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MODAL SPLIT MODELLING USING MULTICRITERIA ANALYSIS AND DISCRETE FUZZY SETS

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Abstract: As users make transport mode choice decisions by taking several factors (criteria) into account, modal split may be regarded as a multicriteria problem and, therefore, solved using well-known multicriteria analysis methods Many of the possible factors of relevance for modal split are hard to quantify precisely and reliably the way users do. Decisions are made by users who evaluate these factors as they see, feel or estimate them. The incorporation of fuzzy sets theory into the modal split modelling procedure is primarily intended to allow users to give "less precise" answers to questions (in questionnaires) about relevant parameters (e.g., work trip duration: "short", "long", "around 5 minutes", etc.) as well as to permit transportation planners to process these data and use them later. This is why the TOPSIS method, as a multicriteria method adapted to handling imprecise discrete quantities, can be employed for modal split modelling. This paper presents an attempt at modal split modelling using multicriteria analysis and discrete fuzzy sets.

Keywords: Modal split, fuzzy sets, multicriteria analysis.

1. INTRODUCTION

Selecting the best solution from a set of alternatives by multicriteria analysis is a problem encountered frequently in practice. The choice of criteria and the determination of their values for given alternative solutions is an essential step in defining a control or decision choice problem. Fuzzy sets theory, as a possible approach to handling uncertainty in multicriteria analysis problems, has already found its application to this domain (PROMETHEE, AHP) [11, 1]. The fact that many real problems involve imprecisely expressed values or relative importances of criteria has motivated intensive research efforts in this area.[1]

One way to overcome the impossibility of expressing some quantities precisely is to describe them in terms of fuzzy sets or numbers whose membership function is often triangular or trapezoidal in form [12]. Some quantities are discrete by nature, while some others can be discretized for a particular problem and, consequently, described by discrete fuzzy sets. Of the many multicriteria methods whose original versions do not allow the treatment of uncertainty, we have decided to use the TOPSIS[1] method to demonstrate the introduction of discrete fuzzy sets into multicriteria ranking problems [5]

As users make transport mode choice decisions by taking several factors (criteria) into account, modal split may be regarded as a multicriteria problem and, therefore, solved using well-known multicriteria analysis methods. The result of this analysis is a final ranking list and/or the best among the offered alternatives. From the modal split standpoint, the final ranking list can be interpreted as the share of particular transport modes in the distribution of a certain number of trips.

Many of the possible factors of relevance for modal split are hard to quantify precisely and reliably the way users do. Decisions are made by users who evaluate these factors as they see, feel or estimate them.

By its nature, the procedure of expressing these parameters by actual numerical values involves a certain degree of error that is sometimes allowable, but may also be unacceptable. Of course, there also exists the possibility of expressing these parameters stochastically, i.e., in terms of probability distribution functions. This requires uniform conditions for selecting a sample and collecting data by questionnaires, and these are sometimes difficult to ensure. One of the ways to overcome these difficulties in some cases is to employ fuzzy sets theory.

The incorporation of fuzzy sets theory into the modal split modelling procedure is primarily intended to allow users to give "less precise" answers to questions (in questionnaires) about relevant parameters (e.g., work trip duration: "short", "long", "around 5 minutes", etc.) as well as to permit transportation planners to process these data and use them later.

If it is possible to describe the factors affecting modal split by a fuzzy set, they may be either discrete in nature (i.e., specified by a set of a number of values) or continual. Even if they are continual, they may be discretized for the given conditions and, consequently, described by a discrete fuzzy set. This is why the TOPSIS method, as a multicriteria method adapted to handling imprecise discrete quantities, can be employed for modal split modelling. This paper presents an attempt at modal split modelling using multicriteria analysis and discrete fuzzy sets.

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[1] The classical TOPSIS method is intended for the ranking of alternatives according to their distances from an ideal and antiideal solution. Finding these distances gives a measure of deviation for each alternative and ranking these values in a decreasing order yields a final ranking list.

2. WHAT IS THE MODAL SPLIT?

The modal split in transportation planning is an estimate of the possible volume of travel in a particular mode, i.e. the share of a specific transport mode in total travel demand.

The modal split is an element of a transport system development strategy for an area under consideration.

A large number of factors affect the modal split. Several different approaches to the modal split have been used. The methods applied differ depending on research goals, level and character, on information availability, etc. About 300 different modal split methods were known as far back as 1970 [3]. The method used for modal split forecasting depends on the overall planning procedure, i.e. on whether this method precedes or follows the determination of trip distribution. Depending on the calibration procedure, models can be classified into static and analytical, models based on choice probability, on user behaviour, etc. Models can be aggregate or disaggregate, depending on whether the basic unit under consideration is a spatial unit or an individual user. Binary and multimodal models can be distinguished according to the number of travel modes.

A transport system user's choice of the mode of transport is neither a static nor random process. This process is affected by several different factors [6] which can be classified into the following three groups:

- travel characteristics
- passenger characteristics
- transport system characteristics.

The main travel characteristics affecting a transport system user's choice of travel mode are: trip purpose, distance, duration, orientation in space, etc. For example, the modal split of work trips differs considerably from that of shopping trips. There exist radial-type trips directed to a center, trips from one residential area to another, trips from residential to work zones or some special-purpose zones, etc.

The modal split is also affected by the socio-economic characteristics of an individual or a household. These characteristics include: income, the number of cars, family size, the number of employed, age and education structure, etc. One of the most important factors of the modal split is the degree of motorization, because it directly determines the size of the population having the choice between a car and public transport in contrast to those who have no car and must use public transport.

Population density is also one of the factors used in analyzing and forecasting the modal split. The percentage of trips by public transport decreases with decreasing population density. This is explained by the fact that low-density areas can hardly be served by public transport at an adequate service level which would simultaneously be economically acceptable.

The notion of service level includes many transport system characteristics that affect, often decisively, the distribution between individual and public transport. Travel time and travel cost are the most widely used measures for comparing the efficiency or appropriateness of different means of transport (car/public transport); the results of these comparisons are expressed either as travel time or travel cost ratios or as their differences. The total travel time by public transport comprises the time in drive, terminal (pedestrian) times at trip source and destination points as well as the delay and mode switching times. In addition to the time in drive, the travel time by car is characterized, by a considerable portion of terminal time at trip destinations which depends on parking conditions.

Frequently, existing modal split models are not based on sufficient knowledge of individuals' life and work reality. The models usually give an adequate description of the physical characteristics of a transport system, but they often give an incomplete description of the social conditions under which trips are made. For a better analysis and modelling of user behaviour, it is necessary to study different components simultaneously: economic, social, psychological as well as the transport system components that affect user behaviour. Such a generalized approach should be provided using diverse methods that allow user behaviour to be studied from an individual's standpoint. The explanations of user behaviour (such as the travel mode choice) must take into account both the real components faced by an individual and the characteristics of the lifestyle (household, employment) that affect an individual's time and the organization of his environment. The real characteristics of an individual's lifestyle and the importance he attaches to them provide a background of behaviour analysis [4]

2.1. What is a nonaggregate approach to transportation planning?

Models based on aggregation at a transportation zone level explain interzonal differences but do not explain the differences among units within one zone [4]. Intrazonal behaviour is not homogenous in real-life conditions; moreover, intrazonal behaviour can be considerably more diverse compared to interzonal differences, especially if spatially large zones are considered. If a model is not applicable to different areas, its validity is questionable when the model is used in different zones of the same area. A significant difference occurs between the basic state and the values obtained by the model and this error is then introduced into the forecast.

As a separate forecast is made for each spatial zone, all data about the socio-economic characteristics and the transportation system must be at the zone level, but these are difficult to estimate for a future state.

It is characteristic of the aggregate approach that intrazonal differences in behaviour are neglected, so a considerable amount of important information about families and their behaviour is lost through the aggregation procedure.

The aggregate approach to modelling does not take intrazonal trips into account. There are many transportation studies that treat very large zones in which the intrazonal flows are relatively large but are not included in the model. The spatial boundaries "created" by the planner are not known to the user whose actual behaviour is different from the planner's assumptions.

Aggregation-based models produce significant differences even for the behaviour of homogeneous groups whose features are included in the model. These models may be incorrect because they do not explain individual user behaviour well enough, on the one hand, and do not use the available data about households that have been collected by surveys, on the other.

The disaggregate approach to modelling is based on the parameters of individual behaviour – of either a household or an inhabitant. Such an approach permits the real behaviour of household members and their trips to be treated and the studied parameters to be utilized more efficiently. The richer the data considered, the better the model's chances explaining individual differences. Considering individual behaviour and trying to discover actual relationships, one has greater chances of developing a model that is applicable, with certain constraints, to different areas and different populations.

The shortcomings of the disaggregate approach are a considerably longer and more expensive data acquisition and processing procedure, more complex interpretation of graphs, and difficulties in forming the units at the required level.

The definition of the model itself is not a problem in the disaggregate approach, the main problem is the impossibility to estimate future variable parameters at the required level of detail. This applies especially to long-term transportation forecasts.

As far as short-term studies of the effects of some measures are concerned, the disaggregate approach is much more suitable than the aggregate one. It requires a smaller amount of data and the observed existing state provides a sufficiently reliable background for short-term forecasting purposes. Citizens' views and opinions can also be obtained in this way. This is why the disaggregate approach is a valuable tool used by decision makers in evaluating the situation and analyzing the consequences of their decisions.

3. CRITERIA FOR TRAVEL MODE CHOICE

It is a very delicate task to select the parameters and criteria on the basis of which modal split decisions are made. In support of this statement, let us say that since the 1970s, both and in Yugoslavia and abroad, intensive efforts have been focussed on studying transportation system users' attitudes regarding the parameters that affect modal split. It has been shown in many of these studies, such as those by Hartgen and Tanner [3], Nicolaidis [10], Watson [14], Hauser, Tylbot and Koppelman [4], that the most important modal split parameters from the user's standpoint are:

- time (composite)
- cost
- comfort
- distance
- trip purpose

- trip frequency
- income.

In the mid-seventies the Transportation Planning Department of the Faculty of Traffic and Transport Engineering in Belgrade was among the first in Europe to study transport user behaviour and attitudes. In spite of the lack of relevant literature at that time, the first investigations were made to discover user attitudes regarding parameters relevant for travel route choice and user estimates of pedestrian, delay and driving times by passenger cars and public transport.

Studying travel time values in Belgrade, J. Jovi} [9] found that transportation system users highly overestimate travel time duration (they think that pedestrian, delay and driving times are two to three times longer than they actually are), and travel time is one of the most important parameters for modal split decisions.

One of the most comprehensive studies of user attitudes in Yugoslavia was made in 1984 by the Transportation Planning Department of the Faculty of Traffic and Transport Engineering in Belgrade. User attitudes and opinions concerning the transportation system of the city of Belgrade were investigated for the purpose of making Belgrade's Transportation System Study [14]... One of the main conclusions was that the citizens of Belgrade were the most sensitive to travel time and comfort in making their modal split decisions.

To the best of the author's knowledge, the latest study of transportation user attitudes towards travel mode choice in our conditions was carried out in 1991 [9]. A series of surveys was performed to investigate user attitudes on travel time, comfort, cost, etc. These surveys helped reduce the wide range of influential parameters to the following three basic:

- travel (duration) time consisting of:
- travel comfort
- travel cost.

Of the components of travel time (system access time – "door"-to-station time, delay time, driving time, transfer time, terminal time – exit station-to-"door" time), driving and pedestrian times are the most important to users. This is why driving time (min), pedestrian time (min), comfort (evaluation) and cost (monetary units) have been accepted as relevant criteria for the selection and ranking of alternatives.

4. MATHEMATICAL DESCRIPTION OF THE METHOD APPLIED TO MODAL SPLIT MODELLING

The multicriteria problem considered is to rank alternatives according to K criteria simultaneously. The set of alternatives is finite and has N elements.

The following notation is used for criteria values by alternatives that are specified by a discrete fuzzy set (DFS) [2]:

- F_i^k, $k=1,...,K, i \in A$, stands for the value of criterion k for the i-th alternative and is expressed by a discrete fuzzy set defined in its domain $x_i^k = \{x_m\}_i^k$, $m=1,...,M$, $i \in A$, $k=1,...,K$.

- $\mu_{F_i^k}(x_m)$ stands for the belief that an element x_m from domain $X=\{x_m\}$ belongs to DFS F_i^k.

- W_k, $k=1,...,K$ stands for the relative importance, or weight, of criterion k. It may be a specified coefficient or a fuzzy number.

In the case we are treating the multicriteria problem is defined as the choice of travel mode by a transportation system user. Two alternatives are given: passenger car (PC) and public transport (PT).

The notation described above applies to this problem as well:

- F_i^k, $k=1,2,3,4$, $i \in \{PA, JP\}$, stands for the value of criterion k for the i-th alternative and is expressed by a discrete fuzzy set defined in its domain $X_i^k = \{x_m\}_i^k$, $m=1,...,M$; $i \in \{PA, JP\}$, $k=1,2,3,4$.

- W_k, $k=1,2,3,4$ stands for the relative importance, or weight, of criterion k. It may be a specified coefficient or a fuzzy number.

- $\mu_{F_i^k}(x_m)$ stands for the belief that an element x_m from domain $X=\{x_m\}$ belongs to DFS F_i^k.

Let us illustrate this by an example: for the "passenger car" alternative, the following driving time values:

- 10 minutes
- 15 minutes
- 25 minutes

are known together with the following beliefs that respective driving times will be chosen:

$$\mu = \begin{cases} 0.28, & \text{for} \quad x=10 \\ 0.32, & \text{for} \quad x=15 \\ 0.35, & \text{for} \quad x=25 \\ 0, & \text{for} \quad x \notin X = \{10,15,25\} \end{cases} \tag{1}$$

These driving time and belief values were obtained in the previously mentioned studies. In the general case, beliefs can be determined using the Saaty method [1]. In the case of modal split criteria, a belief can be determined as the percentage of the studied user sample that chooses a given criterion value. The discrete fuzzy set specified in this way is presented in Fig. 1 and has the following meanings:

- driving time by passenger car will be 10 minutes with a membership degree of 0.28
- driving time by passenger car will be 15 minutes with a membership degree of 0.32
- driving time by passenger car will be 25 minutes with a membership degree of 0.35.

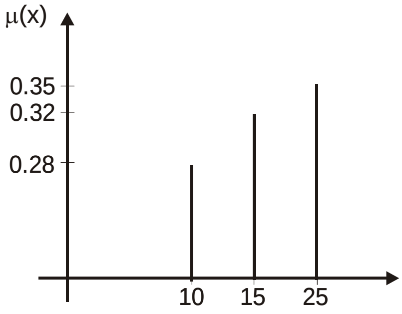

Figure 1: Driving time by passenger car specified by a discrete fuzzy set

The statement of the problem of transport mode choice is presented in Table 1.

Table 1: Statement of the problem of transport mode choice by a transportation system user

k	W_k	PC	PT
driving time (min) MIN	1	$\mu_{F_1^1}(x_m)=\begin{cases}0.28, \text{ for } x_1=10\\0.32, \text{ for } x_2=15\\0.35, \text{ for } x_3=25\\0, \text{ for } x\notin X=\{10,15,25\}\end{cases}$	$\mu_{F_1^1}(x_m)=\begin{cases}0.29, \text{ for } x_1=15\\0.31, \text{ for } ax_2=20\\0.29, \text{ for } x_3=25\\0, \text{ for } x\notin X=\{15,20,25\}\end{cases}$
pedestrian time (min) MIN	1	$\mu_{F_2^2}(x_m)=\begin{cases}0.5, \text{ for } x_1=5\\0.4, \text{ for } x_2=20\\0, \text{ for } x\notin X=\{5,20\}\end{cases}$	$\mu_{F_2^2}(x_m)=\begin{cases}0.5, \text{ for } x_1=10\\0.7, \text{ for } x_2=25\\0, \text{ for } x\notin X=\{10,25\}\end{cases}$
comfort (evaluation) MAX	1	$\mu_{F_2^2}(x_m)=\begin{cases}0.5, \text{ for } x_1=5\\0.7, \text{ for } x_2=9\\0, \text{ for } x\notin X=\{5,9\}\end{cases}$	$\mu_{F_2^2}(x_m)=\begin{cases}0.6, \text{ for } x_1=2\\0.3, \text{ for } x_2=6\\0, \text{ for } ax\notin X=\{2,6\}\end{cases}$
cost (m.u.) MIN	1	$\mu_{F_2^2}(x_m)=\begin{cases}0.5, \text{ for } ax_1=400\\0.8, \text{ for } x_2=1000\\0, \text{ for } ax\notin X=\{400,1000\}\end{cases}$	$\mu_{F_1^1}(x_m)=\begin{cases}0.2, \text{ for } x_1=200\\0.8, \text{ for } x_2=300\\0.9, \text{ for } x_3=500\\0, \text{ for } x\notin X=\{200,300,500\}\end{cases}$

PC - passenger car
PT - public transport

5. RESULTS OBTAINED BY APPLYING THE FUZZY TOPSIS METHOD TO DETERMINE RELATIONS IN THE MODAL SPLIT

As the statement of this multicriteria analysis problem involves fuzzy quantities, it is not possible to use directly any of the known multicriteria methods that operate with deterministic inputs. This is why we have decided to fuzzify the TOPSIS method.

The fuzzified TOPSIS method, adapted to the problem under consideration, consists of the following steps:

Step 1. Establishing the ranking of discrete fuzzy sets. Let $\bar{F}_i^k$ be a possible value in domain of F_i^k. The probability $p_{\bar{F}_i^k(x_m)}$ of $\bar{F}_i^k$ being equal to some of the values from domain $X_i^k = \{x_m\}_i^k$ of F_i^k is:

$$p_{\bar{F}_i^k}(x_m) = \mu_{F_i^k}(x_m)\left[\sum_{m=1}^{M}\mu_{F_i^k}(x_m)\right]^{-1}, \quad i = 1....,N,\ k = 1,...M \tag{2}$$

The probability distribution function is:

$$P_{F_i^k}(x_m) = \sum_{\substack{x_r < x_m \\ x_r \in X}} p_{\bar{F}_i^k}(x_r) \tag{3}$$

The measure of belief that F_i^k is smaller than F_j^k according to criterion k is:

- for a criterion to be maximized

$$m_{ij}^k(F_i^k < F_j^k) = \frac{W_k}{\sum_{k=1}^{K} W_k}\sum_{m=1}^{M} p_{\bar{F}_i^k}(x_m)[1 - P_{F_j^k}(x_{m+1})] \tag{4}$$

$\forall\, i, j \in A$ except $i = j;\ k = 1,...,K$

- for a criterion to be minimized

$$m_{ij}^k(F_i^k \geq F_j^k) = \frac{W_k}{\sum_{k=1}^{k} W_k}\left[1 - \sum_{m=1}^{M} p_{\bar{F}_i^k}(x_m)[1 - P_{F_j^k}(x_{m+1})]\right] \tag{5}$$

$\forall\, i, j \in A$ except $i = j;\ k = 1,...,K$

The measure showing how much alternative i is outranked by all other alternatives together according to criterion k is:

$$M_i^k = \sum_{j=1}^{N} m_{ij}^k, \quad i = 1,\dots,N;\ k = 1,\dots,K \tag{6}$$

Step 2. Finding the ideal and antiideal solution. After calculating all m_{ij}^k for all alternatives according to all criteria, matrices $\left\| m_{ij} \right\|^k$ are formed for each criterion. In the given example, these matrices are:

$$\begin{array}{cccc}
\text{for } k_1 m_{ij}^1 & \text{for } k_2 m_{ij}^2 & \text{for } k_3 m_{ij}^3 & \text{for } k_3 m_{ij}^3 \\
\left\| \begin{matrix} 0 & 0.49 \\ 0.074 & 0 \end{matrix} \right\| \begin{matrix} M_1^1 \\ M_2^1 \end{matrix} &
\left\| \begin{matrix} 0 & 0.189 \\ 0.811 & 0 \end{matrix} \right\| \begin{matrix} M_1^2 \\ M_2^2 \end{matrix} &
\left\| \begin{matrix} 0 & 0.138 \\ 0.851 & 0 \end{matrix} \right\| \begin{matrix} M_1^3 \\ M_2^3 \end{matrix} &
\left\| \begin{matrix} 0 & 0.889 \\ 0.1102 & 0 \end{matrix} \right\| \begin{matrix} M_1^3 \\ M_2^3 \end{matrix} \\
\min & \min & \max & \min
\end{array}$$

The elements of the indicators of ideal and antiideal solutions are obtained as follows:

$$M_{id} = (M_{JP}^1, M_{JP}^2, M_{PA}^3, M_{JP}^4)$$
$$M_{aid} = (M_{PA}^1, M_{PA}^2, M_{JP}^3, M_{PA}^4)$$

Mean beliefs that alternative i is worse than the ideal solution (D^+) and better than the antiideal solution (D^-) are calculated in the following way:

$$\begin{aligned} D_i^+ &= \sum_{k=1}^{K} m_{i,id}^k, \quad i = 1,\dots,N \\ D_i^- &= \sum_{k=1}^{K} m_{i,aid}^k, \quad i = 1,\dots,N \end{aligned} \tag{7}$$

where $m_{i,id}^k$ is the belief that alternative i is worse than the ideal solution according to criterion k, and $m_{i,aid}^k$ the belief that alternative i is better than the antiideal solution according to criterion k.

In the example considered here, this is:

$$D_{(PA)}^+ = 0.392$$
$$D_{(JP)}^+ = 0.2128$$

$$D_{(PA)}^- = 0.345$$
$$D_{(JP)}^- = 0.0275$$

Step 3. Finding the ranking order of alternatives. The measure of belief that alternative i is the last in the ranking order is calculated as follows:

$$D_i = \frac{D_i^+}{D_i^+ + D_i^-} \qquad (8)$$
$$0 \le D_i \le 1$$

Alternatives are ranked according to the decreasing order of D_i values. In our example we have:

$$D_{(PA)} = 0.532$$
$$D_{(JP)} = 0.886$$

so the final ranking order of alternatives is given in Fig. 2:

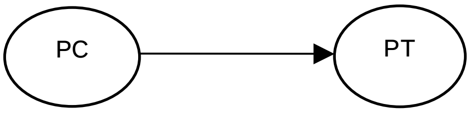

Figure 2: Graphical presentation of the ranking order of alternatives

To determine the percentage share of transport modes in the modal split, we will calculate the values:

$$D_i^* = 1 - D_i \qquad (9)$$

$$D_{(PA)}^* = 0.468$$
$$D_{(JP)}^* = 0.114$$

and normalize them.

After normalization we obtain:

$$D_{(PA)}^* = 0.79$$
$$D_{(JP)}^* = 0.21$$

These results indicate that the share of passenger car and public transport in the modal split is given by the following ratio:

$$PC = 79\%, \;\; PT = 21\%$$

This result shows the ratio in which passenger car trips will isolate from the matrix of motorized work trips and, thus, load the existing road network. To be usable for modal split modelling, this ratio has to be verified on real data. For the purposes of the present paper, we have accepted the ratio $PC = 79\%, PT = 21\%$ obtained by traffic surveys reported in [9]. Differences between the real data obtained by surveys and the results obtained by applying the TOPSIS method are less than 15%, which is an acceptable deviation.

6. CONCLUSION

Modal split modelling depends on numerous parameters that are diverse in nature. The values of these parameters are obtained from a data base made on the basis of traffic surveys whose quality depends on data acquisition and processing. Therefore, it is sometimes impossible to express all the required parameters precisely. This problem can be overcome by describing the given parameters in terms of discrete or continuous fuzzy sets. On the other hand, as the modal split is a multicriteria problem, we thought it would be interesting to model the modal split using a multicriteria analysis method.

The TOPSIS method, adapted for handling uncertainty, has given the expected result, i.e., it has permitted finding a relation in the modal split in the specified example. To be able to validate the final suitability of this approach for modal split modelling, more detailed studies are required, first of all of the possibility of describing the relevant modal split parameters by discrete fuzzy sets.

The applied procedure is based on survey results. Thus, for practical applications, surveys with a representative sample should be made. As standard planning procedure includes household surveys with a representative sample, the input data needed to use this method can be collected at such time.

The method described in this paper is universally applicable, but reasonable and competent usage is expected.

It would be useful to continue these studies in other areas and with representative spatial samples in order to broaden the application of the proposed procedure. It would be particularly beneficial to find out whether individual users have the same attitudes at travel source and destination points. Surveys carried out under the BETRAS [7] study have indicated that one person can have different estimates and views of travel time and comfort requirements at different source points.

Although travel cost has been studied in detail in many papers, further research should be extended to include the so-called "generalized cost" by applying the theory of fuzzy sets. This has not been done so far, although there are some indications that the use of these theories could facilitate and clarify the user's decision making procedure.

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