Grouping of Optimized Pedestrian Routes for Multi-Modal Route Planning: A Comparison of Two Cities

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Abstract. The purpose of multi-modal route planners is to provide the user with the optimal route between trip start and destination, where the route may utilize several transportation modes including public transportation. The optimal route is defined over a set of evaluation criteria considered by the user during the route selection process. Especially in the case of multi-modal transportation, numerous evaluation criteria play a role in the traveler's route choice. Thus the number of requested search parameters in the route planner may be large, and the user interface is overcrowded easily. Based on a set of pedestrian routes that are optimized for various criteria in multi-modal, inner-urban transportation networks of two European cities, an exploratory study based on Principal Components Analysis (PCA) identifies underlying factors that capture the correlations among route selection criteria. The results show how the variability of routes can be parsimoniously described with a smaller set of components, and how these findings can be used to simplify the user interface design of multi-modal route planners.

Keywords. Multi-modal route planning, spatial decision support, user interface design, pedestrian navigation, network analysis

1. Introduction

Various existing route planners provide access to public transportation systems, which encourage their use and help reduce individual car traffic. Especially when it comes to multi-modal route planning, the number of optimization criteria involved in the decision making process is extensive, and user interfaces may be complicated to use. A simple user interface is crucial for the success of a route planning system. This research aims at finding underlying factors that explain the variability of routes between trip start and destination that are optimized for various criteria. The results can be used to simplify the route planner user interface by reducing the number of parameter settings input by the user.

Route selection problems commonly involve a set of route alternatives from which a choice of an alternative must be made under consideration of several evaluation criteria. This is also true for the use of a route planner if the user can specify route preferences. With this paper, we address route selection within the framework of multi-attribute decision making (MADM). The MADM framework involves a selection among a limited set of alternatives and has a single, implicitly defined objective (Malczewski 1999). The objective is functionally related to, or derived from the set of attributes, and alternatives are described by their attributes. Solving a MADM problem involves the sorting and ranking of alternatives according to an underlying decision rule. A decision rule is a procedure that integrates information on alternatives and the decision maker's preferences to produce an evaluation of the set of alternatives. Two classes of decision rules can be distinguished: compensatory and non-compensatory. The compensatory approach is based on the assumption that the high performance of an alternative achieved in one or more criteria can compensate for the weak performance of the same alternative in other criteria. Contrarily, under the non-compensatory approach a poor performance by an alternative in a criterion cannot be offset by another criterion's good outcome.

Evaluation criteria (which are also called attributes or decision variables in the MADM framework) include benefit criteria and cost criteria. For a benefit criterion, a higher attribute score is more attractive, whereas for cost criteria, a lower score is more desirable. Eliminatory constraints impose limitations on the set of decision alternatives. An alternative is feasible if it satisfies all eliminatory constraints.

1.1. Route Selection Criteria for Pedestrians in Multi-Modal Networks

Whereas pedestrian route choice has been studied for many years, research on route preferences in multi-modal trips is sparsely reported in literature. Findings from both areas are relevant, as a multi-modal route planner should provide the user with the necessary choice options for defining and selecting the optimal route. Generally speaking, the set of attributes must be complete to cover all relevant aspects of a decision problem (Keeny and Raiffa 1993).

An empirical study by Heye and Timpf (2003) investigated factors that influenced the complexity of transfer processes in public transportation networks. The four most frequently mentioned physical characteristics of transfer points in participants' responses were transfer distance, streets to cross, signage, and number of lines. Whereas minimizing time is one of the most widely used optimization criteria in multi-modal route planning, for budget tourists and the general public cost is often as important as time optimization (Chiu et al. 2005). Avoidance of uncertainties about travel conditions has also been found important. For example, studies have shown that public transportation for which travel time uncertainties are relatively low in cities where public transportation is favored, overpasses private transportation when travel times are rather similar (Peytchev and Claramunt 2001).

In pedestrian navigation shortest routes are often chosen, although pedestrians are seldom aware that they are minimizing distance as a primary strategy (Lausto and Murole 1974). The disutility of a route depends, besides distance or travel time, also on the proximity of obstacles or other physical obstructions, the number of sharp turns, the expected number of interactions with other pedestrians (Hoogendoorn and Bovy 2004), and on traffic, number of crossings, amount of crime, attractions, and weather protection (Senevirante and Morrall 1986). A study by Daamen et al. (2005)

examined the influences of changes of vertical levels on passenger route choice and showed that stairs provided highest disutility, followed by ramps and escalators. Golledge (1995) identified relevant route selection criteria for pedestrian navigation in a known campus environment. In questionnaires, subjects rated shortest route, route taking the least time, and route proceeding in the direction of destination as the most important criteria. Fewest turns, first noticed, and usual route were the next important criteria. Muraleetharan and Hagiwara (2007) investigated the benefits of improving the overall level-of-service (LOS) at walkways and crosswalks. The results indicate that on longer travel paths, pedestrians divert from the shortest-path route and use high LOS sidewalks and crosswalks. On the contrary, when the destination is less than a few hundred meters away from the start, the probability that a pedestrian would utilize the shortest route becomes high, regardless of the route-LOS.

1.2. Designs of Multi-Modal Route Planners

A growing number of electronic multi-modal route planners that are freely available on the Internet provide evidence for the increasing popularity of these spatial decision support tools. To give an idea of frequent route planner functionalities this section reviews the pedestrian related route choice options provided in three selected multi-modal route planners for Europe (BayernInfo 2008; JPL 2008; SCOTTY 2008). All three route planners support non-compensatory decision making by allowing the user to set a single optimization criterion, and/or by setting eliminatory constraints. Thus the route planners do not provide importance weighting and the selection of compromise routes. JPL (2008), a journey planner for London, provides a selection option between fastest route, route with fewest changes, and routes with least walking between stops, whereas the other two route planners use a default optimization function that is hidden from the user. The latter two route planners allow, however, to set the maximum number of transfers as an eliminatory constraint instead. All three route planners provide an option to deselect undesired public transportation means, and to specify the maximum walking distance or time. With JPL (2008), the user can set mobility requirements, such as avoiding stairs. Further, it provides an option to search for walk-only routes if they are faster than with public transit. This function is, however, redundant if fastest route is chosen as optimization criterion. Other relevant route selection criteria, such as route with short transfer waiting times, are not included in any of the three planners. Chiu et al. (2005) suggest that users of multi-modal route planners should be offered with comparisons between fastest and cheapest route, as one optimization criterion may not provide the optimal route.

Related research found that route selection criteria used in bicycle trip planning can be grouped into four general criteria (Hochmair 2004; Hochmair 2007). If public transportation planning is combined with bicycle route planning, the criteria can be grouped into five general criteria, which are fast, simple, quiet, scenic, and safe (Hochmair 2008). Based on Principal Components Analysis (PCA) and the use of street and public transit datasets from two European cities, this research will expand previous research to pedestrian route planning in combination with transit transportation.

1.3. Structure of the Paper

The remainder of this paper is structured as follows. Section 2 describes the setup of the computer-based exploratory study, and section 3 formulates the challenges and computational approaches for seeking a Pareto optimal set of routes in a multi-modal transportation network. Section 4 analyses the retrieved route sets using PCA and discusses its results with respect to the user interface design of route planners. Conclusions and future work are presented in section 5.

2. Design of the Exploratory Study

2.1 Test Networks

The datasets represent part of the street and public transportation networks of Vienna, Austria (**Fig. 1**a), and Bremen, Germany (**Fig. 1**b).

(a) (b)

Fig. 1. Layout of street and public transportation networks for Vienna (a) and Bremen (b)

The Vienna test network has 631 links and 404 nodes, the Bremen test network 701 links and 470 nodes. A node is defined as intersection or end of a cul-de-sac, and a link is a roadway or transit segment between two nodes. In the Vienna test area, public transportation is provided through three metro lines (U2, U3, U6) (dashed lines), 15 tram lines (5, 6, 9, 18, 33, 37, 38, 40, 41, 42, 43, 44, 46, 49, J) (dark continuous lines), and two bus routes (13A, 48A) (light continuous lines). Metro-stops are marked with "U" symbols, and tram and bus stops with color-coded circles. The Bremen test area has 7 tram lines (1, 2, 3, 4, 6, 8, 10) and three bus routes (22, 24, 25). The transit density, which we define as total length of public transit edges over total length of street edges, amounts to 40.3% in the Vienna test network, and to 17.7% in the Bremen network. The timetables of public transportation used in the network modeling can be found at *http://efa.vor.at/wvb/index_en.htm* for Vienna, and at *http://www.bsag.de/eng* for Bremen. None of the two test areas contains pedestrian zones.

For the exploratory study, a set of 50 start-destination pairs was selected from each test network. For each of these pairs, a set of Pareto optimal paths was explored as described further below. The search algorithm was programmed in Delphi and run on a desktop PC.

2.2 Route Selection Criteria Included in the Optimization Process

As far as possible, the route selection criteria in pedestrian navigation and public transit use identified in previous work were implemented in the network structure and the algorithm for seeking Pareto optimal route sets (**Table 1**). A path is called Pareto optimal if no other path from the available route set has (a) a better value for at least one criterion and (b) at least equally good values for all other criteria. Such path is also called non-dominated. The set of non-dominated paths is the Pareto optimal route set.

Table 1. Route selection criteria used in the optimization process

Street level		**Public Transit level**		**Combined level**	
Link-related	*Node-related*	*Link-related*	*Node-related*	*Link-related*	*Node-related*
Walking distance	Traffic lights	Transfers	Choice options at transfer	Travel time	Turns and transfers combined
Parks	Intersections	Trip fare			
Sights	Turns				
Shopping streets	Street crossings during public transportation transfer	Transfer waiting time			
		Public transportation portion			

The 15 route attributes are measured as ratio values. The Bremen test area is mostly residential and does not include sights, which makes 14 attributes for that network. As all transit vehicles in both public transit networks will be wheelchair accessible in the near future, mobility requirements were excluded from the set of optimization criteria in the study. The distinction into link-related and node-related criteria refers to whether the attribute values are stored with links or nodes in the network graph. Cost criteria are underlined, whereas benefit criteria are printed as plain text.

3. Modeling Approach

3.1 Problem Formulation

It has been found earlier by Vilfredo Pareto that even without making any multicriteria decisions the solution space of a multi-criteria problem is already partially ordered so that all dominated solutions can be eliminated from consideration before the multicriteria decisions are made (Pareto 1896). In consequence, we explore underlying factors among route characteristics based on a set of Pareto optimal routes. The methods used to seek the Pareto frontier will be described.

Single-criterion shortest path problems (SSP) find the shortest path using a single optimization criterion, e.g., travel time, whereas multi-criteria shortest path problems (MSPP) consider two or more independent criteria in evaluating the solution. Solving a SSP or MSPP can help to build the Pareto optimal route set. Historically many MSPP are reduced to a SPP by using a weighted linear combination of all criteria as the cost function. However, it may be difficult to compute an appropriate set of weightings for the criteria involved, and optimal solutions may be overlooked (Mooney and Winstanley 2006). Even the bicriteria path-problem in a graph is NP-hard, but pseudo-polynomial time algorithms are known that find all Pareto paths in a graph in time polynomial in the number of paths and nodes (Hansen 1980). The problem is that with a MSPP there may exist an exponential number of non-dominated solutions in the worst case. An SPP or MSPP path approach cannot solve problems that involve benefit criteria, as there exists no polynomial-time algorithm for the longest path problem if the network contains negative cycles (Hardgrave and Nemhauser 1962). The latter is generally true for street networks. This paper uses a genetic algorithm to optimize routes regarding benefit criteria, such as parks, and Dijkstra's algorithm to minimize cost criteria of a route, e.g., travel time.

Multi-modal route planning systems need to account for the transfer between different transportation modes. This involves modeling of the physical complexity of the transfers (Heye and Timpf 2003), or modeling of a dynamic waiting time that depends on the time the commuter arrives at the station and the departure time of the vehicle. For both public networks a fixed amount is charged per trip. The fare is independent of the number of transfers made or stops traveled.

3.2 Network Modeling and Graphs

The basic model of the road network is a weighted, directed node graph G=(V,E) which comprises a set of vertices V and edges E connecting these vertices. Edges carry values for cost and benefit criteria, such as distance or number of sights. In addition to this, vertex cost, i.e., cost associated with each pair of connected edges in the node graph, need to be included as well. For this purpose the node graph is mapped to a line graph $D(N_D, E_D)$, which allows cost functions for traversing a segment and a vertex in the node graph to be attached as attributes to graph elements in a line graph. For details the reader is referred to related work (Winter 2002).

The line graph is particularly useful for finding routes which minimize cost between connected edges, such as waiting time at traffic lights or intersections, turn cost, or cost associated with choice options at transfers. The SP algorithm is executed on the line graph of the original network graph. In search for routes that minimize a street bound cost criterion (e.g., turns), public transportation segments are excluded from the SP route search, and a route that is exclusively running on street segments is returned. A walking speed of 4 km/h is assumed for a pedestrian.

3.3 Modeling Travel on Public Transportation Routes

To model the transfer between transportation modes, a technique based on node explosion (Spiess and Florian 1989; Meng et al. 1999) is used. This approach takes the node graph of the street network and transforms it into the expanded node graph G'=(V', E') through the following steps (**Fig. 2**):

For each directed public transportation route K, do the following:

- For each stop v_i along the route add a new vertex $v_{i,K}$ to the expanded graph.
- Replace each directed edge $e_{i\text{-}j}$ along its route by three new directed edges, namely (a) an *access* edge $e_{i\text{-}i,K}$ that connects the access point v_i to the transit route, (b) a *traveling* edge $e_{i,K\text{-}j,K}$ that represents the commuter travel on the transit route from stop v_i to v_j, and (c) an *alighting* edge for exiting the transit route K at stop v_j.
- Add *transfer* edges $e_{i,K\text{-}i,L}$ (dashed lines) to all other traveling edges.

After node explosion, the expanded node graph is mapped to a line graph to facilitate all necessary shortest path computations.

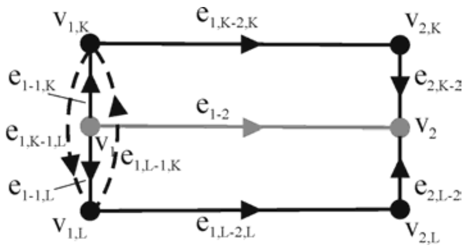


Fig. 2. Node explosion shown for two public transportation routes

3.4 Genetic Algorithm Framework

Over the last three decades genetic algorithms (GA) (Holland 1992), which are more recently also referred to as evolutionary algorithms (EAs), have gained high importance for exploring the Pareto front in multi-objective problems that are too complex to be solved by exact methods (Zitzler et al. 2000). Horn (1997) provides an overview of common methods that seek the Pareto front. Independent sampling (Fourman 1985) performs multiple single-criterion searches to optimize one criterion or a linear combination of criteria at a time where weights are varied from search to search. Simultaneous parallel search for multiple members of the Pareto optimal front includes among others criteria selection, aggregation selection, and Pareto selection. Pareto selection favors Pareto optimal solutions above others. Many of these efforts have incorporated some form of active diversity promotion, such as GA niching (Goldberg 1987), to find and maintain an even distribution sampling of points along the Pareto front.

Fig. 3 depicts the structure of the genetic algorithm used in the exploratory network application.

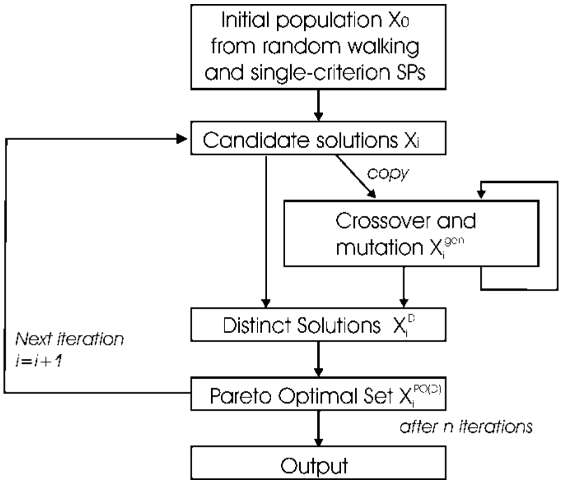


Fig. 3. Genetic algorithm for searching Pareto optimal routes

An initial population X_0 is created through random walking (Costelloe et al. 2001) on the line graph of the expanded node graph. In addition to this, initial routes are found through separate single-criterion SP computations that minimize walking distance, travel time, traffic lights, intersections, and turns. This gives the "corners" of the Pareto optimal surface for cost criteria. Next, a repeated standard one-point crossover and mutation are executed to find additional solutions on the Pareto front. A copy of X_i ensures that good solutions are not destroyed during crossover and mutation. This is followed by the elimination of duplicate solutions from the intersection of X_i and the modified set X_i^{gen}. Pareto elitist selection gives the Pareto optimal set of candidates $X_i^{PO(D)}$ which provides the population for the next iteration and grows with each of the 10 iterations used. No objectives are specified at this point, thus a fitness function and quality metric are not included in the framework.

Crossover describes the process where two chromosomes (the parents) line up and then swap the portions of their genetic code beyond the crossover point which creates two offspring. In the framework of this paper, candidate routes can be viewed as chromosomes, with the sequence of route segments being their genes (**Fig. 4**a).

Mutations make a random modification of the chromosomes. Whereas mutation is traditionally applied on one string (chromosome), the approach in this paper uses two parents to create a mutated offspring that replaces one parent. A random path is computed to connect the two randomly chosen points on both parent routes and to mutate the first parent (**Fig. 4**b).

Offspring with a walking distance more than twice the shortest path walking distance, or offspring with more than twice the fastest travel time were removed from the route pool, as these routes were presumed unacceptable by a user.

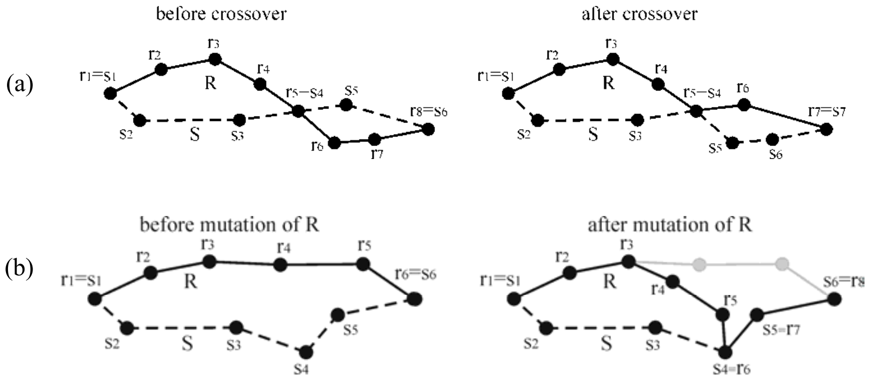


Fig. 4. Crossover (a) and mutation (b)

4. Results

913 (Vienna) and 1367 (Bremen) Pareto optimal paths were found in the search process for the 50 start-destination pairs. Some characteristics are summarized in **Table 2**.

Table 2. Descriptive values of the Pareto optimal route sets

	Vienna		**Bremen**	
Attribute	*Mean*	*SD (±)*	*Mean*	*SD (±)*
Total distance [m]	2589	787	3498	1154
Walking distance [m]	1493	740	2483	994
Trip time [min]	29.6	7.4	44.5	13.2
PT portion [%]	35.5	34.8	23.3	29.3
Waiting time [min]	5.6	3.8	9.2	6.6
Transfers	2.4	1.2	2.0	1.1
Choices at transfers	10.8	7.0	7.8	4.5
Turns	5.4	4.0	7.8	4.4

Waiting time, transfers, and choices at transfers are derived from routes that use public transit. Entering a transit route from the street level is counted as one transfer. The table shows that a smaller transit density in the Bremen network (see section 2.1) leads to a significantly smaller portion of public transit use (thus a larger portion walked in trips), a longer waiting time, and a smaller number of transfers and choices at transfers (p=0.000 for all four criteria; Mann Whitney Test).

4.1 Principal Components Analysis

This section explores whether the variability of the Pareto optimal route set can be more parsimoniously described by a smaller number of components using Principal Components Analysis (PCA). PCA involves a mathematical procedure that transforms a number of (possibly) correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible. That is, PCA chooses the first PCA axis as that line that goes through the centroid, but also minimizes the square of the distance of each point to that line. Each succeeding component accounts for as much of the remaining variability as possible. If as many components are retained as original variables specified, all variability will be accounted for. The trick is to retain the fewest number of components that explain the substantive amount of variance. Every axis has an eigenvalue associated with it, which is related to the amount of variation explained by the axis. The sum of eigenvalues amounts to the number of variables.

Except for the public transportation portion of a route (given in %) and trip fare, all route values, such as portion of parks along a route given in meters, were divided by the shortest path distance of the start-destination pair for cost criteria, or the actual path distance for benefit criteria, respectively. This scaling makes route characteristics for different start-destination pairs comparable, because attribute values, such as cultural landmarks passed by, generally increase with a longer trip distance. We model the complexity of a multi-modal route as a linear combination of turns and route transfers, because both the street and the public transit portion of a route contribute to route complexity. Based on the Pareto optimal route set, a combined complexity measure of *c=1*turns+3*transfers* for Vienna, and *c=1*turns+1.3*transfers* for Bremen was found to yield positive correlations between turns and transfers, and the combined complexity measure (Vienna: $r_{turn,c}$=0.690; $r_{transfer,c}$=0.453; p=0.000; Bremen: $r_{turn,c}$=0.424; $r_{transfer,c}$=0.749; p=0.000). These two linear combinations were used to calculate corresponding values for routes.

After the scaling, all attribute values were standardized using Z-scores. By standardizing, all variables have a standard deviation of 1, and the centroid of the whole data set is zero. A PCA on a standardized data set is an eigenanalysis of the correlation matrix, which must be applied if variables are measured in different units.

Table 3 lists the variance accounted for by successive components. The eigenvalues in the “Total” column describe the observed variance explained by each component. In the Vienna data set, for example, the first component with an eigenvalue of 7.382 accounts for about 49% of the variability of the 15 variables. Values are similar for Bremen.

Applying the Kaiser criterion, which suggests to retain all components with an eigenvalue of 1 or higher, yields four components for Vienna, and three for Bremen. In the Bremen data set, the variance explained by the fourth (6.7%) and fifth (5.8%) component are close to the third component (7.2%) so that consideration of four or five components to explain the variance seems justified as well. The first four components account for about 82% (Vienna) and 84% (Bremen) of the variance, as shown under "Cumulative %".

Table 3. Results of the PCA: Extracted components with initial eigenvalues and explained variances for Vienna and Bremen

Compo-nent	**Initial Eigenvalues (Vienna)**			**Initial Eigenvalues (Bremen)**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.382	49.211	**49.211**	6.634	47.387	**47.387**
2	2.501	16.677	**65.888**	3.156	22.541	**69.927**
3	1.376	9.171	**75.059**	1.011	7.223	**77.150**
4	1.093	7.284	**82.343**	0.941	6.723	**83.874**
5	0.639	4.263	86.606	0.818	5.845	89.719
6	0.611	4.074	90.680	0.501	3.579	93.297
7	0.525	3.500	94.180	0.380	2.711	96.008
8	0.270	1.799	95.979	0.213	1.521	97.529
9	0.246	1.637	97.616	0.161	1.147	98.676
10	0.176	1.172	98.788	0.091	0.653	99.328
11	0.074	0.491	99.278	0.061	0.439	99.767
12	0.061	0.404	99.683	0.030	0.212	99.979
13	0.041	0.276	99.959	0.003	0.021	100.000
14	0.006	0.041	100.000	0.000	0.000	100.000
15	0.000	0.000	100.000	-	-	-

Component loadings describe the correlation between components and variables, i.e., which of the original 15 (14) variables contribute to which component. To obtain a clear pattern of loadings, an orthogonal rotation that maximizes the variance on the new axes is obtained. The rotated component matrices (**Table 4** for Vienna and **Table 5** for Bremen) reveal what the different components represent. For example, the second column in **Table 4** means that the value of a route along the second axis of PCA is 0.858 times the standardized walking distance plus 0.424 times the standardized number of traffic lights, etc.

The meaning attached to rotated components is subjective and sometimes ambiguous, however, some tendencies can be identified.

For the Vienna dataset, the first component is marked by high loadings on attributes associated with route complexity, such as transfers, and street crossings and choice options at transfers. Although this component receives high loadings on fare and waiting time, the correlation with public transit is smaller than 0.6. Based on this and on the fact that the first component—as the only component—receives a high loading on the combined route complexity measure (last row), this component can be mostly ascribed to route simplicity.

The second component receives high loadings on walking distance, turns, intersections, travel time, and a negative loading on public transit portion. Although turns contribute to route complexity, the combined measure shows only a small correlation with this component, thus finding a simple route is not strongly supported by this component. In summary, this component could either be ascribed to fast route, or to public transit use, or a combination of the two. As public transit will generally be associated with reaching one's destination faster, the public transit part is omitted in our description of the component.

The meaning of the third component can be ascribed to route scenery, whereas the fourth component has high loadings on shopping streets. It is interesting to see that the shopping component appears instead of a safety related component which has been identified as the fourth component for bicycle navigation in previous work (Hochmair 2007).

Table 4. Rotated component matrix for Vienna with four components retained. Component loadings > 0.6 or < -0.6 are printed in boldface

	Component			
	1	2	3	4
Walking distance	-0.434	**0.858**	0.180	0.074
Traffic lights	-0.441	0.428	0.412	0.411
Turns	-0.115	**0.882**	0.001	-0.197
Parks	-0.118	0.172	**0.805**	-0.153
Sights	-0.098	0.084	**0.871**	0.090
Shopping streets	-0.012	-0.035	-0.061	**0.926**
Intersections	-0.417	**0.854**	0.193	0.041
Travel time	0.142	**0.865**	0.190	0.095
Transfers	**0.911**	-0.335	-0.106	-0.019
Fare	**0.649**	-0.598	-0.061	-0.038
Waiting time	**0.817**	-0.288	-0.029	-0.040
PT portion	0.593	**-0.753**	-0.166	-0.048
Street crossings	**0.746**	-0.023	-0.115	0.054
Choice options	**0.813**	-0.369	-0.140	-0.022
Turns, Transfers	**0.788**	0.474	-0.103	-0.198
Meaning attached to rotated components	*simple*	*fast*	*scenic*	*shopping*

With four components, the Bremen data set reveals a similar pattern of loadings as the Vienna data set (right part in **Table 5**). As the Bremen data set does not include sights the third component can be solely ascribed to parks along the route. Another noticeable difference is that the first component receives a comparably higher loading on the PT portion than the Vienna dataset.

When using three components (left part in **Table 5**), the loadings on the first two components show similar patterns as before. The last two components merge into a third component with a positive loading on shopping streets and a negative loading on parks. Reducing the weight for this component returns routes with fewer shopping streets and more parks. Thus this component can be referred to as quiet routes. When taking into account that shopping streets have not been identified as a prominent criterion in route selection in previous work, a three components solution would be as justified as a four components solution both for the Vienna and the Bremen data set. It would, however, be of interest to see whether the inclusion of pedestrian zones in the test networks would impact the component structures.

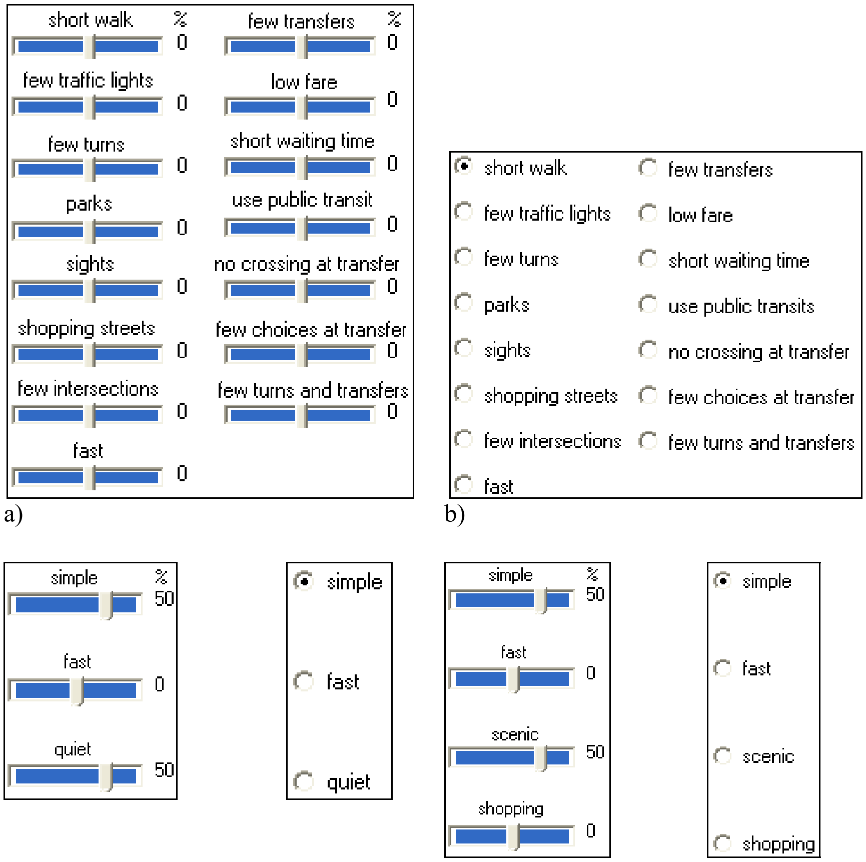
Table 5. Rotated component matrix for Bremen with three and four components retained. Component loadings > 0.6 or < -0.6 are printed in boldface

	Component			**Component**			
	1	2	3	1	2	3	4
Walking distance	-0.432	**0.870**	-0.090	-0.412	**0.869**	0.162	0.035
Traffic lights	-0.373	0.390	0.192	-0.346	0.449	-0.273	-0.046
Turns	-0.100	**0.866**	0.048	-0.076	**0.864**	0.044	0.096
Parks	-0.075	0.271	**-0.753**	-0.111	0.149	**0.948**	-0.013
Shopping streets	0.031	0.236	**0.616**	0.014	0.114	-0.007	**0.986**
Intersections	-0.399	**0.852**	0.064	-0.372	**0.868**	-0.004	0.072
Travel time	0.337	**0.872**	-0.084	0.357	**0.849**	0.183	0.045
Transfers	**0.965**	-0.162	0.025	**0.961**	-0.183	-0.021	-0.011
Fare	**0.800**	-0.284	0.081	**0.791**	-0.313	-0.032	0.077
Waiting time	**0.901**	-0.139	0.015	**0.898**	-0.159	-0.012	-0.015
PT portion	**0.781**	-0.542	0.082	**0.765**	-0.568	-0.063	0.052
Street crossings	**0.794**	-0.074	0.032	**0.796**	-0.083	-0.051	-0.037
Choice options	**0.957**	-0.139	0.015	**0.954**	-0.161	-0.010	-0.015
Turns, Transfers	**0.850**	0.428	0.045	**0.863**	0.406	0.019	0.048
Meaning attached to rotated components	*simple*	*fast*	*quiet*	*simple*	*fast*	*parks*	*shopping*

4.2 Implications for the User Interface Design

When using the 15 (14) factor loadings in each of the four (three) components as coefficients in a weighted linear combination of the z-scored criterion values, a large percentage (between 75% and 84%) of all Pareto optimal routes can be accessed. Without going into detail on how the optimal route, based on user preferences and settings, can be computed (Hochmair 2008), **Fig. 5** shows some user interface designs that reflect the findings of PCA.

The design in **Fig. 5**a allows the user to weight all 15 original multi-modal route selection criteria, which can be simplified to three or four slider bars based on the PCA results (**Fig. 5**c,e). Searching for a route that is optimized for exactly one of the three (four) components can be implemented through radio buttons (**Fig. 5**d,f), which simplifies the selection process compared to a comprehensive design (**Fig. 5**b). Additional check boxes to set eliminatory constraints (e.g., avoid unpaved streets), and edit fields to specify thresholds (e.g., set maximum cycling distance accepted) will be helpful in specifying the optimal route search parameters (Hochmair and Rinner 2005).



a) b) c) d) e) f)

Fig. 5. User interface designs: Slider bars and radio buttons for all 15 original criteria (a,b), and slider bars and radio buttons for three (c,d) and four (e,f) components

5. Conclusions and Future Work

The results of this explorative study show that a high number of route selection criteria in multi-modal pedestrian trips can be more parsimoniously described through three or four components. Although both analyzed networks reveal a significant difference in transit density, PCA gives similar results for both networks. This suggests that for other cities, as long as they provide public transportation, a similar grouping of route selection criteria and, in consequence, a similar simplification of user interfaces for route planners seems plausible. A possible variation in results may, however, be found if analyzed travel routes become longer (both in terms of distance and travel time), or when the type of environment changes, such as on an inter-urban trip with rural and urban regions involved.. This, however, is largely speculative at this point and must be subject to future research.

Another aspect of future work is to compare the presented results to real world travel behavior, i.e., how travel routes observed in an urban environment can be grouped based on PCA. Real world data collection is feasible but challenging. Harvey et al. (2008), for example, analyze bicycle commuter behavior that relies on the use of Global Positioning System (GPS)-based data collection. For multi-modal transportation modes, GPS may not suffice due to signal blockage inside buildings. Independent of the method used, future work should also take into consideration upcoming transportation means for pedestrians, such as the growing number of public bicycle rental programs in European cities, which offer free (or nearly free) access to bicycles for inner-city transportation.

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