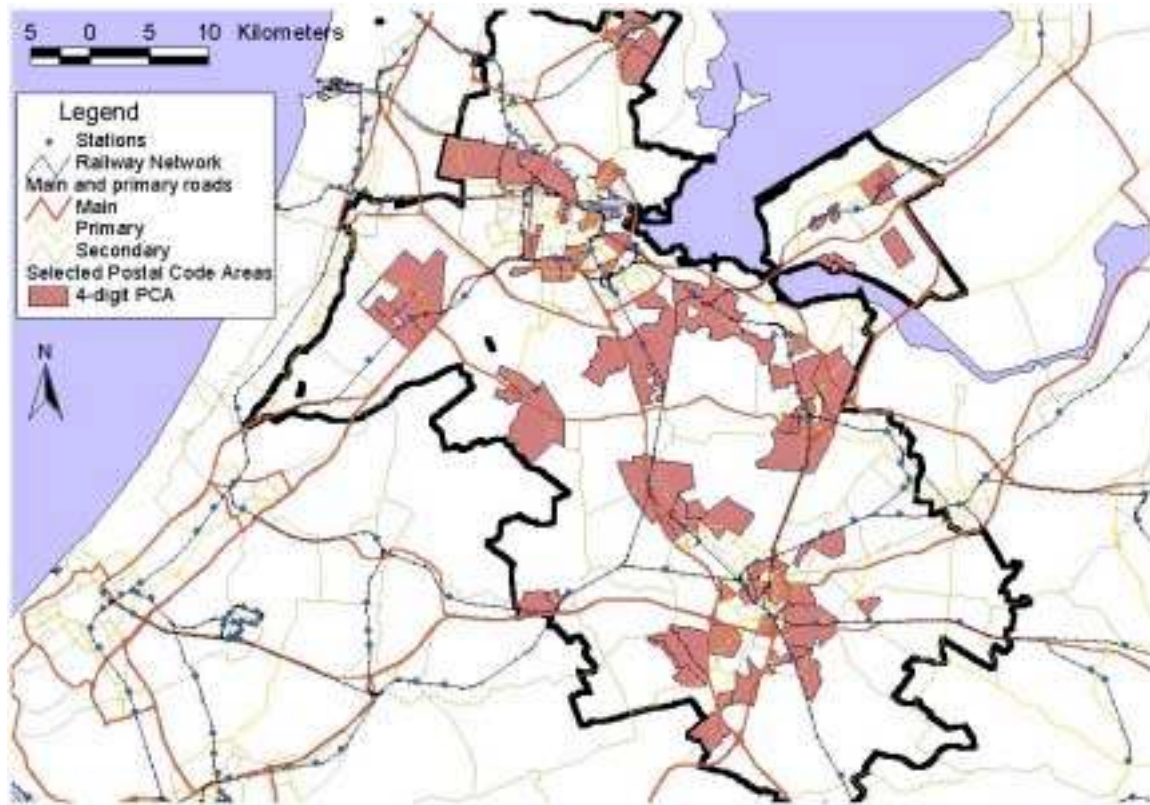
Figure 7.2: Selected neighborhoods (Graphic source: Krygsman, 2004)

The data of 6950 activity patterns of 3575 individuals, belonging to these 1966 households, were finally employed for the analysis.

In addition to diary data, the part of the questionnaire concerned with the scheduling details are used in the present analysis. In this part of the questionnaire, respondents could indicate for each implemented (out-of-home) activity when the activity was last conducted and when the decision to conduct the activity was made. Furthermore, respondents could indicate whether an activity planned for the reported activity pattern was cancelled and, if so, the reason why the activity was cancelled. The question about the implementation history – i.e. when the activity was last conducted − is used here together with the duration and schedule data.

7.3   Activity-travel diary data used to estimate the utility functions

The dimensions of an activity-travel pattern considered in the current analysis included activity type, location and transport mode. Activities were classified as indicated in Table 7.1. A total of twenty-one activity categories were distinguished to specify the activity-travel patterns for the present study.

Table 7.1: List of activities

	out-of-home activities	in-home activities
fixed activities	work/education, medical, sport, church, union, cultural, waiting and etc.	sleep, personal care, eating, childcare, work/education, illness, waiting and etc.
flexible activities	grocery shopping, non-grocery shopping, personal business, social, outside-entertainment, recreation	social, in-home task , in-home leisure

The categorization is based on two criteria: whether an activity is conducted inside or outside home, and whether an activity is assumed to be flexible in determining duration and frequency or fixed. Strictly speaking, all activities can be conducted anywhere, and no activities are completely fixed in duration and frequency. These criteria were however useful in deciding on the categorization. For the interested reader, a recent discussion on the activity categorization can be found in Doherty (2003).

The 'work/education' category also includes voluntary, non-paid work. The category 'cultural' includes activities such as visiting a theater, concert or museum. The 'grocery shopping' category includes visits to a supermarket, butcher, bakery, etc. for daily goods. The 'non-grocery shopping' category also includes window-shopping. The 'personal business' category includes visits to bank, post office, library, snack bar, etc. The category 'social' includes paying visit to family or friends and receiving visit. 'Outside-entertainment' includes such activities as eating outside, visiting a café, discotheque or other out-of-home entertaining location. The 'recreation' category includes visiting a swimming pool or amusement/natural park.

Table 7.2 shows the frequency and average duration of activities. For example, grocery shopping appears in 20.7 % of the activity patterns. On average, the in-home task and in-home leisure activities occur almost everyday, whereas grocery shopping is conducted once in five days.

Table 7.2: % Frequency of activity occurrences per activity pattern

Activity	% freq	Duration in minutes	Activity	% freq	Duration in minutes
Dshop	20.7	31.6	Medical	5.2	47.2
nDshop	13.0	58.1	sport	8.9	102.2
Pbiz	4.8	30.0	church	1.6	114.0
social	28.6	159.3	union	2.9	164.1
entertain	9.1	113.5	cultural	3.1	150.6
recreat	5.0	133.5	other out	17.8	68.4
task	81.7	150.6	childcare	25.9	78.3
leis	92.8	224.1	illness	0.1	1047.6
pickup	2.6	23.6			
work/edu	72.7	418.4			
# episodes per activity pattern: Mean=14.39 (STD=5.31)					

Note: Dshop denotes grocery shopping, nDshop non-grocery shopping, Pbiz personal business, entertain outside-entertainment, recreat recreation, task in-home task, leis in-home leisure, work/edu work/education, other out other out-of-home activity and Pcare personal care activity.

Table 7.3: # activity episodes with particular location and transport mode per activity pattern

Attributes	Level	Mean	STD
activity location	home	11.99	5.28
	work	0.66	0.88
	other	1.73	1.96
transport mode	no	10.61	4.92
	slow	1.91	2.06
	public	0.33	0.75
	auto	1.33	1.73

Non-grocery shopping is conducted once a week, and recreation is conducted much less frequently. The table also states that, on average, an activity pattern has fourteen episodes. The average durations as shown in the table were calculated across occurrences of an activity, whereby the activity may occur multiple times in an activity pattern. On average, grocery shopping and personal business activities took about half an hour, non-grocery shopping activity lasted about an hour, whereas social, out-of-home entertainment and recreation activities took much longer.

Each activity involves a choice such as the location where the activity is conducted and transportation mode used to reach the activity's location from the previous location. Activity location categories include 'home', 'work' and 'elsewhere' Transport mode categories include 'no transport mode', 'slow', 'public' and 'auto'. The slow mode includes walk, bike, scooter and motorbike. The public mode includes bus, tram, metro, taxi and train. The auto mode includes the categories 'driver' and 'passenger'. In case of a multi-modal trip involving multiple stages of different modes, the present study encodes the main mode as the mode of the trip stage of the longest time of the trip to the activity location. The 'in-home task' category includes housekeeping, telebanking, teleshopping and other in-home activities. The 'in-home leisure' category includes free-time activities such as reading, TV watching, internet and relaxation.

Table 7.3 reports the distributions of these choice facets across activities per activity pattern. The number of episodes at the work location is 0.66 per activity pattern, which shows that the work activity is not often split into different episodes within activity patterns. The 11.99 episodes at the home location indicate that most of the fourteen activity-episodes are in-home activities.

The cluster analysis considered all twenty-one activity categories for pairwise comparison of activity-travel patterns, whereas the estimation used only the flexible activities, assuming the fixed activities as given. As said, the entire diary data set contains 6950 activity patterns. However, after removing missing values and outliers, 5904 activity patterns remained for analysis.

As indicated before, the question on the implementation history of activities was important for the analysis. Table 7.4 shows the mean and standard deviation of the implementation history of the flexible activity categories. The figures are generally consistent with the frequency data of Table 7.2, except that the grocery shopping is slightly over-reported.

Table 7.4: Average history of activity implementation (in days)

Activity	Mean	STD
Dshop	2.8	1.9
nDshop	7.0	6.8
Pbiz	19.6	15.6
social	8.3	8.0
entertain	8.2	8.9
recreat	10.7	20.8

On average across activities, respondents reported that the same activity was implemented on the same day in 7.9 % of the occurrences, in the same week in 71.1 % of the occurrences, in the same month in 13.8 % of the occurrences, in the same year in 6.5 % of the occurrences or earlier in 0.7 % of the occurrences. Implementation of an activity that was implemented on the same day or one day ago amounts to 37 % of the occurrences. Implementation of an activity that was implemented within two weeks ago amounts to 86.5 % of the occurrences. Implementation of an activity that was implemented within one month ago amounts to 93.2 % of the occurrences. These figures clearly indicate that daily life mostly consists of highly routinized activities, as the name of our model, *Aurora*, implies.

The term, 'routinized,' however does not mean that activities do not need a scheduling effort or that they are not subject to schedule adaptation. It simply means that those activities are included in the schedule often or regularly. The scheduling decisions on the details of the activities are made rather dynamically. As for the planning horizon, activities were implemented routinely in 40.5 % of the occurrences or were instantaneously implemented in 14.5 % of the occurrences, on the same day in 13.2 % of the occurrences, in the same week in 14.7 % of the occurrences and earlier in 17.1 % of the occurrences. Virtually no deliberate decision is required to include a routine activity in the schedule. Likewise, the instantaneous decision or a decision planned on the same day does not seem to require much planning effort, but may be impulsive. A week ahead or even earlier decision on the other hand likely involves a deliberate planning effort. The proportion of impulsive activities (14.5+13.2 = 27.7 %) is approximately equal to the proportion of activities involving a deliberate decision (14.7+17.1 = 31.8 %).

The dynamic nature of rescheduling decisions is more evident when we consider the cancellation rate. Of the implemented activities, 28 % were originally not in the plan. On the other hand, of the planned activities, 13 % were not implemented on the day considered. The reported reason of these cancellations is time pressure during the implementation of the schedule in 27.7 % of the cancellations, change of the schedule in 15.1 % of the cancellations, replacement with another activity in 10.3 % of the cancellations, unordinary event happening in 8.9 % of the cancellations, traffic congestion in 1.1 % of the cancellations and other reasons such as sickness, etc. in 36.9 % of the cancellations.

In addition to the diary data, the cluster analysis also used the socioeconomic and situational data to profile the resulting clusters. These data concern personal, household and institutional attributes such as gender, car availability, income, age, weekly working hours, the presence/absence of children in the household, and the day of the week on which the schedule is implemented.

Table 7.5: Socioeconomic characteristics of 3575 individuals and situational characteristics
of the activity patterns (%)

Variable	Value
gender (PP)	female (52.3), male (47.7)
car availability (PP)	not always available (46.2), always available (53.8)
children (HH)	no (47.7), yes (52.3)
diary day 1 (SS)	weekday (84.3), weekend (15.7)
diary day 2 (SS)	weekday (84.0), weekend (16.0)
income (PP)	0 (13.0), 0~10000 (7.5), 10000~20000 (6.4), 20000~30000 (9.2), 30000~40000 (12.8), 40000~50000 (13.3), 50000~60000 (11.4), 60000~70000 (7.3), 70000~ (19.2)
age (PP)	Mean 42.68 (STD 15.18)
weekly work hours (PP)	Mean 21.71 (STD=19.37)

Note: 'HH' denotes that the value of the variable is specific to the household of the person, 'PP' the person, and
'SS' each activity pattern.

Table 7.5 shows the distributions of these variables associated with activity patterns. The
categorical variables including gender, car availability, presence of children in the household
and income are all approximately evenly distributed across the categories that were defined.
The mean values of the metric variables also seem reasonable.

7.4 Estimation of activity utility functions

7.4.1 Principles and scheme of analysis

The estimation of activity utility functions is based on the observed activity durations and
histories in the reported activity patterns. The utility functions were estimated first on the
entire data set and then separately for each segment of more or less homogeneous activity-
travel patterns. The latter estimation at the segment level will reveal any heterogeneity in the
utility functions underlying activity-travel patterns. In this section, we will discuss the results
of these two estimations in turn.

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 attributes included in the analysis were
activity type, location and transportation mode. The multidimensional sequence alignment
method proposed in Chapter 4 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.

Having identified the clusters or segments, the segments were profiled using properties of the activity patterns and the socioeconomic characteristics associated with the activity patterns. Profiles were created using descriptive statistics (mean values) of the relevant properties of activity patterns and associated socioeconomic variables of each segment. The results were tested on statistical significance in a subsequent logistic regression analysis.

Finally, the activity utility functions for each segment were estimated using the estimation method developed in Chapter 6. The estimated parameters were evaluated against two criteria. The first is the stability of the solution over repeated estimation runs on the same data. This was motivated by the fact that the proposed estimation method uses a heuristic search algorithm. The solution may therefore differ depending on the initialization and the probabilistic search processes, and thus, the consistency of the generated solutions is an issue. The second criterion is that the estimated utility parameters should be interpretable for each activity and for each segment. For example, the in-home leisure activity likely has a flatter utility function than the grocery shopping activity. It can also be expected that the activity patterns of busy people would show steeper utility functions than the activity patterns associated with, for example, retired people.

The analysis also involved a comparison of the aggregate and the segment-level results. The expectation is that the stability and interpretability of the estimated parameters will be better with the segment-level model than for the aggregate model because the segments are based on more homogeneous activity patterns.

7.4.2 Estimation method

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 some cross-sectional characteristics of the activity patterns. The mathematical equations underlying the applied estimation method stay the same as equations (6.5) to (6.11) of Chapter 6. Equation (6.11) that specifies the function of the time pressure level was further specified as follows:

$$TP_s = \delta_1(X_1)_s + \delta_2(X_2)_s \qquad\qquad (7.1)$$

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 (7.1) 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. In the proposed estimation method, the parameters of the time-pressure function are estimated simultaneously with the parameters of the utility functions, as explained in the previous chapter.

A preliminary study suggested the following range of real numbers to be used for simulating the parameter estimates as: $\alpha = -300\sim500$, $\beta = 0.01\sim1.0$, $\gamma = 0.1\sim1.0$, $\alpha_x = 0\sim100$, $\beta_x = 0.01\sim10$, and $U_x = 0\sim10000$. The values of β that are bigger than 1.0 offer no substantial difference from 1.0 in terms of the steepness of the overall utility function. No activity is expected to have a warming-up phase longer than the saturated phase so that $\gamma > 1.0$. These ranges are determined based on the observed ranges of estimated values in the preliminary study.

7.4.3 Aggregate model

The estimation of activity utility functions was conducted on the entire activity patterns in the data. In the following, we first describe the data that we used for this estimation and then report the estimation results with regard to the *stability* of the estimates over runs and the *interpretability* of the estimated utility functions.

Data: The total number of activity patterns identified as useful in principle for the estimation is 5904. This number was, however, too large for the present study. A sub-sample was used to reduce the computation time. For the overall estimation, a total of 303 activity patterns were randomly selected from the entire data set of 5904 activity patterns. The selection was not completely random because a pure random selection would not provide enough observations for activities such as personal business and recreation. A subset of activity patterns was obtained such that each activity appears at least 60 times in the selection. For each activity pattern, we record the list of activities, their duration and history. In each activity pattern, if multiple episodes of an activity occur, the duration of that activity was computed as the sum of durations across the episodes. Hence, the activity subdivision in episodes was not considered. The history of an activity is defined as the history recorded for the first occurrence of that activity.

Table 7.6 shows the percent frequency of activities both for the entire sample and the sub-sample used for estimation. For example, grocery shopping appears in 22 schedules out of 100 in the entire sample, whereas 33 schedules out of 100 in the sub-sample. Table 7.7 lists descriptive statistics for the selected 303 cases. Fortunately, the mean and standard deviation of activity duration and history show that the sub-sample is virtually indifferent from the entire sample, despite the biased selection. This means that the sub-sample can be safely used to replace the entire sample.

Table 7.6: % Frequency of activity occurrences per activity pattern

	Dshop	nDshop	Pbiz	social	entertain	recreat	task	leis
All data	22	14	6	19	9	5	81	90
303 data	33	25	20	25	20	20	85	91

Table 7.7: Activity duration and history of selected 303 activity patterns

Activity	# occurrences	duration (minutes)		history (days)	
		Mean	STD	Mean	STD
Dshop	101	28.2	18.3	2.68	1.8
nDshop	75	61.4	40.7	7.41	7.0
Pbiz	61	23.1	18.2	18.80	14.7
social	76	144.5	97.6	7.53	7.5
entertain	62	108.6	79.1	8.42	9.2
recreat	60	84.5	63.7	9.42	19.1
task	259	152.1	117.5		
leis	275	206.7	134.0		

Note: By definition, the everyday activities, in-home task and in-home leisure, do not have history information.

Stability: An estimation run was repeated 30 times to examine the stability of the parameter estimates across runs. Each run involved random initializations of the genetic algorithm.

Table 7.8: Correlations between parameter estimates

	Dshop						nDshop				
	α	β	γ	α_x	β_x		α	β	γ	α_x	β_x
β	-0.13					β	-0.41*				
γ	0.57**	0.20				γ	0.32	-0.24			
α_x	0.07	0.03	-0.09			α_x	-0.07	0.52**	-0.30		
β_x	0.01	-0.27	0.10	-0.46*		β_x	-0.22	-0.12	0.40*	-0.48**	
U_x	-0.24	0.14	-0.18	0.27	0.07	U_x	0.09	0.09	0.12	0.37	-0.44*

	Pbiz						social				
	α	β	γ	α_x	β_x		α	β	γ	α_x	β_x
β	-0.41					β	-0.81**				
γ	0.32	-0.24				γ	0.05	0.08			
α_x	-0.07	0.52	-0.30			α_x	-0.27	0.30	-0.31		
β_x	-0.22	-0.12	0.40	-0.48		β_x	-0.02	-0.06	0.36	-0.64**	
U_x	0.09	0.09	0.12	0.37	-0.44	U_x	0.34	-0.21	0.00	0.12	-0.30

	entertain						recreat				
	α	β	γ	α_x	β_x		α	β	γ	α_x	β_x
β	0.55**					β	-0.44*				
γ	0.21	0.25				γ	0.21	0.04			
α_x	-0.09	-0.26	-0.06			α_x	0.19	-0.03	-0.04		
β_x	0.24	0.24	0.03	-0.43*		β_x	-0.30	0.11	-0.07	-0.41*	
U_x	0.00	0.13	-0.25	0.19	-0.22	U_x	0.07	0.03	0.12	-0.22	0.14

	task				leis		
	α	β	γ		α	β	γ
β	-0.57**			β	0.16		
γ	0.61**	-0.11		γ	0.83**	0.21	
U_x	0.01	-0.28	-0.02	U_x	0.08	0.69**	0.14

Note: * and ** denotes that the correlation is significant at the 0.05 and 0.01 levels, respectively.

Similar to the findings in estimation on the simulated activity pattern data in the previous chapter, certain parameters were highly correlated (Figure 7.3), which is typical for this kind of non-linear equations including a large number of parameters (Table 7.8).
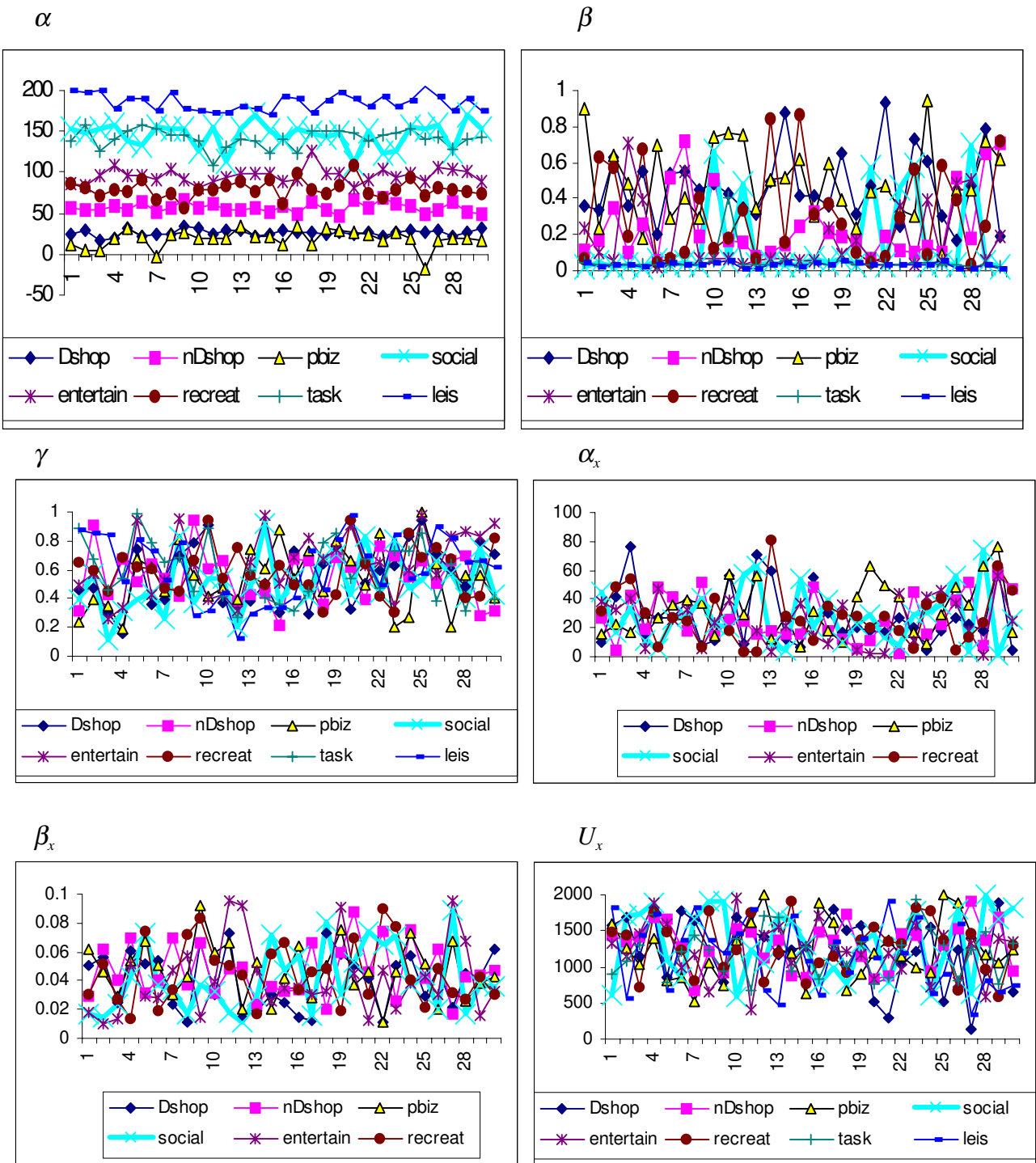
Figure 7.3: Estimated parameter values across 30 runs using simultaneous estimation

Therefore, 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, it was decided to estimate parameters in the following order: α, β, γ, α_x, β_x and U_x.

α

β

γ

α_x

β_x

U_x
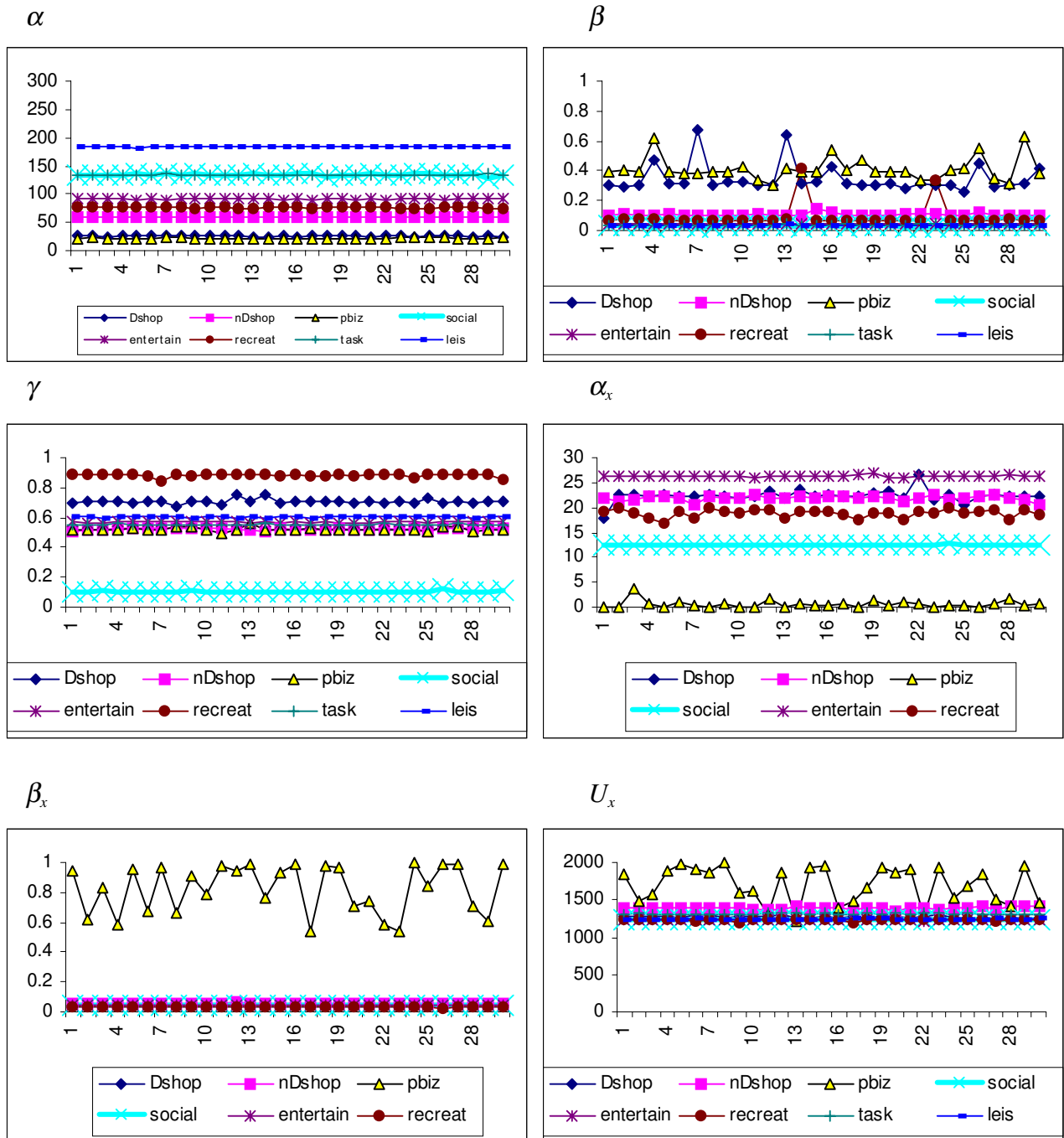
Figure 7.4: Estimated parameter values over 30 runs using sequential estimation

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 results are shown in Figure 7.4. As shown in the figure, the stability of the parameter estimates across runs is dramatically improved. Personal business shows the least stability, which is likely due to the small number of observations with relatively small variations in duration (see Table 7.7).

Interpretability: The sizes of parameter estimates for the different activities were studied to examine the face validity of the model. By taking the averages across 30 runs, the parameter estimates were obtained as shown in Table 7.9. The α estimates are all slightly smaller than the average duration of the corresponding activity, which implies that individuals on average conduct the activities a little longer beyond the maximum marginal utility point. An activity likely continues while it gains utility at an increasing rate and stops somewhere when the marginal gain is decreasing because the duration allocation is a competition between activities to occupy longer durations, which is judged by the marginal gains of total utility. The order of magnitude of the α estimates is [leis > task = social > entertain > recreat > nDshop > Dshop > Pbiz], where task at home and social activities are almost the same, and grocery shopping and personal business are also quite similar. Note that non-grocery shopping is in-between outside entertainment and recreation activities.

The β estimate size is consistent with one's expectations as [Pbiz > Dshop > nDshop > recreat > entertain = task = leis = social]. Personal business and grocery shopping have relatively high values, while all others are more flexible.   An activity with a β-value bigger than 0.2 represents a very inflexible activity in terms of duration adjustment. Grocery shopping and personal business do not have much variation in duration and indeed have high β values. An interesting result is that non-grocery shopping including window-shopping has almost the same β estimate as recreation.

As the value of the γ estimate approaches 1, the S-shape becomes symmetric, and a vice versa. The order of the estimated sizes of this parameter is [recreat > Dshop > leis = entertain = task = nDshop = Pbiz > social], implying that recreation has a nearly symmetric utility curve and a relatively long warming-up period, whereas the marginal utility of social activities is mostly diminishing across the duration range.

Table 7.9: Parameter estimates of selected 303 activity patterns

Activity	α	β	γ	α_x	β_x	U_x
Dshop	25.77	0.347	0.707	22.34	0.045	1274
nDshop	58.97	0.108	0.522	21.92	0.057	1392
Pbiz	22.20	0.412	0.520	0.59	0.823	1695
social	134.87	0.029	0.104	12.54	0.044	1242
entertainm	90.68	0.047	0.572	26.27	0.044	1241
recreat	76.14	0.091	0.882	18.85	0.030	1231
task	134.53	0.039	0.552			1313
leis	183.47	0.035	0.603			1243

Both shopping activities are closer to the more symmetric recreation than to the more asymmetric social activity, implying that they have relatively long warming-up periods. In-home task and in-home leisure activities were also expected to have a mostly diminishing marginal utility, but are rather unexpectedly similar to other activities.

Like the α parameter, the α_x parameter value reflects the timing of the start of diminishing marginal utility for the $U^{\max}$ curve. The diminishing phase of $U^{\max}$ starts very early for personal business activities and very late for outside-entertainment activities. History does not seem to play a role at all in case of personal business. The marginal utility of $U^{\max}$ for entertainment activities on the other hand increases over a longer time, namely for about a month. All other activities are in-between the extremes. The order is [entertain > Dshop = nDshop > recreat > social > Pbiz].

The estimation of β_x parameters results in a very clear difference between personal business with a very high value, and all other activities with very low values. This implies that personal business activities have a very low flexibility and need to be urgently implemented after a certain number of days since the last implementation, whereas other activities need not. The non-daily shopping's β_x is a bit higher than that of other activities, and this parameter is lowest for the recreation activity. Again, however, differences are not very significant.

Finally, the U_x estimates are quite homogeneous across activities. The U_x estimate is rather high for personal business activities, but at the same time is also highly unstable across runs. Non-grocery shopping has the next highest U_x value, followed by in-home task activity, which is perhaps because of a high level of indirect utility, rewarded for the completion of the task. The estimates for the remaining activities are remarkably similar. In sum, the overall estimation results in well interpretable parameter values for the activities in general.

Figure 7.5 displays the resulting U and $U^{\max}$ functions of all eight activities. In the U-graph, $U^{\max}$ is set equal to U_x. The $U^{\max}$-graph suggests that a further simplification of this function might be possible by using a constant value for personal business activity's $U^{\max}$ and a linear function for other activities.
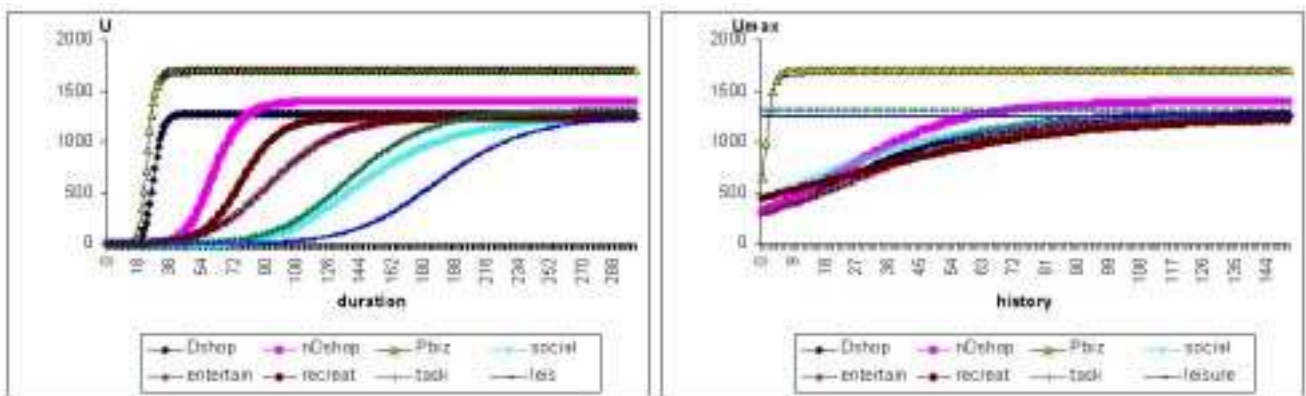
Figure 7.5: Estimated U and $U^{\max}$ functions of selected 303 activity patterns

7.4.4 Segment-level model

The estimation of activity utility functions was also conducted for segments of homogeneous activity patterns. To this end, first, the activity patterns of the data were clustered into a limited number of segments with regard to their multidimensional sequential information by using the multidimensional sequence alignment method developed in Part-I of this thesis. In the following, we first describe the results of the cluster analysis and then report the segment-level estimation results. Again, we discuss the estimation results here with regard to the *stability* of the estimates across runs and the *interpretability* of the estimated utility functions, and compare them with the results of the aggregate model.

Cluster analysis

Data: The total number of activity patterns identified useful for the analysis is 5904. Again, this number is too large for the comparison of multidimensional activity-travel patterns in the present study. The number of pairwise comparisons is 17,425,656, which is far too large to complete in reasonable time. We therefore decided to randomly sample 1000 activity patterns out of 5904 only for the reason of reducing computation time. A set of randomly selected 1000 activity patterns requires 499,500 pairwise comparisons of three-dimensional activity-travel patterns, which was possible to finish in 15 days of computation time on a Pentium II PC of 450 MHz. Tables 7.10 and 7.11 show some statistics of the selected activity patterns. The percent frequency of activities in the random selection (% frequency, mean and standard deviation) do not show notable differences from those in the entire data set of 5904 activity patterns (compare with Table 7.2). In that sense, the selected subset of activity patterns can be said to be representative of the entire data set.

Pairwise comparison: The 499,500 pairwise comparisons including the dimensions of activity type, location and transport mode were conducted using the Hybrid MDSAM as developed in Chapter 4, which combines dynamic programming and genetic algorithms. The weights of 2, 1 and 1 units were assigned to activity type, location and transport mode attributes, respectively. The genetic parameter values were set as follows.

Table 7.10: % Frequency of activity occurrences per activity pattern

Activity	% freq	Activity	% freq
Dshop	21.4	medical	4.8
nDshop	13.3	sport	9.4
Pbiz	5.4	church	1.8
social	28.6	union	2.9
entertain	8.9	cultural	3.0
recreat	3.8	other out	17.7
task	80.9	childcare	26.9
leis	93.2	illness	0.2
pickup	3.7		
work/edu	72.9		
# episodes per activity pattern: Mean 14.41 (STD=5.42)			

Table 7.11: Number of activity episodes with particular locations and transport modes per activity pattern

Attributes	Level	Mean	STD
activity location	home	11.91	5.49
	work	0.70	0.93
	other	1.80	2.23
transport mode	no	10.62	5.14
	slow	1.93	2.08
	public	0.35	0.74
	auto	1.27	1.67

- Number of solution candidates for an iteration = 100
- Stop condition = 50 iterations of successive generations of no improvement
- Elitism size = 1
- Neighborhood size = 1
- Diagonal path probability = 60%
- Probability of choosing reproduction/crossover/mutation for each iteration = 20/70/10
- Number of solution candidates selected for crossover from the previous pool = 40
- Number of solution candidates selected for mutation from the previous pool = 20
- Selection of solution candidates for modification = Random selection with replacement
- Crossover type = one-point crossover
- Mutation type = point mutation
- Probability of mutating a parameter of the solution candidate selected for mutation = 1%

Cluster solution and profiling: In an ordinary cluster analysis using commercial software such as SPSS, the objects to be clustered are represented by a set of cross-sectional variables. For example, individuals are often clustered in terms of their socioeconomic characteristics such as income, age, gender, etc. However, activity-travel patterns cannot be clustered in this way because the patterns cannot directly be compared on any cross-sectional variables but on their sequential and interdependency information by using the proposed multidimensional alignment method. In other words, we have only the pairwise distances between activity-travel patterns, but we do not have any numerical data points describing the activity pattern itself. As a consequence, this does not allow any non-hierarchical clustering algorithms such as *K*-means analysis, which requires the mid points of segments that can be obtained only when the numerical data points of individual objects are available. The hierarchical algorithm is therefore the only option, as it requires only the information of the pairwise distances between objects.

Ward method was used for iterative hierarchical clustering. The SPSS Cluster Analysis provides a tree-like dendrogram that connects homogeneous cases into larger and larger segments. Based on the dendrogram, seven clusters (or segments) could be identified.

Tables 7.12, 7.13 and 7.14 summarize the cross-sectional characteristics of the activity patterns and the socioeconomic/situational characteristics associated with the activity patterns for each segment. Regarding cross-sectional characteristics, Table 7.12 describes the average relative frequency of each activity per activity pattern, whereas Table

7.13 reports the average number of episodes associated with each location and transport mode.

Table 7.12: % Frequency of activity occurrences per activity pattern per 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

Table 7.13: # activity episodes with particular locations and modes per pattern and segment

Attribute	Level	Segment1 (160)	Segment2 (301)	Segment3 (114)	Segment4 (149)	Segment5 (90)	Segment6 (111)	Segment7 (75)
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

Table 7.14: Socioeconomic/situational characteristics

	Variable	Segment1 (160)	Segment2 (301)	Segment3 (114)	Segment4 (149)	Segment5 (90)	Segment6 (111)	Segment7 (75)
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

Based on the characteristics of activity patterns and the socioeconomic/situational characteristics of seven clusters as shown in these tables, we can describe each segment's profile. Segments 2 and 4 represent work-oriented, simple activity patterns of long working young people. Their cross-sectional characteristics state that the number of episodes per activity pattern is the smallest among all seven segments, and work/education activities have high frequency while the implementation of most other activities is suppressed. They do not engage often in shopping, personal business or social activities. It is very rare that they participate in a childcare activity. They even sometimes skip the in-home task activity, which is supposed to be an everyday activity. The associated socioeconomic characteristics of these two segments tell that they are relatively young and childfree, their income is high, and they have a long weekly working hour. Most instances of the segment consist of weekday activity patterns. However, differences between the two segments can also be found. Segment 2 is more home-activity oriented after work, while Segment 4 is more out-of-home oriented. This is shown by that Segment 4 has high occurrence for outside-entertainment and cultural activities and low occurrence for in-home leisure activity, while for Segment 2 this is the other way around. Additionally, car is more often available in activity patterns of Segment 4 than Segment 2. Segment 2 can therefore be labeled as 'work-home only activity patterns,' while Segment 4 can be labeled as 'activity patterns of work-and-outside activities.'

In contrast to Segments 2 and 4, Segment 3 shows activity patterns typically of relatively work-free older people who conduct many activity episodes on a day. These people very often conduct grocery and non-grocery shopping activities and social activities. While being relatively free from work/education activity, they often visit church, medical center, theater or museum. Although they mostly originate from childfree households, childcare is often included. In sum, Segment 3 can be labeled as 'work-free old people's busy activity patterns.'

Segment 5 consists of the activity patterns of relatively young people. Like Segment 2, the activity patterns are also very work-oriented with smaller frequency of shopping activities and everyday-based in-home leisure activities. Their working hour is not that long as in Segment 2, but is still much longer than in Segment 3. The activity patterns are often from households with children, but the childcare frequency is not very high but more or less the same as in Segment 3. The most distinguishable figure of this segment is the frequency of sport activity, which is much higher compared to all other segments. This segment can be labeled as 'work-oriented, sportive activity patterns.'

Segments 6 and 7 represent the activity patterns typically of the youngest persons among all seven segments. The activity patterns are also characterized by high frequency of childcare activities. The childcare frequency is higher than 90%, and most of the activity patterns are from households with children. The difference between the two is as follows. Segment 7 shows more female-oriented characteristics with less work, more shopping and high occurrence of social activities. On the other hand, Segment 6 shows a higher frequency of work and the highest frequency of pickup and medical visits. Recreation also has a high frequency for Segment 6, which is accompanied by high frequency of childcare activities. Segment 6's weekly working hour is much longer than Segment 7, and car is in majority of cases available for Segment 6 but not for Segment 7. Segment 6 can be labeled as 'the activity patterns of both work and childcare-oriented, busy young people,' while Segment 7

may be called 'the work-free, childcare and entertaining-oriented young females' activity patterns.'

Finally, Segment 1 is rather different from all others. The activity patterns of this segment are least concerned with work activity, but show highest occurrence of social and recreation activities and also high occurrence of cultural, outside-entertainment, sport and grocery shopping activities. The associated age is high on average, weekly working hour is very short, car is often available, and most of all, the day of the week that these schedules were conducted fell in a weekend. This segment can be labeled 'entertaining activity patterns.'

Following these descriptive analyses on the segment profiles, a series of binary logistic regression analyses were conducted to examine the extracted segment profiles in terms of statistical significance. Given the membership of each activity pattern to one of the seven segments as the dependent variable, two types of independent variables were input to the binary logistic regression analyses, respectively: i.e., activity pattern characteristics and socioeconomic/situational characteristics associated with the activity patterns.

Table 7.15: Estimated binary logistic regression model of activity-pattern characteristics

	Variables	Estimates	sig.		Variables	Estimates	sig.
Segment 1	a_Dshop	.529	.034	Segment 5	a_Dshop	-.791	.020
	a_social	.986	.000		a_pickup	-1.099	.148
	a_task	1.420	.000		a_work/edu	2.515	.000
	a_leis	2.629	.000		n_act	.112	.000
	a_work/edu	-1.573	.000		Constant	-5.693	.000
	l_work	-.587	.008				
	l_elsewhere	-.173	.021				
	m_slow	.274	.000				
	m_public	-.531	.027				
	m_auto	.151	.065				
	n_act	-.204	.000				
	Constant	-.095	.847				
Segment 2	a_recreat	-2.097	.045	Segment 6	a_social	-.486	.076
	a_leis	1.863	.000		a_recreat	1.183	.008
	a_work/edu	1.705	.000		a_leis	-.634	.078
	l_work	.424	.000		a_pickup	1.665	.000
	m_slow	.096	.047		a_work/edu	.979	.002
	m_public	.176	.086		l_work	-.351	.027
	n_act	-.236	.000		l_elsewhere	-.167	.025
	Constant	-.745	.235		m_auto	.110	.088
					Constant	-.587	.149
Segment 3	a_Dshop	.650	.017	Segment 7	a_workedu	-.685	.043
	a_nDshop	.729	.011		l_elsewhere	-.395	.001
	a_recreat	-1.363	.109		m_public	-1.596	.090
	a_task	6.969	.538		n_act	.426	.000
	a_work.edu	-.632	.021		Constant	-9.548	.000
	l_work	-.581	.024				
	m_slow	-.244	.000				
	m_auto	-.266	.001				
	n_act	.182	.000				
	Constant	-7.584	.183				
Segment 4	a_horeca	.967	.036				
	a_recreat	1.710	.041				
	a_task	1.360	.000				
	l_work	1.159	.000				
	l_elsewhere	1.397	.000				
	n_act	-1.385	.000				
	Constant	10.711	.000				

Table 7.16: Estimated binary logistic regression model of socioeconomic/situational characteristics

	Variables	Estimates	sig.		Variables	Estimates	sig.
Segment 1	age	.025	.004	Segment 5	male	.754	.007
	car available	.666	.004		car available	-.958	.001
	work hour	-.017	.006		weekend	-1.357	.025
	weekend	1.592	.000		Constant	-2.990	.000
	Constant	-2.142	.000				
Segment 2	car available	-.451	.009	Segment 6	age	-.047	.002
	children	-.583	.001		male	-.938	.004
	work hour	.027	.000		income	.224	.001
	weekend	-1.579	.000		car available	.617	.026
	Constant	-2.204	.000		children	4.578	.000
					weekend	-.873	.056
					Constant	-3.421	.000
Segment 3	age	.043	.000	Segment 7	male	-1.249	.000
	income	-.216	.000		children	2.437	.000
	work hour	-.027	.002		work hour	-.017	.061
	weekend	.659	.031		Constant	-2.802	.000
	Constant	-2.216	.000				
Segment 4	age	-.019	.029				
	male	.538	.020				
	car available	.461	.038				
	children	-1.011	.000				
	work hour	.011	.070				
	Constant	-1.238	.007				

The employed independent variable input method was the backward removal method with the probability of removal of 0.1 and the number of iterations of 20. Each of two binary logistic regression analyses, respectively based on the independent variables of activity-pattern characteristics and the socioeconomic/situational independent variables, provided the list of significant independent variables with their marginal contributions to the membership of each segment and their statistical significance.

As for the analysis based on the activity-pattern characteristics, the independent variables include: (1) The presence/absence of grocery shopping, non-grocery shopping, personal business, social, outside-entertainment, recreation, in-home task, in-home leisure, pickup and work/education activities; (2) The activity locations at work and elsewhere; (3) Transportation modes distinguishing slow, public and auto; (4) The number of activities per schedule on average. As for the analysis based on the socioeconomic/situational characteristics associated with the activity patterns, the independent variables include: (1) gender of the person; (2) car availability of the person; (3) children in household; (4) day of the week of the schedule; (5) income of the person; (6) age of the person; (7) weekly work hours of the person. The results of the binary logistic regression analysis based on each type of independent variables are shown in Tables 7.15 and 7.16. These results show that the logistic regression analyses support the segment profiles that were derived from the descriptive analyses.

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 results are examined with regard to the stability of the estimates over repeated runs of different initializations of the heuristic estimation procedure and the interpretability of the estimated values.

Data: Whereas the classification study was based on activity-travel patterns of categorical attribute dimensions of activity type, location and transport mode, the estimation uses metric data of activity duration and history. We accordingly reconstructed the input data of activity patterns just as for the aggregate model.

A concern with the data preparation for the estimation in this case is that some activities do not provide enough observations for some segments. Personal business, outside-entertainment and recreation activities fall in this category. Even worse is that other key activities such as grocery and non-grocery shopping activities and social activities do not have enough observations for certain segments because of many missing values in activity history information. For example, Segment 4 consisting of 149 activity patterns has only nine activity patterns including a grocery-shopping activity, two activity patterns including a non-grocery shopping activity and five activity patterns including a social activity with both duration and history information. Given the number of parameters of six to be estimated for each activity, this situation does not allow the estimation of these activities. We therefore decided not to estimate parameters for the three activities with the smaller number of observations (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 bigger 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. Segment Group 2 (SG2) consists of Segments 2 and 4. Segment Group 3 (SG3) consists of Segments 3 and 7. Table 7.17 provides the number of observations of grocery shopping, non-grocery shopping and social activities before and after the merging.

Table 7.17 in combination with Table 7.13 also indicates that the primary difference between segments was the average number of episodes per activity pattern. This implies that the length of the activity pattern had the biggest influence on splitting the segments in the first place. 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 a mixture of Segment Group 2 and Segment Group 3. It consists of the segments of activity patterns of long working people (Segments 5 and 6) and of non-work entertaining people (Segment 1). They are combined into one segment because of the following reasons. Although Segments 5 and 6 people work long, they participate in other activities too (sport for Segment 5 and childcare for Segment 6), which complicates the activity patterns more than those of Segments 2 and 4 and increases the number of activity episodes per activity pattern on average. Segment 1 people are mostly participating in non-work activities, but their activity patterns are not as simple as those of Segments 2 and 4 because they also participate in shopping, social and sport activities frequently.

Table 7.17: The number of observations of activities in each activity-pattern segment

Seg Group	SG1 (361)				SG2 (450)			SG3 (189)		
Segment	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

Stability: An estimation run was repeated 30 times to examine the stability of the parameter estimates across runs. Each run involved random initializations of the genetic algorithm. Given the high correlations between parameter estimates, the current segment-wise estimation also applied the sequential estimation strategy. The estimation results across 30 runs are shown in Figures 7.4 to 7.6 for Segment Groups 1 to 3, respectively.

Parameter estimates of social activity in Segment Group 2 are the least stable among activities, which is likely due to the small number of observations. U^{max} is the least stable parameter, which is likely due to the wide range of possible solutions. β_x is also less consistent, which perhaps is due to the smaller marginal impacts on the utility level. Overall, the parameter estimates across runs are quite stable. It is however not obvious whether the stability of the parameter estimates of activities for each segment is improved compared to the overall estimation. This is because the number of observations for each activity is smaller, which may counterbalance the effect of more homogeneous activity patterns.

Interpretability: The sizes of parameter estimates for the different activities were examined to assess the face validity regarding the profiles of the segments. By taking the averages across 30 runs, the parameter estimates were obtained as shown in Table 7.18. 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 Segment Group 2's α of social activity is very big while Segment Group 3's α of in-home task is very large. The α of Segment Group 1 show approximately average trends between Segment Groups 2 and 3 across activities.

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 Segment Groups 1 and 2, while it is rather big in Segment Group 3. The biggest difference in β size between segments can be found in grocery shopping activity. The β of Segment Group 2 is very large, whereas Segment Group 3's is very small that is almost the same as the β of non-grocery shopping. Segment Group 1 shows again an in-between figure.

The overall level of the γ parameter value is higher in Segment Group 3 than in Segment Group 2, but one cannot say that there is a significant difference. The lowest γ value activity is social activity in Segment Group 3, whereas this parameter is lowest for non-grocery shopping in Segment Groups 1 and 2. The difference between Segment Groups 1 and 3 is bigger than that between Segment Groups 2 and 3 in this parameter.
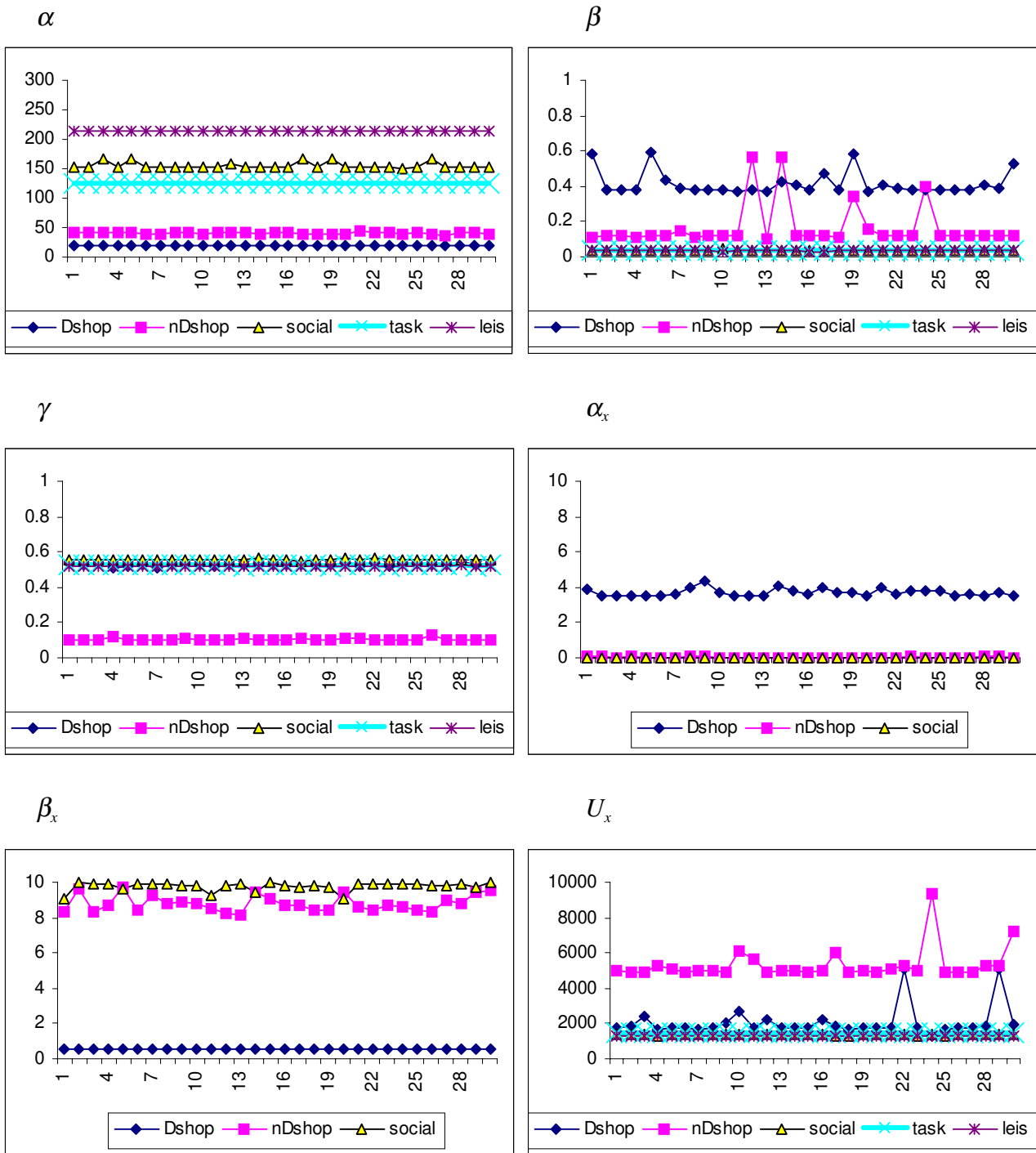
Figure 7.4: Segment Group 1 (Segments 1, 5 and 6: 361 activity patterns)
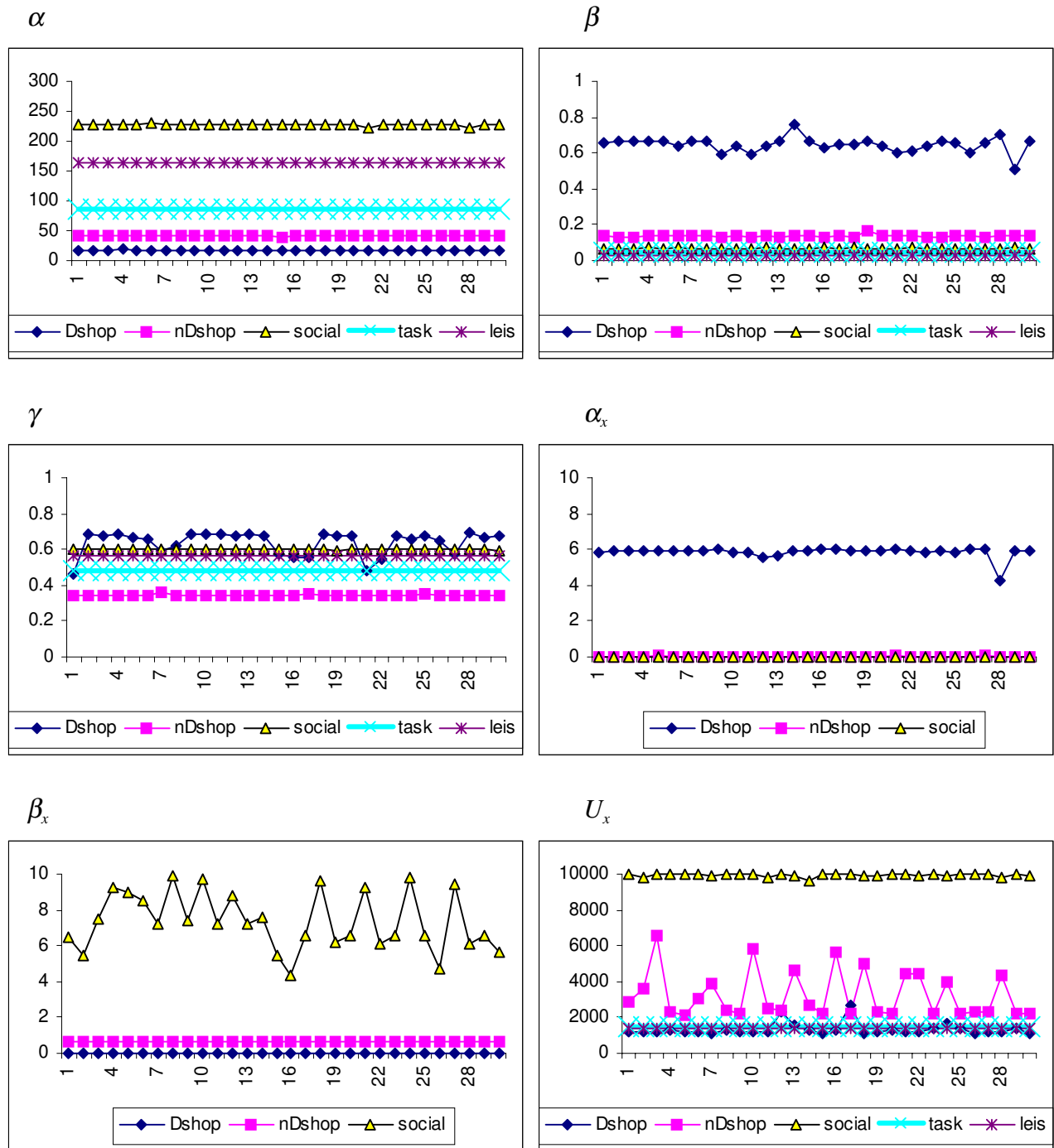
Figure 7.5: Segment Group 2 (Segments 2 and 4: 450 activity patterns)
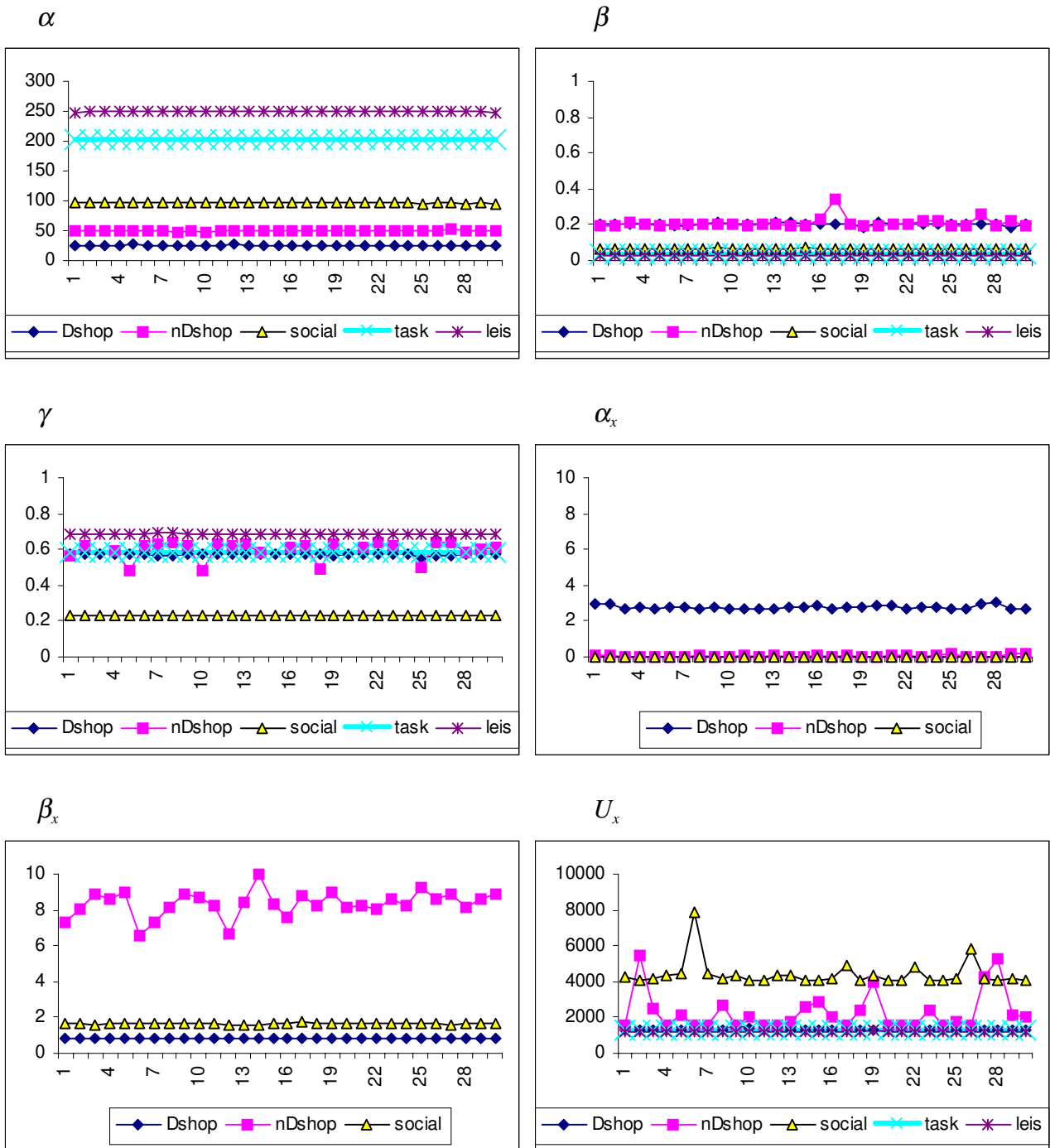
Figure 7.6: Segment Group 3 (Segments 3 and 7: 189 activity patterns)

Table 7.18: Parameter estimates of Segment Groups

Parameter estimates of Segment Group 1 (SG1)					
Activity	α	β	γ	α_x	β_x	U_x
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)					
Activity	α	β	γ	α_x	β_x	U_x
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)					
Activity	α	β	γ	α_x	β_x	U_x
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 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 Segment Group 2 is about six days while that in Segment Group 3 is three days. Segment Group 1 again shows an in-between figure.

The β_x parameter estimates is extraordinarily high for the social activity in Segment Group 2 and for non-grocery shopping in Segment Group 3. Moreover, Segment Group 1 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 Segment Group 3 than in Segment Group 2.

The U_x estimates are also less reliable than others, 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 Segment Group 1) than other activities', and social

activity's U_x is highest in Segment Group 3. Grocery shopping activity's U_x is highest in Segment Group 1.

As the final analysis for examining the existence of significant differences in parameter estimates between the three segments, an ANOVA procedure was taken for each of six parameters of each of five activities to study the between-segment differences of the parameter estimates compared to the within-segment differences. Table 7.19 shows that the difference in the parameter estimates are clear between segments and strongly supports the relevance of the clustering the segments of more homogeneous activity-patterns in order to gain more insights from the estimation into activity utility functions.

In sum, the estimation results do differ between classified segments and are interpretable and consistent with the activity-pattern and socioeconomic/situational profiles of the segments, except for some activities for which there were not enough observations. In particular, more observations are required for non-daily shopping and social activities for more reliable estimates. The parameter estimation results are clearly distinguishing between labels of each segment of homogeneous activity-travel patterns, and the interpretability is improved in this segmentwise estimation compared to the overall estimation.

7.5   Conclusions and discussion

The aim of this chapter was to estimate the activity utility functions underlying the Aurora model. To that effect, a total of 303 activity patterns were selected from the Amadeus data set for overall estimation of the activity utility functions, and a total of 1000 activity patterns were randomly drawn for a cluster analysis and subsequent segment-level estimation.

Overall, the results of estimating the activity utility functions are stable and interpretable. The results of the estimations suggest that all the parameter values differ substantially between segments, providing evidence that the sensitivity of utility to the marginal change in duration differs between groups, and therefore that schedule adaptation behavior substantially differs between groups. Some interesting differences can be observed. The α parameter for social activities for Segment Group 2 (young, work-oriented) is significantly higher than for the other segments. This suggests that young, work-oriented individuals tend to be involved in social activities for a longer time to derive a certain utility value. In contrast, this parameter for this group is smaller for task and leisure activities, which is highest for Segment Group 3 (elderly and women). As for the β parameters, the results indicate that Segment Group 2 (young, work-oriented) is more sensitive to changes in shopping time duration for daily grocery goods compared to the other segments, suggesting a higher time pressure. An interesting result stemming from the estimated γ parameters is that the marginal utility for non-grocery shopping relatively quickly diminishes for Segment Group 1 (others).

As for activity history, the α_x parameters level shows almost no difference between segments for non-grocery shopping and social activities.

Table 7.19: ANOVA test results of difference in parameter estimates between segments

Parameter	Activity		Sum of Squares	d.f.	Mean Square	F	sig.
α	Dshop	Between-G	1281.70	2	640.85	6709.32	0.00
		Within-G	8.31	87	0.10		
		Total	1290.01	89			
	nDshop	Between-G	1649.62	2	824.81	507.30	0.00
		Within-G	141.45	87	1.63		
		Total	1791.07	89			
	social	Between-G	260612.12	2	130306.06	12686.35	0.00
		Within-G	893.61	87	10.27		
		Total	261505.73	89			
	task	Between-G	210706.35	2	105353.17	2616572.8	0.00
		Within-G	3.50	87	0.04		
		Total	210709.85	89			
	leis	Between-G	112249.01	2	56124.51	127361.46	0.00
		Within-G	38.34	87	0.44		
		Total	112287.35	89			
β	Dshop	Between-G	2.93	2	1.46	703.53	0.00
		Within-G	0.18	87	0.00		
		Total	3.11	89			
	nDshop	Between-G	0.08	2	0.04	7.64	0.00
		Within-G	0.48	87	0.01		
		Total	0.57	89			
	social	Between-G	0.02	2	0.01	5619.13	0.00
		Within-G	0.00	87	0.00		
		Total	0.02	89			
	task	Between-G	0.00	2	0.00	9124.30	0.00
		Within-G	0.00	87	0.00		
		Total	0.00	89			
	leis	Between-G	0.00	2	0.00	20016.10	0.00
		Within-G	0.00	87	0.00		
		Total	0.00	89			
γ	Dshop	Between-G	0.19	2	0.10	68.46	0.00
		Within-G	0.12	87	0.00		
		Total	0.31	89			
	nDshop	Between-G	3.36	2	1.68	2210.08	0.00
		Within-G	0.06	83	0.00		
		Total	3.42	85			
	social	Between-G	2.46	2	1.23	140689.49	0.00
		Within-G	0.00	87	0.00		
		Total	2.46	89			
	task	Between-G	0.15	2	0.07	49042.28	0.00
		Within-G	0.00	87	0.00		
		Total	0.15	89			
	leis	Between-G	0.44	2	0.22	221174.17	0.00
		Within-G	0.00	87	0.00		
		Total	0.44	89			

to be continued

α_x	Dshop	Between-G	150.40	2	75.20	1458.08	0.00
		Within-G	4.49	87	0.05		
		Total	154.89	89			
	nDshop	Between-G	0.02	2	0.01	6.79	0.00
		Within-G	0.11	87	0.00		
		Total	0.13	89			
	social	Between-G	0.00	2	0.00	0.25	0.78
		Within-G	0.01	87	0.00		
		Total	0.01	89			
β_x	Dshop	Between-G	11.46	2	5.73	1001776.1	0.00
		Within-G	0.00	87	0.00		
		Total	11.46	89			
	nDshop	Between-G	1250.91	2	625.45	2585.23	0.00
		Within-G	21.05	87	0.24		
		Total	1271.96	89			
	social	Between-G	1043.28	2	521.64	582.78	0.00
		Within-G	77.87	87	0.90		
		Total	1121.15	89			
U_x	Dshop	Between-G	5242433.41	2	2621216.71	41.85	0.00
		Within-G	5323844.80	85	62633.47		
		Total	10566278.21	87			
	nDshop	Between-G	118696622.95	2	59348311.47	58.56	0.00
		Within-G	86146351.02	85	1013486.48		
		Total	204842973.97	87			
	social	Between-G	1138653273.9	2	569326636.95	2971.54	0.00
		Within-G	16668599.72	87	191593.10		
		Total	1155321873.6	89			
	task	Between-G	608133.15	2	304066.57	12871.76	0.00
		Within-G	2055.18	87	23.62		
		Total	610188.33	89			
	leis	Between-G	254885.54	2	127442.77	6140.39	0.00
		Within-G	1805.67	87	20.75		
		Total	256691.21	89			

The parameter is however highest for Segment Group 2 (young, work-oriented) for grocery shopping, suggesting that people in this group have longer interval between shopping events (or lower frequency of shopping activities). The β_x parameter estimates are extraordinarily high for non-grocery shopping in Segment Group 2 (young, work-oriented) and for social activities in Segment Group 3 (elderly and women). The estimates suggest that young, work-oriented people have a strong preference for the (long) non-grocery shopping interval, whereas elderly and women have a strong preference for specific social activities' interval. Considering the large size of these values, however, the results may reflect that the system failed to converge to reliable estimates because of a lack of observations of these activities. Grocery sopping on the other hand is stable perhaps because it has more observations than the others. The U_x of social activities is relatively low for Segment Group 1 (others) suggesting that the maximum utility level for this segment does not build up because they conduct social activities more frequently. In contrast, Segment Group 2 (young, work-oriented) has a very high value of U_x for social activities probably because they conduct social activities relatively rarely. Overall, the analysis results prove the face validity of the

estimated parameter values and indicate that segment-wise estimation of the activity utility functions is needed.

The results suggest that the estimation method is suitable to estimate utility functions from activity duration data. The resulting estimated utility functions could be used to simulate and predict schedule adaptation of individuals, faced with time pressure. With some exceptions, especially some activities that do not have enough observations, the results can be interpreted well.

Ultimately, the application of the A*urora* model requires the implementation of the other part of the model, the search tree, as well. That part of the model simulates the decision processes given estimated activity utility functions. Only at the level of the complete schedule model, the implications of the parameter estimates for the adaptive behavior of the model can be tested. The method proposed relies on the assumption that the marginal utilities of activities in the same schedule are equal. A concern is that the observed duration may not always be stable in terms of the marginal utility because of imperfect information, fatigue and discontinuous constraints such as opening hours, which may result in prediction error. It should be tested whether the search tree component is able to reproduce observed activity patterns and plausible adaptation processes given the estimated parameters.

8 Conclusions 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 Aurora model assumes that utility is a continuous function of the duration of activities. Unlike existing time-allocation models, the utility function 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 (asymptotic) 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. Decision heuristics as opposed to optimization are used. 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.

The development of the model involved several operational problems that needed to be solved. First, the sequence of activities is of central concern of any model of activity rescheduling behavior. This implies that the similarity measure used to classify activity-travel patterns should be sensitive to differences in activity sequence between activity-travel patterns. Because commonly used Euclidean distance measures are not sensitive to such differences, and signal processing measures have some other disadvantages, a new measure had to be developed. Exploring some options, it was decided to elaborate and extent sequence alignment methods. In particular, the uni-dimensional sequence alignment method was generalized to a multidimensional sequence alignment method. The advantage of this multidimensional measure is that it captures the interdependencies in the various facets of activity rescheduling decisions. To reflect and emphasize the wider application of the developed measures, it was decided to organize the thesis in two parts, the first part devoted to the measurement of activity-travel patterns. The alternative would have been just to devote a single, condensed chapter on the new multidimensional sequence alignment measure. This part now discusses in more detail the original measure, the generalizations that were formulated and some examples using empirical data to show the potential of the newly suggested measures, doing more justice to these contributions to the literature and the substantially improved possibilities for descriptive analysis of activity-travel patterns.

Secondly, sequence alignment measures equate similarity to the amount of effort required to make two sequences of information identical and, therefore, any exact algorithm used to calculate the similarity in a multi-dimensional space encounters the problem of

combinatorial explosion in the number of alternative trajectories. Computing times will then become prohibitive for real-sized samples. If the aim of the study is to classify activity-travel patterns, this may mean that one can only use a (small) sub-sample for classification. We therefore developed and tested several heuristic algorithms and ultimately decided that a combination of a dynamic programming algorithm and a dedicated genetic algorithm produced the best results. It reduced the computing time for 1540 comparisons of 56 three-dimensional patterns from 76 minutes and 54 seconds to 27 seconds, without affecting the performance of the solution too much (83.8 percent correct solutions). Overall then, the numerical and empirical evidence suggest that the newly developed generalizations of the uni-dimensional sequence alignment method, together with the specific algorithms that were developed potentially offer a valuable way of measuring similarity between activity-travel patterns.

Future research using other datasets should learn whether the results that we obtained are typical for the datasets that we used or are generalizable results across time, space and culture. The specific way of addressing the problem may also be used in other types of data analysis. In terms of segmentation, the focus of the present analysis was similar to cluster analysis. The aim is to classify activity-travel patterns. Another line of interesting descriptive analysis, more akin to techniques such as factor analysis, would be to identify the common elements in activity-travel patterns. Algorithms for uni-dimensional sequences already exist, but it would be interesting to extend these in future research to multi-dimensional, multi-faceted activity profiles.

A third operational problem that was encountered concerns the estimation of the asymmetric S-shaped utility function of the Aurora model. Although we feel this specification has some theoretical appeal, it implies that the parameters of the utility function are difficult to estimate: an algebraic solution is not available, the underlying schedule decisions are non-linear and state-dependent, and the model should meet several discontinuous constraints. It was decided to explore the potential of an intelligent, theory-driven approach. This newly developed estimation method is based on the critical assumption that observed activity-travel patterns exhibit a state of equilibrium of equal marginal utility across activities embedded in the activity-travel pattern. A tailored genetic algorithm was then developed to search the solution space. Because it turned out that the various parameters representing the utility functions are highly correlated, it is desirable to adopt a sequential estimation approach, which produced convincingly the best results. The method was specially developed for the case where duration and activity history data at the daily schedule level are available. The results of an exploration of the performance of this sequential approach suggest that it is a potentially powerful approach for estimating the utility functions underlying the Aurora model.

It has to be acknowledged however that the estimation problem that was addressed in this study only partially solves the estimation problem. In the present study, the maximum utility was related to history only; other facets of activity schedules were not addressed. Moreover, the reliability of some of the history data may be an issue in the sense that the data that were used were not collected specifically with Aurora in mind. Better history data might have produced even more convincing results. Future research should address this issue and also explore the generalizability of the newly developed method to the problem of multi-faceted utility functions. Another issue that deserves further attention is the assumption of

the linear function that is used to reflect time pressure. It may be that nonlinear, bi-modal functions are more flexible allowing the algorithm to find better parameter estimates. Future research should shed a better light on this issue.

The decision to develop first a method based on cross-sectional (outcome) activity-travel data also has some important ramifications for a future research agenda and the current status of the Aurora model. First, the assumption of equal marginal utility does not only apply to rescheduling decisions, but can also be used in models of activity scheduling behavior. This means that Aurora can also be viewed as a model of activity scheduling behavior, starting with an empty agenda. It is also the reason why at certain places we did not differentiate between scheduling and rescheduling behavior. Secondly, critics may argue that the evidence that was provided cannot be viewed as evidence of rescheduling behavior and also that the suggested estimation method does not involve any rescheduling data. Such criticism would be fair and indeed it is desirable to collect rescheduling data and examine whether the positive results that were obtained in this study generalize to such data. The structure of the data however would remain the same and there is no reason to believe that the guiding principle of equal marginal utility would not equally apply to rescheduling data.

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 in the search tree that drive this process, and that potentially make the rescheduling process differentiate from an equilibrium state. Alternatively, 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.

A full-fledged implementation of the model also implies that one would have to simulate activity (re)scheduling decisions of a whole population of at least a larger sample if one would be satisfied with a general set of correction factors. Despite the tremendous improvement in the computing times of the various algorithms that were developed, the current test of the model was based on a sub-sample of 303 multidimensional activity-travel patterns only instead of the entire sample of 6950 activity-travel patterns. It seems that parameter estimation based on a substantially larger sample is impossible at the current level of knowledge and technology, and hence alternatives should be explored. In particular, in future research, it may be interesting to explore the possibility of developing a learning algorithm, starting with a relatively small, but representative sub-sample and then sequentially adding cases according to some criteria until a stable set of parameters is obtained. Even better would be an approach in which such a learning algorithm would simultaneously identify homogeneous, but distinctive segments. Additional cases could then be added to the clusters using profiling.

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. The project has made several contributions to the literature, but additional work is required before the model can be used in a micro-simulation of dynamic activity-travel choice. The

conceptual framework includes several new concepts and represents a view of linking traditional utility theory to a more process-oriented view of complex decision-making. The estimation method that was developed can also be used in other contexts 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 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.

Before a full operational Aurora model will be available, however, some additional problems need to be addressed in future research projects. The most important of these are testing the behavior of the model in scheduling activities, estimating the parameters characterizing the search tree and incorporating the model in an agent-based simulation of dynamic activity-travel choice behavior. The results obtained thus far suggest that addressing these issues is worthwhile.

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English Summary

Transportation policy is mostly concerned with the physical planning of the transportation network and land use, and transportation demand management. Among these, transportation demand management becomes increasingly more important as it focuses on the optimal use of the existing infrastructure. Recently, substantial progress has been made in developing so-called activity-based models of transport demand. These models focus on the complex interdependencies in the various facets of activity-travel patterns and hence offer a valuable alternative to the traditional four-step approach to transport demand forecasting. Despite the rapid and continuing progress, most of these activity-based models, however, are based on correlations between facets of activity-travel patterns and a set of "explanatory" variables. They are concerned with structure and outcome, not with the process. Models that generate an activity schedule or adjust an existing schedule as a function of sudden changes in the environment or the transportation system or unexpected events in the implementation of a planned schedule are still rare. However, especially these types of models are required to predict the impact of transportation demand management on (the dynamics of) daily activity-travel patterns.

The importance of this field of research becomes obvious if it is realized that transportation systems and urban environments are highly dynamic, non-stationary and uncertain. Individuals need to schedule and reschedule their activities in ever changing decision contexts associated with changes of transportation environment. In doing so, they potentially can change multiple facets of their activity schedule. Existing models however typically focus on a particular choice facet isolated from others or do not deal with daily dynamics.

To contribute to this rapidly evolving field of research, the aim of this Ph.D. research project is to explore the possibilities of developing a comprehensive model of dynamic activity (re)scheduling 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 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.

To account for heterogeneity, the estimated model is based on a classification of activity-travel patterns. Because such a classification requires an adequate, sequence-sensitive and multidimensional similarity measure, which appeared not to be available, a sub-goal of the project was to develop a measure that can capture sequential differences between activity-travel patterns and that can be used to classify activity-travel patterns. To this effect, the thesis is organized in two main parts and a series of chapters. The first part is concerned with the measurement of the similarity, while the second part is concerned with the model of activity (re)scheduling behavior. To position the research project, first, in Chapter 2, a brief summary of the state-of-art in activity-based modeling is given. In particular, this chapter concentrates on previous research on measuring and classifying activity-travel patterns and on cross-sectional and dynamic models of activity-travel patterns.

Based on this literature review, the first part of the study began with Chapter 3 that introduced a sequence alignment method to measure similarity between activity sequences. First, the original method was applied to capture the sequential information embedded in activity data. An empirical analysis using the original sequence alignment in the context of shopping history sequence data illustrated that the segmentation does involve not only information about activity composition but also information of sequential relationships between activities. The latter type of information is not captured by traditional Euclidean similarity measures. Then, the original sequence alignment measure was extended in various ways. First, a position-sensitive method was developed. A subsequent analysis of activity diary data showed that the extended position-sensitive alignment method could further distinguish activity sequences with regard to the number of positions by which activities are to be reordered in order to make two sequences equal.

Secondly, and most importantly for the present study, a multidimensional sequence alignment method was proposed. This multidimensional method is of great importance because it reflects the fact that activity-scheduling decisions are interrelated in the sense that decisions are often made on multiple choice-facets. This multidimensional extension of the uni-dimensional alignment method is developed in Chapter 4. The quintessence of the method is that it captures the interdependencies among the multiple facets of a particular activity, while maintaining the fundamental property of sequence alignment methods of capturing both the sequential and compositional information embedded in a string of information: an activity-travel pattern in our case. The proposed method was tested using empirical activity diary data. The results suggest that the proposed method indeed can capture these relationships and produces a segmentation that is distinctive from the results of conventional Euclidean measures and simple sums of uni-dimensional alignment methods.

When developing this method, the combinatorial explosion of alternative candidate solutions implied very high computing times. These times would be prohibitive for using the suggested measure as a measure of goodness-of-fit in parameter estimation. Hence, several heuristic algorithms were explored and compared in terms of their performance. The results reported in Chapter 4 indicate that a hybrid method, combining a dynamic programming technique, used to find an initial solution, and a genetic algorithm-based method performed best.

The results of a comparative analysis of the proposed method involving a Euclidean distance measure, previously often used in activity analysis, a signal processing theoretical method, and the simple sum of uni-dimensional sequence alignment methods, are also reported in Chapter 4. The analysis showed that the similarity measures of the proposed method differ from those of the other measures, implying that the choice of method will have an impact on the cluster solutions/segmentation. It turned out that, at least for the data that were used, the segmentation generated by the proposed method better distinguished activity-pattern characteristics compared to all other measures. Moreover, similar to the results of the signal processing theoretic method, there was a stronger relationship with socio-economic characteristics compared to Euclidean and the simple sum of uni-dimensional alignment measures. These results provide evidence that the proposed method is potentially valuable in measuring the similarity between activity-travel patterns and measuring the goodness-of-fit of a model's predictions against observed activity-travel patterns.

The second part of the study describes the findings of the modeling work. In Chapter 5, the conceptual framework, mathematical specification and operational definitions of the model, titled Aurora (Agent for Utility-driven Rescheduling Of Routinized Activities), are developed. The proposed model assumes that when scheduling or rescheduling activities, individuals attempt to maximize their utility by an iterative heuristic decision-making process, subject to a set of constraints and costing mental effort. The theoretical underpinnings of the model differs from utility-maximizing approaches in that it is assumed that individuals' cognitive capacity is limited, and hence, they use heuristics to find an acceptable alternative within a reasonable amount of time for search and adaptation effort. A set of illustrations using simulated schedule data provided evidence of face validity of the proposed model.

The model developed in Chapter 5 involves a rather complex and unconventional activity utility function incorporating a variety of choice facets and decision-making heuristics operationalized in terms of various scheduling operators for near-best schedule adjustments. These theoretically valuable properties of the utility function, however, make the parameter estimation anything but straightforward: an algebraic solution is not available, the underlying schedule decisions are non-linear and state-dependent, and the model should meet several discontinuous constraints. In Chapter 6, therefore a new method to estimate the activity utility function is suggested. The suggested estimation method is based on the critical assumption that observed activity-travel patterns exhibit an equilibrium state of equal marginal utility across activities for each activity-travel pattern. A tailored genetic algorithm was then developed to search the solution space. The method was specially developed for the case where duration data are available. Before applying the proposed method to real empirical data, the performance of the estimation method was assessed using simulated duration data. The results of estimation on simulated data indicate that the proposed method performs well on exact data and reasonably well on noisy data.

Finally, in Chapter 7, the proposed estimation method was applied to real empirical data collected in the Amsterdam-Utrecht corridor in the year of 2000, involving a total of 6950 activity-travel patterns of 3575 individuals from 1966 households. The estimation was conducted in two phases. First, activity utility functions, involving six parameters for each of eight flexible activities, were estimated for a sub-sample of activity patterns representing the entire data. Secondly, activity utility functions were estimated for three segments, which were derived on the basis of the multidimensional sequence alignment measure, developed in the context of this thesis. While the aggregate estimation focused on overall characteristics of the utility functions of each activity, this segment-based estimation highlighted particular segment-specific sets of activity utility functions. The estimation involves a sub-sample of activity-travel patterns. The results obtained suggest that the Aurora model presents a potentially valuable approach to modeling activity scheduling and rescheduling behavior. The current version of the model suffices to estimate utility functions and characterize the (re)scheduling behavior of individuals. When the goal, however is, to have a full-fledged predictive model of rescheduling decisions, the estimated utility functions should be linked to a dedicated sub-model of recursive decision-making heuristics in a simulation environment.

Samenvatting

Traditioneel is verkeersbeleid sterk gericht op grondgebruik en infrastructuur. Voor de bepaling van de effecten van dat beleid, zijn in de loop der tijd verschillende modellen geformuleerd. Met name het zogenaamde 4-fasen model wordt in de praktijk veelvuldig toegepast. Dit model voorspelt het aantal verplaatsingen per gebied, de verdeling van de vervoerwijze, bestemmingskeuze en routekeuze. Gedurende het laatste decennium is dit model steeds meer vervangen door zogenaamde activiteitengebaseerde modellen. Deze modellen hebben als uitgangspunt de gedachte dat verkeersstromen ontstaan doordat mensen activiteiten verrichten. Activiteitengebaseerde modellen voorspellen welke activiteiten waar worden verricht, hun begin- en eindtijd, soms met wie, routekeuzen en de vervoerwijzen die daarbij worden gebruikt. De complexiteit en de onderlinge afhankelijkheden in activiteitenreispatronen kunnen beter worden afgebeeld en deze modellen hebben daardoor potentieel meer waarde voor verkeersplanning, met name voor die aspecten die zich richten op de structurele relaties tussen verdeling van grondgebruik, infrastructuur en activiteitenreispatronen.

In de praktijk valt de laatste tijd veel meer aandacht te constateren voor verkeersmanagement teneinde de bestaande infrastructuur optimaal te benutten. Dergelijk beleid vereist een ander modeltype. Weliswaar zijn de laatste tijd verschillende modellen voor vertrektijdkeuze en dynamisch routekeuzegedrag ontwikkeld, maar het nadeel van deze modellen is dat ze doorgaans slechts een specifiek aspect van het proces betreffen, zelden worden de effecten van integrale activiteitenpatronen gesimuleerd. Indien individuen echter hun activiteitenagenda moeten aanpassen in verband met onverwachte gebeurtenissen of signalen van intelligente vervoerssystemen, dan kan men dat doen door meerdere facetten van hun activiteitenpatroon aan te passen. Bovendien kan een verandering van een activiteit aan het begin van de keten gevolgen hebben en aanpassingen noodzakelijk maken voor activiteiten later op die dag.

In een poging een bijdrage te leveren aan dit snel ontwikkelend terrein van onderzoek, is het doel van dit promotieonderzoek de mogelijkheden te verkennen van de ontwikkeling van een alomvattend model dat voorspelt hoe individuen hun activiteitenagenda aanpassen in reactie op veranderingen in de verkeersomgeving, tijdsdruk of onverwachte gebeurtenissen. Onder dergelijke omstandigheden kunnen individuen beslissen een of meerdere facetten van hun activiteitenpatroon aan te passen (begin of eindtijd, duur, volgorde van activiteiten, bestemming, vervoerwijze, etc.). Het model moet in staat zijn aanpassingen in een willekeurige combinatie van deze facetten te voorspellen. In het bijzonder dient het model gevoelig te zijn voor aanpassingen in de volgorde van de activiteiten.

De schatting van het model is gebaseerd op een classificatie van activiteitenpatronen. Deze classificatie dient idealiter gebaseerd te zijn op een similariteitsmaat, die gevoelig is voor de volgorde van activiteiten in een activiteitenreispatroon. Omdat een dergelijke maat niet bestaat, is een subdoel van dit promotieonderzoek een maat te ontwikkelen, die verschillen in volgorde tussen activiteitenreispatronen detecteert. Een dergelijke maat kan worden gehanteerd voor het segmenteren van patronen of als maat, die aangeeft hoe goed een model de waarnemingen representeert.

Conform deze doelstellingen is het proefschrift opgebouwd in twee delen. Het eerste deel handelt over het meten van similariteit, terwijl het tweede deel gaat over

modelontwikkeling. Teneinde het project te positioneren in de bestaande literatuur, wordt echter eerst, in Hoofdstuk 2, een korte samenvatting gegeven van de bestaande literatuur op het gebied van activiteitenanalyse. In het bijzonder wordt hier ingegaan op onderzoek over de meting en classificatie van activiteitenpatronen en op modellen over activiteitenreispatronen.

Gebaseerd op deze samenvatting van de bestaande literatuur, wordt in Hoofdstuk 3 het zogenaamde "sequence alignment methode" geïntroduceerd, die kan worden gebruikt voor het meten van de similariteit van activiteitenpatronen en gevoelig is voor de volgorde van de activiteiten. De oorspronkelijke methode wordt toegepast op panelgegevens over winkelgedrag om te illustreren dat deze methode zowel rekening houdt met de samenstelling van de (winkel)activiteiten als met de volgorde informatie in de paneldata. Traditionele maten, gebaseerd op Euclidische afstanden, houden geen rekening met volgorde-informatie. Vervolgens wordt de oorspronkelijke sequence alignment op verschillende wijze uitgebreid. Allereerst wordt een positiegevoelige maat ontwikkeld. Een analyse op gegevens uit activiteitendagboekjes toonde aan dat deze nieuwe maat beter in staat is onderscheid te maken tussen activiteitenpatronen met betrekking tot het aantal positiewisselingen c.q. herschikkingen van activiteiten die nodig zijn om twee sequenties identiek te maken.

Daarnaast is een meerdimensionale maat ontwikkeld. Het belang van deze maat is dat aanpassing van een activiteitenreispatroon meerdere facetten in hun onderlinge samenhang kunnen betreffen. In hoofdstuk 4 wordt deze uitbreiding besproken, en wederom getest op grond van activiteitendagboekjes. De resultaten van deze analyses tonen aan dat de voorgestelde methode goed in staat is de onderling relaties en afhankelijkheden in activiteitenpatronen te meten en resulteert in een segmentatie die duidelijk verschilt van segmentatie op grond van conventionele Euclidische afstandsmaten en de sommering van uni-dimensionele alignment methoden.

Een probleem dat zich voordeed bij de toepassing van deze maat is die van een combinatorische explosie van paden, die doorlopen moeten worden om de similariteit te meten, hetgeen resulteert in lange rekentijden. Lange rekentijden zou betekenen dat de maat niet gebruikt kan worden als een goodness-of-fit maat bij de parameterschatting. Derhalve werden verschillende heuristieken ontwikkeld en met elkaar vergeleken in termen van hun prestatie en rekentijd. De resultaten hiervan worden besproken in Hoofdstuk 4. Het beste resultaat werd verkregen door een hybride methode, waarbij een dynamisch programmerings algoritme werd gebruikt voor het vinden van een initiële oplossing, en vervolgens een genetisch algoritme werd gebruikt voor de verbetering van oplossing.

In Hoofdstuk 4 worden vervolgens de resultaten van een vergelijking van deze methode, een Euclidische afstandsmaat, een methode gebaseerd op signaalverwerking en de som van uni-dimensionele sequence alignment methoden, besproken. De resultaten van deze analyse suggereren dat de similariteitsmaat andere resultaten levert, die beter interpreteerbaar zijn dan de resultaten die de alternatieve methoden genereren. Bovendien vertoonde de segmentatie, net als bij de methode gebaseerd op signaalverwerking, een sterker verband met sociaal-economische kenmerken. Op grond van dit empirisch bewijs, werd besloten deze multidimensionele maat te gebruiken bij de ontwikkeling van het model.

Het tweede deel van deze studie rapporteert over de ontwikkeling van het model, dat het acroniem Aurora (Agent for Utility-driven Rescheduling Of Routinized Activities) kreeg. Het model is gebaseerd op de veronderstelling dat bij het organiseren van activiteiten

in tijd en ruimte individuen proberen hun nut te maximaliseren op grond van een iteratief, heuristisch beslissingsproces, rekening houdend met een serie beperkingen, waaronder hun mentale inspanning. Deze theoretische grondslag verschilt van de nuts-maximimalisatie benaderingen in de veronderstelling dat de cognitieve capaciteit van individuen beperkt is, en dat men daarom heuristieken gebruikt om binnen een bepaalde tijd en inspanning tot een oplossing te komen. De validiteit van het model wordt verkend door het model toe te passen op gesimuleerde data in een aantal typische illustraties.

Het model kent een onconventionele nutsfunctie en heuristieken, die geoperationaliseerd zijn in termen van diverse operatoren. De theoretisch waardevolle aspecten van de nutsfunctie zorgen er echter voor dat de parameterschatting van het model problematisch is: er is geen algebraïsche oplossing, de beslissingen zijn non-linear en toestand-afhankelijk, en het model moet voldoen aan allerlei discontinue beperkingen. In Hoofdstuk 6 wordt daarom een nieuwe methode voor het schatten van de parameters van de nutsfunctie geïntroduceerd. Deze schattingsmethode is gebaseerd op de kritieke veronderstelling dat waargenomen activiteitenreispatronen een evenwicht vertonen, waarbij het marginaal nut van de activiteiten in het activiteitenpatroon gelijk is. Onder deze veronderstelling wordt een specifiek genetisch algoritme ontwikkeld. De methode is met name geschikt voor gegevens over de tijdsduur van de activiteiten. Teneinde de eigenschappen van deze methode te verkennen, is een simulatiestudie met perfecte en imperfecte data uitgevoerd.

In Hoofdstuk 7 tenslotte worden de resultaten van een toepassing van het model en de ontwikkelde schattingsmethode op empirische gegevens besproken. Deze gegevens werden verzameld in de corridor Amsterdam-Utrecht in het jaar 2000, en omvatten 6950 activiteitspatronen van 3575 individuen uit 1966 huishoudens. Allereerst werd het model toegepast op een steekproef van 303 activiteitenpatronen. Vervolgens werd het model toegepast op segmentniveau. Hiertoe werden 1000 activiteitenpatronen gesegmenteerd op grond van de multidimensionale sequence alignment methode, die in het kader van dit proefschrift is ontwikkeld. De resultaten van deze analyses geven aan dat het Aurora model, samen met de specifiek ontwikkelde goodness-of-fit maten en algoritmen, een potentieel waardevolle benadering vormen voor het modelleren van het aanpassingsgedrag van individuen in de context van activiteitenreispatronen. De huidige versie van het model is geschikt voor het schatten van de nutsfunctie en het karakteriseren van het aanpassingsgedrag van individuen. Teneinde een voorspellend model te krijgen is het nodig dat de geschatte nutsfuncties gekoppeld worden aan recursieve beslissingsheuristieken in een simulatieomgeving.

한글 요약

일반적으로, 교통망 하부구조 건설과 토지이용, 교통수요관리 등은 교통정책의 골간을 이룬다. 이 중, 기존 교통하부구조의 최적 이용에 중점을 두는 교통수요관리 정책은 갈수록 그 중요성을 더해가고 있다. 보다 나은 교통수요관리 정책을 지향하는 많은 연구들 중, 통행행태 분석을 위한 활동기반 접근법 (activity-based approach to travel behavior analysis) 이라 명명되는 한 연구 분야가 최근 급격한 발전으로 많은 주목을 끌고 있다. 이 분야로 분류되는 모델들은, 관측되는 통행 패턴을 결과해 내는 다양한 활동 결정 요소들간의 복잡한 상호의존 관계들에 연구의 초점을 두고 있으며, 따라서 교통수요 예측을 위한 기존의 전통적인 4 단계 접근법을 대체하는 대안을 제시하고 있다.

그러나, 급격하고 지속적인 발전에도 불구하고, 대부분의 활동기반 교통수요 모델들은 아직도 활동-통행 패턴의 다양한 결정 요소들과 일단의 설명 변수들간의 정태적 상관관계를 연구하는 데 그치고 있다. 다시 말해, 주어진 '구조'와 그 '결과'에만 관심을 집중하는 반면, 그 '과정'에는 관심이 적다. 일일 활동 패턴이 조직되는 과정을 기술하는 모델이나, 주변 환경과 교통 시스템의 갑작스러운 변화나 계획된 활동들의 수행 중 일어나는 예기치 못한 일들로 현재의 계획을 수정하는 모델들에 관한 연구는 아직도 드물다. 그러나, 이러한 모델들이야말로, 일일 활동-통행 패턴의 변화에 대한 교통수요관리 정책 수단의 영향을 예측하는데 매우 필요하다.

교통 시스템과 도시 환경이 매우 가변적이며, 비선형적이고, 불확실하다는 점에서 활동-통행 패턴 수정에 관한 연구의 중요성은 더욱 강조될 필요가 있다. 교통 환경의 변화로 인해 의사 결정 여건은 항시 변화하며, 사람들은 이에 맞추어 새로운 활동 계획을 세우거나 이미 세워진 활동 계획의 일부를 수정해야 한다. 그 과정에서, 사람들은 종종 활동 계획의 여러 가지 결정 요소들을 한꺼번에 바꾸기도 한다. (예를 들어, 수정된 활동 목적지에 가기 위한 교통 수단 역시 수정 되어야 하는 경우를 생각할 수 있다.) 그러나, 기존의 모델들은 이러한 활동 계획 수정의 모델화에 관심이 없거나, 수정해야 할 결정 요소들의 일부만을 다른 요소들과 고립하여 분석하였다.

빠르게 발전하는 이 분야 연구에 기여하기 위해, 이 박사학위 연구 프로젝트는 활동 계획의 역동적 수정 행태에 관한 심도 있는 모델 개발의 토대를 마련하는 데 목적을 두었다. 모델은, 교통 환경 변화에 대응하는 활동 계획 변화의 예측을 목표로 한다. 변화하는 교통 환경, 시간 제약, 예기치 못한 일들 등을 겪을 때, 활동-통행 계획에서 특정 활동들을 언제 시작하고 얼마 동안 지속하며, 다른 활동들과의 순서는 어때야 하고, 어떤 교통 수단을 타고 어느 곳으로 가서 그 활동들을 수행할 지 등에 관한 결정 각각 혹은 전부 들을 수정하기도 한다. 바람직한 모델은 이러한 결정 요소들을 어떠한 식으로 결합한 활동 계획 수정도 예측할 수 있는 것이어야 한다. 특히, 모델은 활동들의 순서가 어떻게 결정되느냐에 민감하게 반응할 수 있어야 한다.

이러한 모델들을 평가하기 위해서는 예측된 활동-통행 패턴이 관측된 것과 얼마나 차이가 나는가를 판정하는 적합도 측정법이 필요하지만, 기존의 연구에서

이에 맞는 적절한 방법들을 찾을 수 없었기 때문에, 이 프로젝트의 소 목표로 활동-통행 패턴간의 정보 배열의 차이점을 측정하는 방법을 개발하기로 하였다. 이 방법은 활동-통행 패턴들을 유사한 수개의 집단으로 구분하거나, 예측된 패턴과 관측된 패턴간 측정된 적합도에 근거하여 통행수요예측 모델의 계수를 추정하는 데 이용할 수 있다.

이 논문은 크게 2부로 나뉘며, 각 부에서 세부의 장과 절들을 갖도록 구성되었다. 1부는 활동-통행 패턴간의 유사성을 측정하는 방법, 그리고 2부는 활동들이 계획 및 수정되는 것을 예측하는 모델을 각각 서술한다. 우선, 활동기반 연구에서 이 논문이 기여코자 하는 바에 대한 설명을 위해, 2장에서는 최근의 활동기반 모델의 연구 동향이 간략히 요약된다. 특히 이 문헌 연구는 활동-통행 패턴의 측정과 집단 구분에 대한 기존 연구, 그리고 활동-통행 패턴의 정태적 (구성적) 모델과 동태적 (상황적) 모델에 대한 연구들을 집중적으로 논의한다.

1부의 시작인 3장에서는 활동 패턴간의 유사도를 측정하는 정보배열 비교법이 소개된다. 첫째로, 분자생물학에서 개발된 그대로의 측정법이 활동 패턴에 내재된 정보배열을 분석하는데 어떻게 응용되는가에 대한 이론이 소개되고, 실제의 자료분석 사례가 제공된다. 보다 구체적으로, 사람들의 실제 쇼핑 활동 정보에 관한 자료를 기존의 정보배열 분석법으로 분석한 사례연구는, 각 활동 패턴들이 어떠한 활동들로 구성되어 있는가의 정보 뿐만 아니라, 그러한 활동들이 서로간에 어떠한 배열로 연쇄관계를 갖고 있는가의 정보 역시 집단구분에 중요한 역할을 한다는 것을 보여주었다. 특히 배열상의 연쇄관계를 분석할 수 있는 것은, 기존의 유클리드적 측정법이 할 수 없었던, 정보배열 측정법이 갖는 장점이다.

이러한 정보배열 비교법은 그 응용 분야의 확장을 위해 여러 가지 방향으로 수정, 개발될 수 있는데, 3장은 그 하나의 예로, 정보 배열 위치 차이에 민감한 변형된 정보배열 비교법을 개발-소개하였다. 이 방법은, 어떤 한 활동이 정보 배열상에 차지하고 있는 위치가 두 활동 패턴간에 같은가 혹은 다른가의 판단 뿐만 아니라, 다르다면 얼마만큼 다른가의 양적 차이까지 계량화하고 있다. 이 방법을 실제 활동 패턴 자료에 응용한 사례연구는, 실제 활동 패턴들이 이 정보에 대해 차이를 갖고 있으며, 따라서 이 정보가 중요한 의미를 갖는 연구 목적에 이 방법이 유용하게 응용될 수 있음을 보여주었다.

둘째, 이 논문에서 가장 중요한 연구 주제의 하나로, 다차원 정보배열을 측정할 수 있는 방법이 제안된다. 이 다차원 측정법이 매우 유용한 이유는, 활동 계획에 관한 다양한 요소들의 의사결정들이 빈번히 하나의 묶음으로 취급되어 결정되기 때문에 서로간에 밀접히 연관되어 있으며, 다차원 측정법이 그러한 연관성을 그 측도에 실현하기 때문이다. 4장은, 3장에서 소개된 단차원 정보배열 비교법을 다차원으로 확장하고 있다. 이 다차원 방법은, 정보 배열을 구성하고 있는 활동들의 목록과 그 활동들간의 연쇄관계를 계량화한 측도를 정보배열 비교법의 기본적 특성으로서 제공한다는 점에서, 3장에서 소개된 단차원 비교법과 동일하다. 그러나 여기에 더해, 다차원 측정법은 특정한 활동의 여러 가지 결정 요소들간의 상호 연관관계를 계량화한 측도까지 제공한다는 점에서 활동-통행 패턴 분석에 중요한 기여를 하고 있다. 활동 패턴 자료 분석을 통한 경험 연구는 제안된 다차원 측정법이 이러한

연관관계들을 실제로 잘 분석해내며, 이에 기초한 집단 구분은 전통적인 유클리드 측도 혹은 단차원 정보배열 측도의 단순합에 비해 보다 유의미한 집단들을 추출해 냄을 보여주고 있다.

그러나, 예비 최적해의 가능한 조합의 수효가 지나치게 많은 경우가 빈번히 발생하여, 다차원 측정법의 실제 적용이 크게 제약 받는 문제가 생기게 되었다. 컴퓨터 연산에 지나치게 많은 시간이 드는 사실은, 특히 활동 계획 수정 모델의 계수 추정을 위해 예측된 활동-통행 패턴의 적합도를 반복적으로 측정하는 데 제안된 측정법이 현실적으로 쓰이기 어렵다는 것을 의미한다. 이에, 본 연구는 여러 가지의 탐색적 알고리즘들을 개발하고, 그 실행성을 비교하였다. 각각의 알고리즘으로 실제 활동-통행 패턴을 분석한 결과, 신속한 동적 계획법으로 초기해를 정하고 유전자 진화 알고리즘으로 보다 나은, 최적에 가까운 해를 추적해 내는 합성 알고리즘의 실행성이 가장 좋은 것으로 나타났다.

4장은 마지막으로, 제안된 다차원 정보배열 측정법의 실행성을 기존의 측정 방법들 즉, 단차원 정보배열 측정의 단순합, 유클리드식 측정법, 그리고 전자파 움직임에 기반한 측정법 등등의 실행성과 비교하였다. 실제 활동-통행 패턴 자료에 대한 응용 결과를 비교 분석한 결과, 첫째로, 이들 측정법들이 계산해 낸 활동-통행 패턴간 유사 정도의 상대적 측도들은 서로 유의하게 달라, 측정법의 선택이 집단 구분의 결과를 달리할 수 있음을 확인시켜 주었다. 또한 최소한 이 연구에 적용된 자료에 한해서는, 제안된 다차원 정보배열 측정법에 근거한 집단 구분이 기존의 다른 측정법에 근거한 집단 구분에 비해 활동-통행 패턴의 특성 자체에 의해 더욱 잘 설명이 되며, 전자파 움직임에 기반한 방법과 함께, 활동-통행 패턴 주체의 사회경제적 특성과 잘 연관되어 있음이 밝혀졌다. 이 비교 연구의 결과는 다차원 정보 배열 비교법이 관측된 활동-통행 패턴간의 유사도 측정과 예측된 활동-통행 패턴의 관측 패턴에 대한 적합도 측정에 보다 나은 방법을 제시함을 보여주고 있다.

2부는 예측 모델 연구의 성과에 대해 기술하고 있다. 5장에서는 A urora (Agent for Utility-driven Rescheduling Of Routinized Activities) 라고 명명된 모델의 이론 틀과 그것의 수학적 정형화 및 조작적 정의가 상술 된다. 제안된 모델은, 사람들이 활동 계획을 세우거나 수정할 때, 정신적 수고와 불완전한 정보 등등의 제약 하에, 반복적, 탐색적인 의사결정을 통해 그들의 효용을 극대화하려고 노력한다고 가정한다. 모델의 이러한 이론적 기반은, 널리 연구되는 효용 극대화 접근법과 다른데, 이는 우리의 이론이 사람들은 인지 능력에 한계가 있어, 탐색적 방법을 이용해 어느 정도의 시간 내에 적절한 정신적 수고를 들여 타당한 대안을 찾아낸다고 가정하기 때문이다.

5장에서 개발된 모델은 다소 복잡하고 이 응용분야에 잘 알려져 있지 않은 활동 효용 함수를 포함하고 있다. 이 함수는 효용을 창출하는 독립변수로서 다양한 결정 요소를 포함하고 있으며, 준 최적의 활동 계획 수정을 할 수 있도록 다양한 활동 계획 수립 및 수정을 위한 수단을 조작적으로 정의하고 있다. 그러나, 이러한 이론적으로 바람직한 특성은 효용 함수의 추정을 오히려 어렵게 만들었다. 극대화를 위한 대수적 해법이 없고, 관측된 활동-통행 패턴을 이끌어 낸 기저의 의사결정 과정이 비선형이고, 현단계의 의사결정이 전단계의 의사 결정 결과에 영향을 받으며, 모델이 예측한 활동계획은 여러 가지의 불연속적인 제약조건을 만족시켜야 한다.

6 장은 따라서 그러한 특성의 활동 효용 함수를 추정하기 위한 방법을 제안한다. 이 방법은, 관측된 활동-통행 패턴 안의 모든 활동들은 이들 각각이 갖고 있는 활동시간에 대하여 동일한 한계효용을 갖고 있는 것이라는 핵심 가정 하에 개발되었다. 그 해공간의 탐색을 위해 유전자 진화 알고리즘을 문제에 맞게 수정하여 이용하였다. 이 방법은 특히, 활동-통행 패턴 자료에서 활동 시간들의 자료가 주어진 경우를 위해 설계되었다. 제안된 방법을 실제 경험자료에 응용하기 이전에, 그 실행능력이 가상 데이터 분석에 의해 평가되었다. 가상 자료의 추정 결과에 따르면, 제안된 방법은 정확한 자료를 매우 정확히 추정해 내며, 약간의 부정확성이 있는 자료 역시 대체로 잘 추정하였다.

　　　마지막으로, 7 장에서는 제안된 방법을 이용하여, 실제 활동-통행 패턴들이 갖는 활동 효용 함수들이 추정되었다. 자료는 2000 년 암스텔담-유트레히트 회랑 지역에서 설문 수집한 것으로, 1966 가구의 3575 명이 기록한 6950 활동-통행 패턴들이 이용되었다. 추정은 두 가지 형태로 수행되었다. 첫째, 각기 6 개 계수로 구성된 효용 함수를 갖고 있는 8 개 활동들이 전체 자료에서 추출한 303 개의 패턴들에 기초하여 추정되었다. 둘째, 4 장에서 개발된 다차원 정보 배열 비교법을 적용하여 활동-통행 패턴들을 3 개의 유사한 패턴 군으로 묶고, 이러한 패턴 집단 각각에 대해 각 활동의 효용함수를 추정하였다. 앞서의 전체 집단 추정이 각 활동들의 일반적 특성에 초점을 두는 반면, 이 집단별 추정은 활동 효용 함수들의 집단간 차이를 부각시킨다. 1000 패턴이 임의 추출되어 집단별 추정에 이용되었다. 추정의 결과는, 적절한 적합도 측도와 실행 알고리즘을 갖춘 *Aurora* 모델이, 다른 데이터로부터도 유사한 결과를 얻는다면, 활동 계획 및 수정 모델의 연구에 중요한 공헌을 하는 것임을 보여주었다.

　　　현재 단계의 모델은 효용 함수를 추정하고 사람들의 활동 계획 수정 행태를 기술하는 데 성공하고 있다. 하지만, 이 연구의 궁극 목표는 활동 계획 수정의 의사결정의 총체적인 예측모델을 개발하는 것이다. 따라서 다음 단계의 연구에서는, 가상 환경에서의 반복적 의사결정을 조작적으로 정의한 탐색 세부 모델에, 추정된 효용 함수를 연계시켜, 실제 활동-통행 패턴을 예측한 결과를 보고할 것이다.

Curriculum vitae

Chang-Hyeon Joh was born in 1966 in Seoul, Korea. He attained a Bachelor's degree in Geography (major) and Economics (minor) in 1990 from respectively the Department of Geography and the Department of Economics, College of Social Sciences, Seoul National University, Korea. From 1990 to 1992 he served his military duty as an officer in the Korean Army. After this, he completed his Master's study in Transportation Geography at the Department of Geography, College of Social Sciences, Seoul National University, Korea.

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Chang-Hyeon has been involved in several scientific research projects, the results of which were published in urban planning, transportation, marketing, geography and tourism journals. His current research interests concern the modeling of scheduling and rescheduling activity-travel behavior and the use of mobile technology and interactive computer experiments to collect activity-travel data.

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Chang-Hyeon Joh

♦

Being a geographer basically means to appreciate that when events are seen located together in a block of space-time they inevitably expose relations which cannot be traced any more, once we have bunched them into classes and drawn them out of their place in the block.
(Hägerstrand, 1974)

♦

Everything is related with everything else, in a compositional way, contextual way, or both.

♦

Random number generation is too important to believe that it is indeed random.
(Coveyou)

♦

The application or even the structure of activity-based models could be different when people usually conduct out-of-home activities 18 or more hours a day.

♦

Chance comes to the person who is ready to catch.
(Pasteur, 1854)

♦

Everything depends on your mind.
(Buddha)

♦

I am still hungry.
(Guus Hiddink, 2002)