Multi-criteria, personalized route planning using quantifier-guided ordered weighted averaging operators

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ABSTRACT

This paper presents a generic model for using different decision strategies in multi-criteria, personalized route planning. Some researchers have considered user preferences in navigation systems. However, these prior studies typically employed a high tradeoff decision strategy, which used a weighted linear aggregation rule, and neglected other decision strategies. The proposed model integrates a pairwise comparison method and quantifier-guided ordered weighted averaging (OWA) aggregation operators to form a personalized route planning method that incorporates different decision strategies. The model can be used to calculate the impedance of each link regarding user preferences in terms of the route criteria, criteria importance and the selected decision strategy. Regarding the decision strategy, the calculated impedance lies between aggregations that use a logical “and” (which requires all the criteria to be satisfied) and a logical “or” (which requires at least one criterion to be satisfied). The calculated impedance also includes taking the average of the criteria scores. The model results in multiple alternative routes, which apply different decision strategies and provide users with the flexibility to select one of them en-route based on the real world situation. The model also defines the robust personalized route under different decision strategies. The influence of different decision strategies on the results are investigated in an illustrative example. This model is implemented in a web-based geographical information system (GIS) for Isfahan in Iran and verified in a tourist routing scenario. The results demonstrated, in real world situations, the validity of the route planning carried out in the model.

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1. Introduction

Route planning and guidance systems are common decision support systems (McGinty and Smyth, 2000; Park et al., 2007; Jozefowiez et al., 2008; Sadeghi Niaraki and Kim, 2009). Routing algorithms are the main part of these systems. These algorithms are widely used in operational research, computer science, telecommunication, transportation, and geographical information system (GIS). Some well-known models exist for route planning, such as Dijkstra’s algorithm and the A* algorithm (Dijkstra, 1959; Hart et al., 1968). Research was carried out to improve these models, especially through their personalization (e.g., Rogers and Langley, 1998; Smyth and McGinty, 2002; Letchner et al., 2006; Zipf and Jost, 2006; Akasaka and Onisawa, 2008).

A personalized route guidance system provides a proper route based on minimizing a combination of user defined criteria, such as travel distance, travel time, the number of traffic lights, and road types. Selection of the appropriate criteria and defining the importance of each depends on user preferences (e.g., some travelers like high speeds on freeways, while others prefer small scenic roads). A route that incorporates user preferences is ultimately more suitable than the route with the shortest distance or travel time.

In a route planning system, user preferences for each criterion can be identified manually by the system designer (or by the user) or automatically by discovering patterns and regularities in the repeated route choice behaviors of the users. Systems that apply the manual method are called “adaptive personalized route guidance systems”, while systems that use the automatic method are called “adaptive personalized route guidance systems” (Zipf and Jost, 2006).

This study examines adaptive personalized route planning systems. These systems model multi-criteria decision making by considering each route in a network as an alternative and their attributes based on criteria weighed by the user. The goal of the adaptable personalized route planning systems is to aggregate criteria values and their relative weights in order to obtain overall scores for each route and, ultimately, select the best route.

Some researchers have considered user preferences in navigation systems. However, they neglected the user’s decision strategies (Zipf and Jost, 2006; Jozefowiez et al., 2008; Sadeghi Niaraki and...
Kim, 2009). A decision making process defines whether a user insists on satisfying all of his/her preferences regarding the selection of one route from a set of routes. In other words, does he/she desire all the criteria to be satisfied or will he/she be happy if most of the criteria are satisfied? For example, a user may require a scenic route, which means that the route must be near the seaside or a riverside road or green spaces such as parks. The decision strategy represents the spectrum of the user’s desires and satisfaction, which ranges from a situation in which all the criteria are satisfied to the satisfaction of at least one criterion. In this spectrum, there are situations in which the decision maker desires to meet a Q portion of the criteria, where Q is a linguistic term like “most” or “many”. Yager (1988) introduced ordered weighted averaging (OWA) operators to model a family of parameterized decision strategies. This extended decision making process can be applied to route planning in order to provide more realistic results.

This paper proposes a new personalized route planning model based on the integration of pairwise comparison methods and quantifier-guided OWA operators for determining the user’s preferred route. The model is based on a four-step multi-criteria decision-making approach. In the first step the effective criteria in route planning and their corresponding functionalizations are defined. In step two, the relative importance of the criteria showing the user preferences are calculated. In the third step the decision strategies are incorporated into the model by calculating the corresponding order weights of the OWA operator. Step four includes calculation of the impedance of each route using fuzzy quantifier-guided OWA aggregation, determination of the best route by solving the corresponding minimization problem and determination of the robust personalized route regarding different decision strategies. The model allows users to determine different alternative routes by choosing different decision strategies. Then the user has the flexibility of changing his/her route if he/she was not satisfied with one route due to occurrence of problems like crashes or traffic jams. The model also determines a personalized route with the robust deviation shortest route algorithm. Following this route, the user can change his/her route to any other alternative route with minimal effort. An example is presented in this paper to demonstrate the influence of different decision strategies on the outcome of the proposed model. The model is implemented in a web-based GIS for Isfahan in Iran and verified in a tourist routing scenario. The results demonstrated the validity of the routes derived from the model in real-world situations.

Section 2 provides an overview of the related research in personalized route planning. The methods used in this research, including the identification of effective road segment criteria in route planning, the normalization of criteria, calculations for the importance of criteria, the incorporation of decision strategies using fuzzy quantifier-guided OWA operators and the determination of the robust personalized routes are presented in Section 3. Section 4 presents an example using the synthetic graph. In Section 5, the implementation of the model is described and different examples are provided. The model verification is presented in Section 6. Section 7 discusses the practical and theoretical implications of the model. The conclusions and some future studies are presented in Section 8.

2. Related work

In previous studies on user preferences in route guidance systems, some researchers modeled particular parts of the user behavior, such as the desire for the choice of simplest route with the fewest number of turns (Duckham and Kulik, 2003) and the desire for more reliable wayfinding with the least semantically equivalent junctions (Haque et al., 2007). Some other researchers used multi-criteria techniques, such as the Analytical Network Process (ANP) or the Analytical Hierarchical Process (AHP) to model a combination of user desires (Sadeghi Niaraki, 2008; Sadeghi Niaraki and Kim, 2009; Stepanov and Smith, 2009). Furthermore, some personalized route planning models relied on machine learning techniques, which require large amounts of data to provide sufficient results (Rogers and Langley, 1998; Rogers et al., 1999; Park et al., 2007; Choi et al., 2008). More recent studies found that the most direct way to obtain information about user preferences is to simply ask users (Akasaka and Onisawa, 2008; Volkel and Weber, 2008; Sadeghi Niaraki and Kim, 2009).

Golledge (1995) performed experiments that defined the important route selection criteria humans use. Jozezwie et al. (2008) examined routing problems in terms of the definitions, objectives, and multi-objective algorithms proposed for solving these problems. A taxonomic classification of vehicle routing literatures based on the type of study, scenario and physical, information and data characteristics is also presented in Eksioglu et al. (2009).

Winter (2002) modeled the cost of turns in an edge-edge graph and Klippel and Winter (2005) investigated different turns and argued that Y-intersections and other unusual network structures are salient entities along the routes and may be used as landmarks. Klippel (2003) studied the cognitive characteristics of routes. He defined the wayfinding chromosomes as mental conceptualizations of primitive functional route directions and of wayfinding elements. Klippel et al. (in press) analyzed how people describe turning actions at intersections. They provided recommendations to improve the next generation of route guidance systems.

Richter (2009) regionalized the environment by considering the heterogeneity of its structure and applied different route planning strategies for each of the emerging regions to cognitively minimize the complexity of traveled routes. Richter (2007) also presented a process for defining context-specific route directions that are more memorable and includes the spatial situations that can be encountered while following a route.

Zipf and Jost (2006) introduced an ontology for modeling user and context using a vector of criteria and calculating the overall preferences of users in a tour planning application. Sadeghi Niaraki and Kim (2009) integrated AHP and a generic ontology-based architecture to identify and define a class of road segment criteria for personalized route planning. Sadeghi Niaraki (2008) used ANP to model the relative influence among the groups of road segment criteria.

Decision making is a central component in numerous applications like route planning (Geiger and Wenger, 2007; Jozezwie et al., 2008; Sadeghi Niaraki and Kim, 2009). However, developing more realistic results will require more sophisticated score valuation methods than AHP or ANP. Yager (1988) proposed the ordered weighted averaging (OWA) method that provides a parameterized family of aggregation operators including many well-known operators. Investigations were carried out to integrate the OWA concept as a component of multi-criteria decision analysis (Fodor and Roubens, 1992; Fuller, 1996; Herrera et al., 1996). Eastman (1997) implemented the OWA as a module in the IDRISI software, which is also used by Jiang and Eastman (2000) for land use suitability assessment. Malczewski (2006) incorporated the concept of fuzzy (linguistic) quantifiers into the GIS-based land suitability analysis using OWA and showed how a wide range of multi-criteria decision rules (strategies) could be obtained by applying the appropriate fuzzy quantifiers. Rinner and Malczewski (2002) implemented the OWA module in CommonGIS software, which is used in a web environment. Malczewski and Rinner (2005) also included fuzzy quantifier-guided OWA in the CommonGIS OWA module and used it for evaluating residential quality. Boroushaki and Malczewski (2008) implemented an extension of the AHP technique with fuzzy quantifier-guided OWA in ArcGIS software. Rinner
and Raubal (2004) proposed a personalized location-based service (LBS), using OWA, for finding the most preferable hotel.

All of these studies intended to incorporate users’ needs and provide a more satisfactory solution than conventional approaches. Including decision strategies in multi-criteria decision models with OWA operators has not been studied in route planning applications yet. This paper considers that route guidance systems not only generate personalized routes, but they must also include user specific decision strategies in a manner that can provide multiple options regarding the user’s preferred decision strategies. We study the inclusion of different decision strategies in personalized route planning based on an integration of pairwise comparison method and quantifier-guided OWA that provides the user with the flexibility to determine multiple routes regarding different decision strategies.

3. Methodology

Navigation algorithms use a cost function to determine the impedance of a given route. A simple cost function may add up the length of the links in a given route to calculate the total cost of the route. Then the shortest route can be determined by finding the minimum cost route. In a personalized route planning system, in which a vector of criteria values are assigned to each road segment, the cost function aggregates the values regarding the user’s preferences to obtain the overall cost of each road segment.

In this paper, we propose a personalized route planning using a four step multi-criteria decision making approach. The details of this approach include the following (Fig. 1):

1. Identification and normalization of the effective criteria in route planning.
2. Determination of user preferences and calculation of the relative importance of criteria.
3. Calculation of the order weights of the OWA operator, corresponding to each desired decision strategy of the user.
4. Calculation of the impedance of each route using fuzzy quantifier-guided OWA aggregation, determination of the best route by solving the corresponding minimization problem and determination of the robust personalized route regarding different decision strategies.

3.1. Effective road segment criteria in route planning

The route choice criteria used in this paper present fundamental attributes of routes. The availability of selected criteria is considered too. Other criteria, however, could be included based on user preferences.

3.1.1. Road segment criteria definition

The 10 most fundamental attributes of routes are (1) Travel Distance (TD), (2) Travel Time (TT), (3) Type of Road (ToR), (4) Travel Reliability (TR), (5) Directness (Di), (6) Quality of Road (QoR), (7) Width (W), (8) Slope (S), (9) Number of Stop Signs (NoSS) and (10) Number of Scenic Landscapes (NoSL) (Golledge, 1995; Sadeghi Niaraki and Kim, 2009). These criteria are defined in Table 1.

Table 1: Definitions of route choice criteria.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel Distance (TD)</td>
<td>The geometric distance of each road segment</td>
</tr>
<tr>
<td>Travel Time (TT)</td>
<td>Travel duration of each link regarding its average traffic volume</td>
</tr>
<tr>
<td>Type of Road (ToR)</td>
<td>Defined as an expressway, major or minor arterial, etc.</td>
</tr>
<tr>
<td>Travel Reliability (TR)</td>
<td>The probability of a traffic jam due to a crash or another problem</td>
</tr>
<tr>
<td>Directness (Di)</td>
<td>The Euclidian distance between the start and end of each link divided by the link</td>
</tr>
<tr>
<td>Quality of Road (QoR)</td>
<td>Asphalt, gravel road, laterite road, etc.</td>
</tr>
<tr>
<td>Width (W)</td>
<td>The average width of each link</td>
</tr>
<tr>
<td>Slope (S)</td>
<td>The average slope of each link</td>
</tr>
<tr>
<td>Number of Stop Signs (NoSS)</td>
<td>The number of stop signs along the link, such as traffic lights and cross ways</td>
</tr>
<tr>
<td>Number of Scenic Landscapes (NoSL)</td>
<td>The number of scenic landscapes along the link such as historical buildings, green spaces and riversides</td>
</tr>
</tbody>
</table>

These criteria are categorized into qualitative and quantitative variables. TD, TT, TR, Di, W, S, NoSS and NoSL are quantitative criteria. They are measured from a digital map of the road network. The ToR and QoR are considered as qualitative criteria. ToR is a nominal criterion that includes road types such as expressways, major arterials, minor arterials, collectors and local access roads. QoR is also a nominal criterion that includes the variables good asphalt, moderate asphalt, bad asphalt, macadam road, gravel road and laterite road.

3.1.2. Road segment criteria normalization

Various criteria of different alternatives are normalized and combined to make the alternatives comparable. The maximum score procedure is the most common method of normalization which transforms criteria scales into a unique comparable scale. Using this
Table 2: Normalization of the route choice criteria.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Range of original values</th>
<th>Normalized values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel Distance (TD)</td>
<td>[0,∞)</td>
<td>F: [0,∞) → [DTmin/DTmax, 1], F(DT) = DT/DTmax</td>
</tr>
<tr>
<td>Travel Time (TT)</td>
<td>[0,∞)</td>
<td>F: [0,∞) → [TTmin/TTmax, 1], F(TT) = TT/TTmax</td>
</tr>
<tr>
<td>Type of Road (ToR)</td>
<td>(Expressway: 1, major arterial: 2, minor arterial: 3, collector: 4, local access: 5)</td>
<td>F: [1,2,3,4,5] → (1,1/2,1/3,1/4,1/5,1/2,3/2,4/3,5/3/4,5/4,5/4,5/5)</td>
</tr>
<tr>
<td>Travel Reliability (TR)</td>
<td>(0,1]</td>
<td>F: TR → ln(TR)</td>
</tr>
<tr>
<td>Directness (Di)</td>
<td>(0,1]</td>
<td>F: [0,1] → [Di/Dimax, 1], F(Di) = Di/Dimax</td>
</tr>
<tr>
<td>Quality of Road (QoR)</td>
<td>(Good asphalt: 1, moderate asphalt: 2, bad asphalt: 3, macadam road: 4, gravel road: 5, laterite road: 6)</td>
<td>F: [1,2,3,4,5,6] → (1,1/2,1/3,1/4,1/5,1/6,2/3,2/4,2/5,2/6,3/4,3/5,3/6,4/5,4/6,5/6,6)</td>
</tr>
<tr>
<td>Width (W)</td>
<td>[0,∞)</td>
<td>F: [0,∞) → [W/Winax, 1], F(W) = W/Wmax</td>
</tr>
<tr>
<td>Slope (S)</td>
<td>(−100, 100)%</td>
<td>F: [−100, 100) → [S/Smmax, 1], F(S) = S/Smmax, where Sm =</td>
</tr>
<tr>
<td>Number of Stop Signs (NoSS)</td>
<td>[0, 1, 2, ...)</td>
<td>F: [0,1,2,...] → [1,1/2,1/3,2/3,2/4,4,...], F(NoSS) = NoSS/NoSSmax</td>
</tr>
<tr>
<td>Number of Scenic Landscapes (NoSL)</td>
<td>[0, 1, 2, ...)</td>
<td>F: [0,1,2,...] → [1,1/2,1/3,2,3,2/4,4,...], F(NoSL) = NoSL/NoSLmax</td>
</tr>
</tbody>
</table>

The normalized value is obtained by dividing each value by its maximum value for a given criterion [Eq. (1)] (Malczewski, 1999). Before normalizing nominal criteria values, they must first be converted to an ordinal scale with a ranking method

\[ x'_i = \frac{x_i}{x_{max}} \]  

where \( x'_i \) is the normalized value and \( x_i \) is the raw value of a given criterion for the ith alternative, and \( x_{max} \) is the maximum score of the criterion.

The values of normalized scores range from 0 to 1. In a decision situation, if the larger values for a criterion are more preferable, the criterion is referred to as a benefit criterion and if the lower values for a criterion are more desirable, the criterion is called a cost criterion (Malczewski, 1999). In route planning, because the values of criteria are more desirable, the criterion is called a benefit criterion and if the lower values for a criterion are more preferable, the criterion is referred to as a benefit criterion and if the lower values for a criterion are more preferable, the criterion.

Table 2 shows the appropriate normalization functions and their corresponding domain and range for each criterion.

Among the criteria, TD, TT, QoR, NoSS and the absolute value of S are cost criteria normalized by Eq. (1), W and NoSL are benefit criteria normalized by Eq. (2). ToR and Di can have a positive or negative impact on route choice behavior and are considered to be either benefit or cost criteria depending on user preferences.

TR is calculated by determining the probability of congestion occurrence due to a problem like a car accident. \( P_{ij} = 1 - P_{ij} \) presents the reliability of the link \( ij \), where \( P_{ij} \) is the probability of congestion occurrence on this link. Since the individual links operate independently, then the reliability of traveling through a route (a sequence of links) is \( \text{TR}_{ij} = P_{i1} \times P_{12} \times \cdots \times P_{nm} \), where subscripts \( s \) and \( r \) are the notations for origin (start point) and destination (target point) of the route, respectively. The maximum TR is algebraically equivalent to maximize \( \ln(\text{TR}_{ij}) \), where \( \ln \) is the natural logarithm. Thus, applying \( ln \), the reliability of a route is mapped to a cumulative function, \( \ln(\text{TR}_{ij}) = \ln(P_{i1}) + \ln(P_{i2}) + \cdots + \ln(P_{nm}) \) which is more appropriate for routing algorithms. Since \( 0 < P_{ij} < 1 \), then \( \ln(P_{ij}) < 0 \) and the problem of maximum reliability is equivalent to minimize \( -\ln(\text{TR}_{ij}) \). Therefore, \( -\ln(\text{TR}) \) is a cost criterion normalized by Eq. (1).

Regarding the ToR, the cost of selecting a specific type of road is represented by a value of 1 for an expressway, 2 for a major arterial, 3 for a minor arterial, 4 for a collector, and 5 for a local access road. For an individual that prefers to drive on expressways than on major arterials and is reluctant to drive on minor, collector or local roads, these values make the ToR a cost criterion. In the case of an individual who has the opposite preferences, these values make ToR a benefit criterion and must be transformed to a cost criterion through the normalization process with Eq. (2).

For the QoR, a general assumption is made that the users are more reluctant to use laterite roads and gravel roads compared to macadam roads, bad asphalt roads, moderate asphalt roads, and good asphalt roads. This is modeled by assigning a cost value of 6 for laterite road, 5 for gravel road, 4 for macadam road, 3 for bad asphalt roads, 2 for moderate asphalt roads and 1 for good asphalt roads.

3.2 Calculating relative importance of the criteria

The cost of each link is the weighted aggregation of its attributes. The weight vector represents a user model that defines the relative importance of the attributes. These weights (priorities) can be determined through a normal pairwise comparison (Saaty, 1980) or through a structured pairwise comparison (Sharifi et al., 2006).

In a normal pairwise comparison, the judgments are made on scale of 1, 3, 5, 7 and 9 for equal, moderate, strong, very strong and extreme importance, respectively. The scales of 2, 4 and 6 represent intermediate judgments. These scales of importance and their inverses for reverse comparison between the pairs form a matrix. The eigenvector associated with the biggest eigenvalue of this matrix, is the normalized importance weights of criteria (Saaty, 1980). The weights are all positive values ranging from 0 to 1 and sum up to 1.

If the judgments are not transitive, the pairwise comparison may be inconsistent. For example one may judge that TD is as important as TT and TT is as important as TR but TD is not ranked to be as important as TR. Saaty (1980) defined the Consistency Ratio (C.R.) using Eq. (3), which must be lower than 0.1 for a reasonable level of consistency.

\[ \text{C.R.} = \frac{\lambda_{max} - n}{n-1} \]
where $\lambda_{\text{max}}$ is the biggest eigenvalue of the pairwise comparison matrix, $n$ is the number of criteria to be compared and R.I. is the random consistency index. R.I. is a constant value for criteria. Saaty (2008) calculated it as the average of the consistency ratios of a very large sample of randomly generated reciprocal matrices.

In a normal pairwise comparison, no order is followed when comparing a criterion with others. This technique often causes the mentioned inconsistency problem and also entails a large number of comparisons, which makes it difficult to be completed by a user. Structured pairwise comparison improves these problems with a two-step judgment. In the first step, all criteria are sorted in a descending ranked order. In the second step, the relative importance of each of the two consecutive criteria is determined on the scale of “weakly more important” or “strongly more important” (Sharifi et al., 2006). Since the criteria are sorted in a ranked order and the comparisons are conducted between adjacent criteria, these two steps describe the difference between two adjacent ranked criteria. In this process, a “weak” preference represents one unit more important and a “strong” preference represents two units more important (Taleai et al., 2007). The comparisons between non-adjacent criteria are done by summing up the importance units of the previous criteria. For example, in a comparison between three criteria, if the first one is weakly more important than the second one (i.e., one unit more important), which in turn is strongly more important than the third one (i.e., two units more important), then, the first one will be three units more important than the third one.

Once the matrix of the pairwise comparisons is generated, the calculation of the importance weights will be the same as the normal pairwise comparisons.

### 3.3. Modeling decision strategies

In order to form an overall cost of each route, the values of its criteria are aggregated, considering the weight of the importance of each criterion. A primary factor in selecting an aggregation function is the user’s desired decision strategies. One extreme is the situation in which the user desires that all the criteria be satisfied, and at the other extreme the user is satisfied if any of the criteria were met. Different user’s decision strategies, regarding the aggregation of the criteria for each alternative, are located between the mentioned two extreme strategies.

#### 3.3.1. Ordered weighted averaging operators

Yager (1988) introduced OWA operators as a general class of mean-like aggregation operators that include max., min. and average. An $n$-dimensional OWA is a mapping $F: R^n \rightarrow R$ with an associated weighting vector $W = [w_1, w_2, \ldots, w_n]$ in which $w_j \in [0, 1]$, \( \sum_{j=1}^{n} w_j = 1 \). F is defined in Eq. (4) (Yager, 1988):

$$F(x_1, x_2, ..., x_n) = \sum_{j=1}^{\sigma(n)} w_j x_{\sigma(j)}$$

where $\sigma$ is a permutation that sorts the criteria scores $x$ in a descending order ($x_{\sigma(1)} \leq x_{\sigma(2)} \leq \ldots \leq x_{\sigma(n)}$). The ordering of the criteria scores is critical for OWA as it makes OWA a nonlinear aggregation operator. Yager (1988) showed that for any weighting vector, $W$, $\min(x_1) \leq F(x_1, x_2, ..., x_n) \leq \max(x_1)$.

By selecting the appropriate weights in $W$, different arguments can be raised and emphasized based upon their position within the order. For example, if most of the weights were placed near the top of $W$, the criteria with higher scores are emphasized and if the weights were placed near the bottom of $W$, then the criteria with lower scores in the aggregation process are emphasized.

OWA is a general aggregation operator that can represent different aggregation operators by selecting different weights. Yager (1988) introduced two measures which describe the behavior of an OWA operator. The first one is the degree in which an OWA operator behave like an OR operator. This degree is named maxness (initially called orness) and is defined in Eq. (5):

$$\text{maxness}(w_1, w_2, ..., w_n) = \sum_{j=1}^{n} \frac{n-j}{n-1} \cdot w_j$$  \hspace{1cm} (5)

Based on Eq. (5), as the behavior of an aggregation operator goes from minimum to maximum, the maxness degree will range from 0 to 1. The equation shows that for the minimum, maxness(0,0,0,0)=0, for the maximum, maxness(1,1,1,1)=1 and for the average, maxness(1/n,1/n,1/n,...,1/n)=1/2.

The second measure describes the dispersion of the weights and can be used to measure the degree to which all the information available in criteria scores is used. This measure is defined by Eq. (6) (Yager, 1988):

$$\text{dispersion}(w_1, w_2, ..., w_n) = -\sum_{j=1}^{n} w_j \cdot \ln(w_j)$$ \hspace{1cm} (6)

Although the weighting vector $W$ can be determined directly by the user, some approaches exist which are based on maxness and/or dispersion degrees. For example, O’Hagan (1988) proposed a mathematical programming approach based on maximization of the degree of dispersion under the constant degree of maxness. In his approach, the user must specify the degree of maxness that reflects his/her decision strategy. When $W$ becomes more like OR (satisfaction of at least a criterion), its maxness comes closer to 1 and it comes closer to 0 as $W$ becomes more like AND (satisfaction of all criteria). An OWA operator with the majority of its non-zero weights near the top is an OR-like operator. When the majority of the non-zero weights are near the bottom it is an AND-like operator.

Another approach uses linguistic quantifiers. In this approach, the user specifies his/her decision strategy with a linguistic term such as “most” or “many”. This term is used to calculate order of the weights. This approach is more intuitive for this study is described in the following section.

#### 3.3.2. Quantifier-guided OWA operators

Adopting Zadeh’s linguistic quantifier concept (Zadeh, 1983), Yager (1996) introduced quantifier-guided aggregations using OWA. In a quantifier-guided aggregation process, the decision maker provides a decision strategy with a linguistic quantifier that indicates the portion of the criteria he/she feels is necessary for a good solution. The formal decision strategy is “Q criteria must be satisfied by an acceptable alternative”, where Q is substituted with a linguistic quantifier.

Two classes of quantifiers were used: absolute quantifiers for quantifying linguistic variables like “about 4” and “almost 10”, and relative quantifiers, which is used for statements like “few” and “most” (Fuller, 1996). There is no empirical evidence showing the suitability of one of these two classes of linguistic quantifiers for a multi-criteria evaluation (Yager, 1996; Malczewski, 2006). This paper uses a class of the relative quantifiers known as the regular increasing monotone (RIM) quantifiers. This class of quantifiers is most common in personalized systems (Malczewski, 2006). In this approach, $Q(r)$ for each $r \in [0,1]$, represents a membership that indicates the compatibility of $r$ with the concept denoted by $Q$.

There have been several RIM quantifiers introduced in the literature (Chandramohan and Rao, 2005). The simplest and most commonly used method is the exponential function [Eq. (7)] (Fuller, 1996)

$$Q(r) = r^\alpha, \quad \alpha > 0 \quad \text{and} \quad r \in [0,1]$$ \hspace{1cm} (7)

Based on these quantifiers, Yager (1996) computed the weights with Eq. (8)

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right)$$ \hspace{1cm} (8)
3.3.3. Criteria relative importance in quantifier-guided OWA

In many applications of multiple criteria aggregation, including route planning, in addition to the ordered weights of the criteria (\( w_j \)), another weight (\( v_j \)) is required to reflect the relative importance or the priority of the criteria. The former term reflects the decision strategy and the latter allows decision makers to emphasize on some criteria over the others.

Yager (1998) proposed an approach based on fuzzy system modeling that included importance weights in an OWA aggregation process. Malczewski et al. (2003) proposed to calculate the weighted score of each criterion regarding its relative importance (\( v_j \)) at the first step and then OWA incorporates the scores to calculate the overall score of each alternative. The most common approach is based on linguistic quantifiers (Fuller, 1996). Yager and Kelman (1999) used Equation (10) to calculate the order weights (\( w_j \)) regarding the relative criteria importance (\( v_j \)):

\[
W_j = Q \left( \frac{\sum_{k=1}^{j} v_k}{n} \right) - Q \left( \frac{\sum_{k=1}^{j-1} v_k}{n} \right) \quad (10)
\]

Employing the RIM quantifier in Eq. (7), Eq. (11) is obtained, which can be used directly to determine the weight vector based on the weights (\( v_k \)) and the decision strategy indicated by \( \alpha \):

\[
W_j = \left( \frac{\sum_{k=1}^{j} v_k}{n} \right)^\alpha - \left( \frac{\sum_{k=1}^{j-1} v_k}{n} \right)^\alpha \quad (11)
\]

As mentioned in Section 3.2, the relative importance of the criteria can be calculated with a normal or structured pairwise comparison method and sums up to 1. Therefore, Eq. (11) is simplified to Eq. (12):

\[
W_j = \left( \frac{1}{n} \sum_{k=1}^{j} v_k \right)^\alpha - \left( \frac{1}{n} \sum_{k=1}^{j-1} v_k \right)^\alpha \quad (12)
\]

where \( v_k \) is the relative weights and \( \alpha \) is a parameter indicating the decision strategy. Using this equation, the order weight vector, \( W \), can directly be calculated for any decision strategy.

### Table 3

Selected linguistic quantifiers with the corresponding order weights.

<table>
<thead>
<tr>
<th>Decision strategy</th>
<th>Parameter ( \alpha )</th>
<th>Maxness</th>
<th>Order Weights ( (n=10) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>All (AND operator)</td>
<td>( \rightarrow \infty ; (1000) )</td>
<td>0</td>
<td>( w_1 ), ( w_2 ), ( w_3 ), ( w_4 ), ( w_5 )</td>
</tr>
<tr>
<td>Most</td>
<td>5</td>
<td>0.17</td>
<td>0.00, 0.00, 0.00, 0.00, 0.00</td>
</tr>
<tr>
<td>Few</td>
<td>2</td>
<td>0.33</td>
<td>0.01, 0.03, 0.05, 0.07, 0.09</td>
</tr>
<tr>
<td>Half (mean operator)</td>
<td>1</td>
<td>0.5</td>
<td>0.10, 0.10, 0.10, 0.10, 0.10</td>
</tr>
<tr>
<td>Some</td>
<td>0.5</td>
<td>0.68</td>
<td>0.32, 0.13, 0.10, 0.08, 0.07</td>
</tr>
<tr>
<td>At least one (OR operator)</td>
<td>( \rightarrow 0 ; (0.00001) )</td>
<td>1</td>
<td>1.00, 0.00, 0.00, 0.00, 0.00</td>
</tr>
</tbody>
</table>

3.4. Planning personalized routes

After calculating the impedance of each link using the quantifier-guided OWA operators described in Section 3.3, the best route for each decision strategy is determined by solving a minimization problem for the calculated impedances. The best and the worst impedance of each link are also defined by decision strategies requiring “all” and “at least one” of the criteria to be satisfied. Adapting the approach by Montemanni and Gambardella (2004) for finding the shortest route over a network with interval arc cost, an algorithm for robust personalized routing is proposed in this paper and is outlined in Section 3.4.1.

3.4.1. Robust personalized route planning algorithm

Route planning in a network with positive costs for the links can be solved with well-known approaches like Dijkstra’s labeling algorithm. However, when the costs of the links are represented as intervals, a robustness approach is required (Yu and Yang, 1998). If the changes in the inputs of the analysis did not significantly affect the outputs, the analysis is considered to be robust (Malczewski, 1999). Using a robustness approach for personalized route planning, the determined route guarantees good performance under any possible impedance of each link according to the interval provided by the different decision strategies. This would be a route that has the most robust behavior based on changes in decision strategies of the user.

The approach proposed by Montemanni and Gambardella (2004) is adopted in this paper. This method can be used for any general directed graphs including transportation networks and is more comprehensive than the existing approaches, which work only for acyclic, layered graphs (Yu and Yang, 1998; Karasan et al., 2002).

In the robustness approach used in this paper, a directed graph \( G=(V,A) \) is defined with a node set (\( V \)), arc set (\( A \)), start node (origin) \( s \in V \), and a target node (destination) \( t \in V \) and \( C_{ij} = [l_{ij}, u_{ij}] \), where \( l_{ij} \) and \( u_{ij} \) are the lower and the upper bounds of the cost of link \( ij \) and \( 0 \leq l_{ij} \leq u_{ij} \). In this graph, a scenario \( r \), represents a snapshot of the network situation, in which a fixed cost, \( c_{ij}^r \in [l_{ij}, u_{ij}] \), is assigned to each arc \((ij) \in A \). In a scenario \( r \), the robust deviation (RD) for a route \( p \), from \( s \) to \( t \), is \( c_{r}^p - c_{\text{LCR}}^p \), where \( c_{r}^p \) is the cumulative cost of the route \( p \) and \( c_{\text{LCR}}^p \) is the cumulative cost of the least cost route \( \text{LCR} \) between \( s \) and \( t \). For an origin \( s \) and a destination \( t \), a route which has the least robust deviation among all routes from \( s \) to \( t \) and yet has the maximum robust deviation among all possible scenarios is called a robust deviation least cost route (RDLCR). In other words, for any route, \( p \), from an origin \( s \) to a destination \( t \), the least cost route is determined in any possible scenarios and the difference between the cost of this route and \( p \) is denoted as a robust deviation. The maximum robust deviation for the route under consideration is called robustness cost (RC). Among all the routes between \( s \) and \( t \), the route with the minimum robustness cost is the route which guarantees reasonably good performance under any possible configuration of travel costs over the network.
and is named as the robust deviation least cost route. There may be an infinite number of possible scenarios in a network with an interval arc cost, which makes it impossible to investigate all of the scenarios for robustness cost. Given a route \( p \) from \( s \) to \( t \), the maximum robust deviation happens in a scenario in which the costs of every arc on \( p \) are at upper limit, \( u_{ij} \), and the costs of all other arcs are at lower limit, \( l_{ij} \). This property makes it possible to determine the maximum robust deviation without investigating all of the possible scenarios.

Finding all routes from an origin to a destination computationally has a very poor efficiency, especially in a dense network. In this paper, the \( k \)-shortest route algorithm is used to calculate the \( k \) least cost routes from the origin to the destination instead of all the possible routes. Fig. 2 illustrates the algorithm for calculating the robust deviation least cost route.

4. Illustrative example and results

Fig. 3 shows the network to be evaluated and Table 4 illustrates the attributes of its links. The network is a directed graph consisting of six nodes and eight arcs. The personalized route and the robust personalized route between the origin node (\( s \)), and the destination node (\( t \)), are investigated in different decision strategies.

Following the method described in Section 3, four steps are carried out as follows:

Step 1. The attributes in Table 4 are normalized through the formulation described in Table 2. The result is presented in Table 5.

Step 2. User preferences are determined through a normal or structured pairwise comparison of the criteria. Table 6 shows the results of the normal pairwise comparisons.

The consistency ratio calculated using Eq. (3) equals 0.08, which is less than 0.1 and is acceptable. The normalized importance weights of each criterion are 0.08, 0.20, 0.04, 0.23, 0.02, 0.12, 0.05, 0.02, 0.22, and 0.02 for TD, TT, ToR, TR, Di, QoR, W, S, NoSS, and NoSL, respectively.

Step 3. The impedance of each link regarding different decision strategies is calculated using Eqs. (4) and (12). The results are shown in Table 7.

Step 4. Using the calculated costs from Step 3, the best route regarding different decision strategies is calculated. Fig. 4 shows the

### Table 4
Primary attributes of the links shown in Fig. 3.

<table>
<thead>
<tr>
<th></th>
<th>TD</th>
<th>TT</th>
<th>ToR</th>
<th>TR</th>
<th>Di</th>
<th>QoR</th>
<th>W</th>
<th>%</th>
<th>NoSS</th>
<th>NoSL</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-1</td>
<td>1000</td>
<td>15</td>
<td>Minor arterial</td>
<td>0.7</td>
<td>0.8</td>
<td>Bad asphalt</td>
<td>10</td>
<td>5</td>
<td>2</td>
<td>15</td>
</tr>
<tr>
<td>S-2</td>
<td>100</td>
<td>15</td>
<td>Minor arterial</td>
<td>0.8</td>
<td>0.75</td>
<td>Moderate asphalt</td>
<td>15</td>
<td>3</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td>2-1</td>
<td>460</td>
<td>20</td>
<td>Major arterial</td>
<td>1</td>
<td>1</td>
<td>Good asphalt</td>
<td>15</td>
<td>5</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>2-4</td>
<td>1100</td>
<td>26</td>
<td>Expressway</td>
<td>0.1</td>
<td>0.3</td>
<td>Laterite road</td>
<td>10</td>
<td>-10</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>1-3</td>
<td>1600</td>
<td>14</td>
<td>Minor arterial</td>
<td>0.5</td>
<td>0.79</td>
<td>Macadam road</td>
<td>12</td>
<td>15</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>3-4</td>
<td>150</td>
<td>4</td>
<td>Expressway</td>
<td>0.9</td>
<td>0.9</td>
<td>Good asphalt</td>
<td>12</td>
<td>1</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>4-t</td>
<td>340</td>
<td>5</td>
<td>Local access</td>
<td>0.7</td>
<td>1</td>
<td>Laterite road</td>
<td>8</td>
<td>5</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>

### Table 5
The normalized values of the attributes of the links.

<table>
<thead>
<tr>
<th></th>
<th>TD</th>
<th>TT</th>
<th>ToR</th>
<th>TR</th>
<th>Di</th>
<th>QoR</th>
<th>W</th>
<th>%</th>
<th>NoSS</th>
<th>NoSL</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-1</td>
<td>0.62</td>
<td>0.58</td>
<td>0.60</td>
<td>0.15</td>
<td>0.20</td>
<td>0.50</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
<td>0.25</td>
</tr>
<tr>
<td>S-2</td>
<td>0.06</td>
<td>0.58</td>
<td>0.60</td>
<td>0.10</td>
<td>0.25</td>
<td>0.33</td>
<td>0</td>
<td>0.20</td>
<td>0.67</td>
<td>0.50</td>
</tr>
<tr>
<td>2-1</td>
<td>0.29</td>
<td>0.77</td>
<td>0.40</td>
<td>0</td>
<td>0</td>
<td>0.17</td>
<td>0</td>
<td>0.33</td>
<td>0.17</td>
<td>0.50</td>
</tr>
<tr>
<td>2-4</td>
<td>0.69</td>
<td>1</td>
<td>0.20</td>
<td>1</td>
<td>0.70</td>
<td>1</td>
<td>0.33</td>
<td>0.67</td>
<td>0.83</td>
<td>0.50</td>
</tr>
<tr>
<td>1-3</td>
<td>1</td>
<td>0.54</td>
<td>0.60</td>
<td>0.30</td>
<td>0.21</td>
<td>0.67</td>
<td>0.20</td>
<td>1</td>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>3-4</td>
<td>0.09</td>
<td>0.15</td>
<td>0.20</td>
<td>0.05</td>
<td>0.10</td>
<td>0.17</td>
<td>0.20</td>
<td>0.07</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4-t</td>
<td>0.09</td>
<td>0.88</td>
<td>0.40</td>
<td>0.05</td>
<td>0.20</td>
<td>0.17</td>
<td>0.33</td>
<td>0.13</td>
<td>0.17</td>
<td>0.95</td>
</tr>
<tr>
<td>3-t</td>
<td>0.21</td>
<td>0.19</td>
<td>1</td>
<td>0.15</td>
<td>0</td>
<td>1</td>
<td>0.47</td>
<td>0.33</td>
<td>0.50</td>
<td>0.75</td>
</tr>
</tbody>
</table>
Table 6
Normal pairwise comparison of the criteria.

<table>
<thead>
<tr>
<th></th>
<th>TD</th>
<th>TT</th>
<th>ToR</th>
<th>TR</th>
<th>Di</th>
<th>QoR</th>
<th>W</th>
<th>S</th>
<th>NoSS</th>
<th>NoSL</th>
</tr>
</thead>
<tbody>
<tr>
<td>TD</td>
<td>1</td>
<td>1/5</td>
<td>3</td>
<td>1/5</td>
<td>7</td>
<td>1/3</td>
<td>1</td>
<td>7</td>
<td>1/5</td>
<td>9</td>
</tr>
<tr>
<td>TT</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>1</td>
<td>9</td>
<td>3</td>
<td>3</td>
<td>7</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>ToR</td>
<td>1/3</td>
<td>1/7</td>
<td>1</td>
<td>1/7</td>
<td>3</td>
<td>1/5</td>
<td>1</td>
<td>3</td>
<td>1/7</td>
<td>3</td>
</tr>
<tr>
<td>TR</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>1</td>
<td>9</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Di</td>
<td>1/7</td>
<td>1/9</td>
<td>1/3</td>
<td>1/9</td>
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<td>1/5</td>
<td>1/3</td>
<td>1</td>
<td>1/7</td>
<td>1</td>
</tr>
<tr>
<td>QoR</td>
<td>3</td>
<td>1/3</td>
<td>5</td>
<td>1/5</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>7</td>
<td>1/5</td>
<td>5</td>
</tr>
<tr>
<td>W</td>
<td>1</td>
<td>1/3</td>
<td>1</td>
<td>1/7</td>
<td>3</td>
<td>1/7</td>
<td>1</td>
<td>1</td>
<td>1/7</td>
<td>5</td>
</tr>
<tr>
<td>S</td>
<td>1/7</td>
<td>1/7</td>
<td>1/3</td>
<td>1/9</td>
<td>1</td>
<td>1/7</td>
<td>1</td>
<td>1</td>
<td>1/7</td>
<td>7</td>
</tr>
<tr>
<td>NoSS</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>1</td>
<td>7</td>
<td>5</td>
<td>7</td>
<td>7</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>NoSL</td>
<td>1/9</td>
<td>1/9</td>
<td>1/3</td>
<td>1/7</td>
<td>1</td>
<td>1/5</td>
<td>1/5</td>
<td>1</td>
<td>1/9</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 7
Impedances of the links regarding the selected decision strategies.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Most</th>
<th>Many</th>
<th>Half</th>
<th>Some</th>
<th>Few</th>
<th>At least one</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-1</td>
<td>0.15</td>
<td>0.20</td>
<td>0.29</td>
<td>0.39</td>
<td>0.48</td>
<td>0.56</td>
<td>0.62</td>
</tr>
<tr>
<td>S-2</td>
<td>0.00</td>
<td>0.09</td>
<td>0.23</td>
<td>0.37</td>
<td>0.49</td>
<td>0.59</td>
<td>0.67</td>
</tr>
<tr>
<td>2-1</td>
<td>0.00</td>
<td>0.03</td>
<td>0.12</td>
<td>0.27</td>
<td>0.44</td>
<td>0.61</td>
<td>0.77</td>
</tr>
<tr>
<td>2-4</td>
<td>0.20</td>
<td>0.56</td>
<td>0.75</td>
<td>0.85</td>
<td>0.92</td>
<td>0.96</td>
<td>1.00</td>
</tr>
<tr>
<td>1-3</td>
<td>0.20</td>
<td>0.31</td>
<td>0.47</td>
<td>0.63</td>
<td>0.77</td>
<td>0.90</td>
<td>1.00</td>
</tr>
<tr>
<td>3-4</td>
<td>0.00</td>
<td>0.01</td>
<td>0.05</td>
<td>0.09</td>
<td>0.13</td>
<td>0.17</td>
<td>0.20</td>
</tr>
<tr>
<td>4-t</td>
<td>0.05</td>
<td>0.07</td>
<td>0.15</td>
<td>0.31</td>
<td>0.51</td>
<td>0.73</td>
<td>0.95</td>
</tr>
<tr>
<td>3-t</td>
<td>0.00</td>
<td>0.15</td>
<td>0.25</td>
<td>0.41</td>
<td>0.60</td>
<td>0.80</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Fig. 4. The different strategies lead to the different routes.
corresponding routes for the selected decision strategies calculated in Table 7.

Using the two extreme impedance values corresponding to decision strategies for “all” and “at least one”, a network with an interval cost value is constructed. The network and the interval costs are shown in Fig. 5.

Using the algorithm shown in Fig. 2, the robust personalized route is determined. Fig. 6 shows all the possible routes from the origin, $s$, to the destination, $t$, and the corresponding calculations for determining the robust personalized route.

5. Model implementation

The proposed framework for the OWA-based personalized route planning is implemented as a web-based GIS tool with the PHP and Python languages. PHP is a widely used scripting language that was originally designed for web development. It can be embedded into HTML and generally runs on a web server. Python is an object-oriented, high-level programming language. Its high-level data structures, dynamic typing and dynamic binding capabilities make it very attractive for rapid application development. MapServer is an Open Source platform, used for publishing spatial data and interactive mapping applications on the web. MapServer has one of the most powerful cartography systems, provides data under dynamic high quality vectors and also it is one of the most matured web mapping projects since it was originally developed in the mid-1990 at the University of Minnesota in cooperation with NASA. PostgreSQL and PostGIS are also used. PostgreSQL has the...
advantage of being one of the most powerful open source and free object-relational databases. PostGIS provides support for spatial objects to PostgreSQL, allowing PostgreSQL to be used as a spatial database.

The OWA-based personalized routing system provides users with a configuration wizard to set his/her preferences (Figs. 7 and 8). The user settings are saved in his/her profile. On the left side of the wizard, the user can select the desired criteria to be included in personalized route planning. In the middle of the wizard, simple (Fig. 7) and full (Fig. 8) comparison options allow the user to determine the relative importance of the criteria. The simple option employs the structured pairwise comparison method. It is used to weigh the criteria quickly while the full comparison option is based on the normal pairwise comparison method that allows user to fully compare all of the criteria. To facilitate the weighing procedure for the user, two pre-defined scenarios are also provided: (1) a tourist trip, and (2) a business trip. The relative criteria importance for these two scenarios is obtained through a field survey and an interview process. In the right side of the wizard, the users can determine their decision strategies.

After adjusting the settings, the system is ready for use. Fig. 9 illustrates the general user interface of the system.

6. Verification of the model

To verify the model and illustrate its application in a real world routing problem, the transportation network of Isfahan, a city in Iran, was used. Data were collected from the Isfahan Municipality in a digital format at the scale of 1:2000, totalling 6000 km of roads covering 270 sq. km of area. TD, Di, W and S criteria for each link were calculated from the map and TT, ToR, TR, QoR, NoSS and NoSL were obtained from the Department of Traffic and Transportation in the Isfahan Municipality.

The model verification was conducted as a tourist scenario in a well-known environment. Its origin of the trip was the “Abbasi”
hotel and the destination was “Naghshe Jahan” square. Both are considered to be historical locations that are visited by many tourists.

Initially, the route criteria were presented to 32 tourists. Each tourist was asked to weigh the criteria with the structured pairwise comparison method described in Section 3. Then the relative importance of the criteria were calculated using the implemented system and five alternative routing scenarios associated with the “all”, “most”, “half”, “some” and “few” decision strategies were determined. Fig. 10 shows a sample of these routing scenarios.

Afterwards, paper maps were presented to each tourist. Each route map included a detailed description of its characteristics. The tourists were asked to select the best route out of the five routes. Then they were asked to select the second best route out of the remaining four routes. The selection process was repeated to prioritize all of the routes.

The results showed that the route for the scenario “all” was the best route according to 87.5% of tourists. The routing scenario “few” was ranked last by 84.375% of the subjects. The “half”, “most”, and “some” were ranked as the second, third and fourth choice by 81.25%, 75%, and 71.875% of subjects, respectively.

The results verified that the routes corresponded to the decision strategies of “all”, “most”, “half”, “some” and “at least one” are the choices of the users, respectively. These findings confirm that the model and the implemented system function properly in a road network.

7. Discussion

This paper proposed and verified a personalized multipath route planning model with a quantifier-guided OWA multi-criteria decision making technique. The model defined a set of personalized optimum routes from user preferences and decision strategies. The flexible technique of incorporating a pairwise comparison method and a quantifier-guided OWA multi-criteria decision making technique for driving user preferences and user decision strategy proved to be a reliable approach for addressing personalized route planning problems.

The advantages of the model and methods implemented are as follows:

1. In a real world situation, a predetermined route may not be available during a trip due to a variety of reasons, including accident. The multipath routing technique proposed in this paper provides the user with the flexibility of selecting from multiple alternative routes or changing his route toward another route that is available but is less preferable. Extensive research has been undertaken on a multipath routing technique known as the k-shortest route (Yen, 1971; Shier, 1979; Hadjiconstantinou and Christofides, 1999; Roditty, 2007). However, this technique is not widely deployed in practice. The proposed model in this paper is distinct since it is based on real situations and the user can neglect some of his/her preferences by selecting another decision strategy.

2. Using the normalization functions proposed in Table 2, the model is able to effectively include and compare qualitative as well as quantitative criteria associated with the user preference model. This is particularly important given the fact that in personalized route evaluation, there are qualitative criteria as important as the quantitative criteria. Even though many of the relevant route evaluation criteria are not currently available in digital form, the model has enough generality to include other criteria.

3. Since the criteria set and their relative importance varies among individuals and since comparison and weighing are complicated tasks, in addition to a full comparison using a normal comparison method, a simple comparison tool using a structured pairwise comparison method is implemented for a quick weighing of the criteria. Furthermore, two of the most commonly used scenarios for tourists and business trips are predefined and are included in the implemented system. The user can select these predefined scenarios and modify it according to his/her specific preferences.
Fig. 10. Different routing scenarios for the selected linguistic quantifiers.
4. The model provides a robust personalized route regarding the selected decision strategies. This route has the most robust behavior regarding the changes in decision strategy the user made. Following this route, user can change the route to an alternative route with minimal effort.

Besides the advantages of the model, its limitations are as follows:

1. Despite the popularity of the pairwise comparison technique and its structured version, these methods are often noted for their inability to sufficiently handle the inherent uncertainty associated with the mapping of a decision maker’s perceptions to exact numbers. In many practical cases, user judgments are uncertain and the user is unable to assign exact numerical values to the evaluated judgments. Since some of the service evaluation criteria are qualitative, it is very difficult, even for experts, to express the strength of their preferences and to provide exact comparison judgments. A new fuzzy based pairwise comparison method that derives the criteria weights from a fuzzy comparison process, may effectively improve the proposed model.

2. As there are route planning criteria that are time dependent, such as traffic congestion, the incorporation of such dynamic criteria might also improve the model outputs.

8. Conclusions and future works

This paper proposed a multi-criteria decision making model based on integration of a pairwise comparison method and quantifier-guided OWA method for personalized route planning. Personalization and user modeling are central issues that play a major role in modern GIS. This paper extends the personalization in route planning incorporating user preferences about (i) criteria to be included in the routing process, (ii) relative importance of the criteria, (iii) the decision strategy reflecting the portion of the important criteria, which their satisfaction are necessary for an acceptable solution and (iv) proposing personalized multipath routing.

The approach presented enables users to include a wide range of decision strategies, instead of a simple weighted average, into the process of calculating the impedance for each route. This method provides multiple alternative routes that reflect different decision strategies, which enables users to select one of the alternatives en-route. The determined robust personalized route in this paper is the route nearest to an ideal best route for all the decision scenarios. Therefore, if the user selected this route, he/she could switch to any other route with the least possible cost.

The implemented model incorporated the capabilities of fuzzy quantifiers within a web-based GIS system for personalized route planning. The model enhanced the existing web-based decision support systems for route planning. Implementation of this system as a location-based service (LBS) or ubiquitous GIS for in-vehicle usage could incorporate real time information such as traffic volume provided by intelligent transportation systems (ITS), into a personalized route planning model. Incorporating fuzzy numbers in a pairwise comparison to model uncertainties in users’ judgments could be studied in the future. Also, the usability and usefulness of the presented system should be investigated by conducting tests that address both user interface design and the suggested method using feedback provided by users of the web-based system when it becomes fully operational.

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