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Da Ruan · Frank Hardeman
Klaas van der Meer (Eds.)

Intelligent Decision and Policy Making Support Systems

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Preface

Humans have a remarkable capability to perform a wide variety of physical and mental tasks without any measurements or computations. Computerized systems mimicking such a human capacity are often referred to as artificial intelligence and computational intelligent systems. Decision support systems with such computerized systems that make decisions based on perceptions are then called intelligent decision support systems.

This edited book is a collection of a number of representative applications of intelligent decision support systems in society and policy support, including general methodologies, case studies, on-going R&D projects, and practical applications. The volume contains 14 chapters written by 33 authors from Australia, Belgium, China, India, Italy, Japan, Spain, the UK, and the USA. These applications cover *Intelligent Decision and Policy Making Support Systems* ranging from risk modelling for policy making ("Risk Modeling for Policy Making" by Yager), consensus modelling in group decision making ("Fuzzy Logic Approaches to Consensus Modelling in Group Decision Making" by Fedrizzi and Pasi), fuzzy data envelopment analysis ("Decision Making Based on Fuzzy Data Envelopment Analysis" by Guo and Tanaka), cognitive orientation in business intelligence ("Cognitive Orientation in Business Intelligence Systems" by Niu et al.), a personalized pedestrian navigation system ("Personalized Pedestrian Navigation System with Subjective Preference Based Route Selection" by Akasaka and Onisawa), a knowledge-based recommender system ("A Knowledge Based Recommender System Based on Consistent Preference Relations" by Martínez et al.), Web resource discovery and selection ("An Intelligent Recommender System for Web Resource Discovery and Selection" by Chen and Tao), a machine learning-based intelligent decision support system ("An Intelligent Decision Support System Based on Machine Learning and Dynamic Track of Psychological Evaluation Criterion" by Feng), handling uncertain and qualitative information ("Handling Uncertain and Qualitative Information in Impact Assessment: Applications of IDS in Policy Making Support" by Xu et al.), fault diagnosis ("Fuzzy Decision Trees as Intelligent Decision Support Systems for Fault Diagnosis" by Zio et al.), safety analysis

("Linguistic Assessment Approach for Hierarchical Safety Analysis and Synthesis" by Liu et al.), radioactive waste management policy decision making ("A Complex Abstraction Approach to Radioactive Waste Management Policy Decision Making" by Rao), Belgian long-term sustainable energy strategy ("Fuzzy-set Decision Support for a Belgian Long-Term Sustainable Energy Strategy" by Laes et al.), to nuclear emergency management ("On the Constructive Role of Multi-Criteria Analysis in Nuclear Emergency Management" by Turcanu et al.).

The major contributions are from the well-established international FLINS series conferences on applied computational intelligence (1994–2008). We believe intelligent decision support systems will become essential tools for future applications of risk analysis, safety, security, counter-terrorism, public option, and emergency responses in society and policy support.

January 2008

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Contents

Risk Modeling for Policy Making

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Summary. Supporting policy makers requires tools to aid in decision making in risky situations. Fundamental to this kind of decision making is a need to model the uncertainty associated with a course of action, an alternative's uncertainty profile. In addition to this we need to be able to model the responsible agents decision function, their attitude with respect to different uncertain risky situations. In the real world both these kinds of information are to complex, ill defined and imprecise to be able to be realistically modeled by conventional techniques. Here we look at new techniques arising from the modern technologies of computational intelligence and soft computing. The use of fuzzy rule based formulations to model decision functions is investigated. We discuss the role of perception based granular probability distributions as a means of modeling the uncertainty profiles of the alternatives. Tools for evaluating rule based decision functions in the face of perception based uncertainty profiles are presented. We suggest a more intuitive and human friendly way of describing uncertainty profiles is in terms of a perception based granular cumulative probability distribution function. We show how these perception based granular cumulative probability distributions can be expressed in terms of a fuzzy rule based model.

1 Introduction

Policy decisions run the gamut from taxation to health care to education to allocation of resources in combating terrorism. Almost all domains of human experience are effected by local, national or trans-national policy decisions. The support of decisions involving policy in most cases require tools to address issues related to a desire to satisfy multiple, often conflicting, goals and a need to negotiate between numerous, often adversarial, constituencies. In addition choices must be made in the face of uncertainty and associated risks. Further compounding any formal attempt to support policy decisions is the imprecision in much of the information provided by the participating agents. In this work we introduce some tools to address issues related to uncertainty and risk management. We are particularly concerned with problems inherent

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in the imprecision of our knowledge of uncertainty and the imprecision in the characterization of the policy makers risk tolerance.

The need for risk management arises when we have to make a choice involving a risky alternative. One component of a risky alternative is the uncertainty of the payoff (outcome) resulting from its selection, there are more than one possible outcome. Making decisions in the face of uncertain outcomes requires some of representation of our knowledge of uncertainties associated with the possible outcomes, for example probabilities. Often this information is impossible to obtain precisely and may require an imprecise and fuzzy characterization. Here we shall take advantage of Zadeh's [1–4] work on perception based probability information.

A fundamental difficulty that arises when making decisions involving alternatives with uncertain outcomes is the comparison of the alternatives. This is do to the fact that the multiplicity and complexity of these types of the alternatives makes their direct comparison almost impossible. Here we use rule based valuation functions to circumvent this difficulty.

An additional feature that distinguishes a risky alternative from one that is simply uncertain is that at least one of its possible outcomes is bad, 'undesirable' or 'disturbing.' The concept of undesirable is fuzzy and often involves aspects of human perception. Let us try to provide some intuition. Consider a financial decision in which we can make a profit of either \$50, \$100 or \$200. In this case while we have uncertainty with respect to the outcome and a preference for 200 over 100 over 50, we don't have a risky alternative because none of the payoffs are undesirable. On the other hand, consider an alternative with payoffs $\{-\$10,000,\ \$50,\ \$200\}$. This can be considered as a risky alternative because in addition to there being an uncertainty with respect to the outcome, it has at least one undesirable outcome. As another example we can consider is a person who has a non-life threatening medical disorder and is offered a treatment that can either cure his disorder or kill him. This can be clearly seen as a risky alternative. The determination of whether a particular outcome is undesirable is often subjective and context dependent. It is very much dependent on the current state of the decision maker, what in some situations would be considered as disturbing may in other situations not be considered disturbing.

A fundamental point that we want to make here is that the construction of decision functions involving these "risky" alternatives often involves some kind of categorization of outcomes with respect to their being undesirable or bad. From a formal point of view decision making with risky alternatives requires that the possible outcomes be expressed on a scale that is richer then an ordinal scale. The scale used must be of a bi-valent nature [5], having positive and negative members, and thereby enabling the capturing of concepts good and bad. An additional feature is that the concepts used to specify "bad" and "good" outcomes are generally fuzzy and imprecise.

We should note that in addition to comparing risky alternatives risk management involves another important aspect, the creation of new alternatives to better satisfy the needs of the participants. Since this process of alternative creation is generally domain dependent we shall not focus on this important issue. However the tools developed here can play an role in the part of risk management focusing on alternative creation.

2 Modeling the Valuation Function

One approach to addressing the problem of comparing alternatives having uncertain outcomes is to use a valuation function. These functions map the possible payoffs associated with an uncertain alternative into a single scalar value called its valuation. The association of a scalar value with an alternative allows us to easily compare alternatives. Conceptually these valuation functions can be viewed as a mechanism to enable the responsible decision maker to reflect their preferences among different uncertain situations. Statistics such as expected value, median and variance have historically been used to help provide valuation functions. With the consideration of risky alternatives the nature of the decision makers' preferences between different uncertain situations becomes more complex then can be captured by these simple statistics. In order to capture the decision makers preference in these situations we need more sophisticated structures for modeling the valuation functions.

One approach to modeling a decision makers preference structure, i.e. valuation function, is to use a rule based [6]. A rule base consists of a collection of statements, rules, each of which expresses the decision makers valuation (attitude) about a particular uncertain situation. The totality of these individual components constitutes the decision makers preference function. The use of a rule base allows a decision maker to express their preferences in a modular fashion. The facility of using a modular expression of their valuation greatly eases the task of formulating the function.

In Fig. 1 we see how this rule base (knowledge base) is used. An alternative is presented to the rule base which then provides a value for the alternative. The value V is some score associated with the alternative.

Fuzzy system modeling [6, 7] provides a well established framework for constructing these types of models used to capture the decision makers' valuation function in the form of a rule base. An individual component rule in the preference rule base is of the form

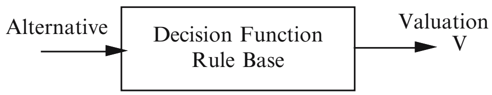

Fig. 1. Rule representation of decision function

If **antecedent** then V *is* S_i

where the term **antecedent** describes some characterization of a risky alternative. An example could be "if an alternative has a very bad outcome with a substantial probability of occurrence then give it a very low value."

In this approach we use predicates to construct the antecedent. Here we use Pred_i to indicate a predicate corresponding to some property or feature of an alternative. For any alternative A we can calculate $\mathrm{Pred}_i(A)$, the degree to which A satisfies the predicate. The antecedent of a rule may consist of a single predicate or a collection of predicates connected by some logical or other aggregation procedure. Typically the antecedent can be expressed in terms of properties associated with surrogate features of the uncertainty profile of an alternative. Things like variance, probability of particular situations, expected values are examples of these features. The consequent of the rule, V *is* S_i indicates a valuation of an alternative that satisfies this rule.

Given a collection of rules[1]

R_i: If Pred_i then V *is* S_i

the general procedure for working with these rules is as follows. For the alternative A we calculate $\mathrm{Pred}_i(A)$, the degree R_i is valid for this alternative. This gives us a collection of pairs $(\mathrm{Pred}_i(A),\ S_i)$. We then aggregate these pairs to get an overall valuation for the alternative being valuated, $V(A) = \mathrm{Agg}_i(\mathrm{Pred}_i(A),\ S_i)$. The methodology used to aggregate these pairs depends upon the structure underlying the partitioning of the uncertainty profile space by the rules. We note in fuzzy systems modeling the most common aggregation is a weighted average

$$V(A) = \frac{\sum_i \mathrm{Pred}_i(A)\ S_i}{\sum_i \mathrm{Pred}_i(A)}$$

Our focus here shall be on the formulation and evaluation of some types of predicates needed to describe antecedents in these rule based models of valuation functions.

3 Valuation Functions and Uncertainty Profiles

Formally a risky alternative is characterized by an **uncertainty profile**. In part an uncertainty profile consists of a collection of possible outcomes (payoffs) that can occur as a result of selecting this alternative. We shall denote this collection of possible payoffs as X. In addition a uncertainty profile usually contains information about the realizability of each of the payoffs. A general

[1] Here for simplicity we assume the antecent is composed of just one predicate. As we noted more generally the antecent can involve multiple predicates.

framework for expressing this information can be had in terms of a monotonic set function $\mu: 2^X \to [0, 1]$ having the properties **1**. $\mu(\varnothing) = 0$, **2**. $\mu(X) = 1$ and **3**. $\mu(A) \geq \mu(B)$ if $B \subseteq A$ [8]. Here μ provides a measure of the belief of finding the actual payoff in the subset A. If as is often the case in many applications we assume μ is additive, $\mu(A \cup B) = \mu(A) + \mu(B)$ for $A \cap B = \varnothing$ then μ is a probability measure.

In the following we assume that the measure associated with the uncertainty profile of an alternative is best captured by a probability model. Thus we are assuming that the payoff of a risky alternative is a random variable **R**. One of our concerns here is with the characterization of the features of this random variable that can be used as predicates in the antecedent of the rules used in the rule base definition of the valuation function. We must emphasize that the representation of the features used must be such that we can evaluate the degree of satisfaction of the associated predicate for an alternative given our knowledge of the uncertainty profile of the alternative. Well established features associated with a random variable are expected value, variance, model and median. A typical example of the use of these features in a rule based is the form

"If the expected payoff *is* ***high*** then V *is* ***good***"

Here the expected value is the feature being used. The predicate here is "the expected payoff *is* ***high***." Thus for a given alternative we must determine the degree to which this is true. Specifically if we have the uncertainty profile of the alternative expressed in terms of a random variable with known probability distribution we can calculate the expected value. With ***high*** expressed as a fuzzy set we can calculate the degree to which the predicate is satisfied. Another example would be a rule of the form

If the expected payoff is **high** and the variance is **small** then
V is **very good**.

Here our antecedent consists of two predicates connected by an "and." The second predicate, the "variance is **small**" uses as its feature the variance. Here then for a given alternative we would calculate its expected value and its variance from its uncertainty profile. We then calculate the satisfaction of each of the two predicates and then take the "anding" of these two values. Using results from multivalued logic [9] we could use the minimum of these values as the "and." It important to emphasize that with the use of predicates and these rules we have circumvented the issue of combining expected values and variances.

In policy making decisions in which we have risky alternatives the responsible decision maker's mental preference structure is generally more complex then that which can expressed simply using the basic features such as expected value and variance. Making decisions in risky environments require us to use more sophisticated features of an alternatives uncertainty profile.

One feature of an uncertainty profile that can play an important role in the formulating decision rules in the face of risky alternatives is the probability of some subset of payoffs. An example of a rule using this type of feature is

"If the probability of having a severe loss *is* **low** then the value of the alternative *is* **high**."

In this case the feature used in the rule is "the alternative's probability of having a severe loss." The predicate here is the degree to which this feature attains a value that is considered as **low**. The process of evaluating this antecedent predicate involves the following. We represent the concept "low probability" as a fuzzy subset, **LOW**, of the unit interval. If Prob(S) is the probability of having a severe loss under the alternative then the degree to which the predicate is satisfied is **LOW**(Prob(S)), the membership grade of value Prob(S) in the fuzzy subset **LOW**.

The issue now becomes that of obtaining Prob(S), the probability of having a severe loss under the alternative. The determination of this depends upon our definition of severe loss and our knowledge about the uncertainty profile associated with the alternative. Initially we shall assume complete information about the probability associated with the random variable, the uncertainty profile of the alternative. If **R** is a continuous random variable, we assume the availability of the probability density function f. If the random variable is discrete we assume the availability of the probability mass function. In addition to our knowledge of the uncertainty profile we need a definition of the concept of "severe loss." Here we can use fuzzy sets to help in the definition. More generally as we shall see the combined use of fuzzy sets with probabilistic information provides a very powerful way to express features that can play a role in constructing intelligent decision making functions. Let us look at this closer.

Consider the payoff random variable whose uncertainty is captured by its probability density function f(x). Let us calculate the "probability of a severe loss." In order to obtain this we first need a definition of the term "severe loss." We define the concept of a severe loss as a fuzzy subset S on X such that S(x) is the degree to which an outcome x satisfies the concept of being a severe loss. Using this definition and the probability density function f(x) we obtain the probability of a severe loss as [10]

$$\mathrm{Prob(S)} = \int_{\mathrm{R}} \mathrm{f(x)\ S(x)\ dx}$$

We note if S is a crisp subset then this becomes $\mathrm{Prob(S)} = \int_{\mathrm{x \in S}} \mathrm{f(x)\ dx}$. For example if S is defined crisply as "any payoff less or equal a" then $\mathrm{Prob(S)} = \int_{-\infty}^{\mathrm{a}} \mathrm{f(x)\ dx}$.

In similar manner we can define the concept of a large payoff as the fuzzy subset L obtain $\mathrm{Prob(Large\ Payoff)} = \int_{\mathrm{R}} \mathrm{f(x)\ L(x)\ dx}$. More generally if E is any linguistically expressed description of the payoff space which can be represented as a fuzzy subset E then we can obtain $\mathrm{Prob(E)} = \int_{\mathrm{R}} \mathrm{f(x)\ E(x)\ dx}$. We emphasize the subjective nature of the concept E and the related fuzzy subset E. This situation comes with positives and negatives. While this allows a user to introduce the concepts needed to describing their preferences it requires a definition be supplied either by the user or via some default supplementary mechanism.

Note: In the case in which the random variable describing the payoffs is discrete and captured by a probability mass P then $\mathrm{Prob(E)} = \sum \mathrm{P(x)\ E(x)}$.

4 Perception Based Granular Probability Distributions

In the complex environment of policy making the information needed to fully detail the probability measure associated with an alternative's uncertainty profile may only be partially or imprecisely available.

Techniques such as the Dempster–Shafer theory of evidence [11] provide useful structures for representation of an alternative's uncertainty profile in the cases of lack of precise knowledge about the exact probability measure. Another approach recently developed by Zadeh [4] is rooted in the observation that much of the information appearing in an alternative's uncertainly profile is based upon the perceptions of the decision maker. In the light of this understanding Zadeh [4] has introduced the idea of **P**erception **B**ased **G**ranular (PBG) probability distributions to address situations in which we have less than perfect information about the uncertainty profile. We now consider the situation where this is the case.

Zadeh [4] observed that the type of probability information associated with an uncertainty profile is generally a reflection of perceptions as well as measurements by the decision making entity. He suggested that an appropriate way of representing this type of information is with a **P**erception **B**ased **G**ranular (PBG) probability distribution. With the aid of a PBG probability distribution the human can very naturally express their perceptions of an uncertainty profile. As we shall see a PBG probability distributions generalize the idea of ordinary probability distribution.

Let **R** be a random variable whose domain X is a subset of the real line. A PBG probability distribution consists of a collection of tuples $(\mathrm{A_i},\ \mathrm{Q_i})$. Within each tuple $\mathrm{A_i}$ is an imprecise element from the domain X of **R** represented as a fuzzy subset of X. $\mathrm{Q_i}$ is an amount of probability allocated to that range, generally having a imprecise linguistic nature and expressed as a fuzzy subset of the unit interval. For example if **R** takes its values in the interval $\mathrm{X} = [-10 \text{ to } 10]$ then an example of a such a PBG probability distribution is

$$\text{(low, about 0.5), (near zero, about 0.3), (near 10, about 0.2)}$$

In order to further discuss PBG probability distributions we must first distinguish between two types of situations regarding the underlying domains. The first is when X is a continuous subset of the real line, $\mathrm{X} = [\mathrm{a},\ \mathrm{b}]$, and the second is when X is discrete $\mathrm{X} = \{\mathrm{x_1}, \ldots, \mathrm{x_n}\}$.

We first consider the case in which X is discrete. Here the underlying measure is a probability distribution P, whose actual values are unknown. The PBG probability distribution is providing partial information about the underlying probability distribution. Let us look at this situation. First we recall with $X = \{x_1, \ldots, x_n\}$ then a valid probability distribution P on X is a collection $[p_1, \ldots, p_n]$ such that $\mathrm{Prob}(x_i) = p_i$ and $p_i \in [0, 1]$ and $\sum_{i=1}^{n} p_i = 1$. We shall let P_X be the set of all valid probability distributions on X.

Formally a PBG probability distribution induces a possibility distribution over all the valid probability distribution over X. Let $K = \{(A_i, Q_i)|i = 1, \ldots, m\}$ be a PBG probability distribution on X. If $\prod_K$ is the induced possibility distribution then for each valid probability distribution, $P \in P_X$, $\prod_K(P)$ indicates the possibility that P is the actual probability distribution on X.

With $P = [p_1, \ldots, p_n]$ in the following we describe one approach to determine $\prod_K(P)$ given $K = ((A_i, Q_i)|i = 1, \ldots, m\}$.

(1) For each A_i calculate $\mathrm{Prob}(A_i)$ using P: $\mathrm{Prob}(A_i|P) = \sum_{j=1}^{n} A_i(x_j)\ p_j$
(2) For each i calculate, $\tau_i = Q_i(\mathrm{Prob}(A_i|p))$. This is the compatibility of P with Q_i
(3) $\prod_K(P) = \mathrm{Min}_i[\tau_i]$

In the case in which $X = [a, b]$, it is continuous, the random variable is characterized by a probability measure. Here the PBG probability distribution is only providing partial information about underlying probability measure. We note that a valid probability measure f associated with X is such that $f(x) \geq 0$ for all $x \in [a, b]$ and $\int_a^b f(x)dx = 1$. We let F_X be the collection of all valid probability measures on X. In this case a PBG probability induces a possibility distribution over the set F_X. Again we shall assume $K = ((A_i, Q_i), I = 1, \ldots, m)$ is the PBG probability distribution corresponding to the uncertainty profile. We let $\prod_K$ be the induced possibility distribution over F_X. Here $\prod_K(f)$ indicates the possibility that f can be the actual probability measure given K. We determine $\prod_K(f)$ as follows:

(1) For each A_i we calculate $\mathrm{Prob}(A_i|f) = \int_a^b f(x)\ A_i(x)\ dx$
(2) For each i calculate, $\tau_i = Q_i(\mathrm{Prob}(A_i|p))$. This is the compatibility of f with Q
(3) $\prod_K(f) = \mathrm{Min}_i[t_i]$

Let us look at this nature of the PBG probability distribution in more detail. As we shall subsequently see a PBG probability distribution is essentially a generalization of the idea of an ordinary probability distribution. Consider the PBG probability distribution $((A_i, Q_i), i = 1, \ldots, m)$. First we note that each Q_i is a fuzzy number drawn from the unit interval I, it is normal and unimodal. In particular there exists an $r \in [0, 1]$ such that $Q_i(r) = 1$. In addition since it is unimodal, there exist two values a_i and $b_i \in I$ such that

1. $Q_i(r)$ is non-decreasing for $r \in [0,\ a_i]$
2. $Q_i(r) = 1$ for $r \in [a_i,\ b_i]$
3. $Q_i(r)$ is non-increasing for $r \in [b_i,\ 1]$

One implication of the unimodality of the granular probabilities is the interval nature of the associated level sets [12]. Thus if Q_i^α is the α-level set of Q_i, $Q_i^\alpha = \{r/Q_i(r) \geq \alpha\}$, then $Q_i^\alpha = [l_i(\alpha),\ u_i(\alpha)]$. It is also the case that the unimodality of Q_i implies that if $\alpha > \beta$ then $Q_i^\alpha \subseteq Q_i^\beta$, the level sets are nested.

We should note two special cases of these granular probabilities. The first is the case when Q_i is a precise value q_i in I, $Q_i = \{q_i\}$. The second is when Q_i is an interval, $Q_i = [a_i,\ b_i]$. Here $Q_i(r) = 1$ for $r \in [a_i,\ b_i]$ and $Q_i(r) = 0$ for $r \notin [a_i,\ b_i]$.

Generally the A_i are human comprehensible concepts associated with the space X. As discussed by Gardenfors [13] concepts on a domain are expressed as convex subsets. Thus formally the A_i are normal and unimodal, they are fuzzy numbers from the domain X. Two special cases of A_i are singletons and crisp intervals.

5 Evaluating Decision Functions with PBG Uncertainty Profiles

Previously we indicated that the rules based approach for specifying the decision making entities valuation function can involve rules in which we have antecedent terms of the form:

$$\text{If Prob(Fuzzy Event) } is \text{ Large then} \ldots \qquad \text{(I)}$$

Here we shall investigate a method for evaluating the satisfaction of this type of antecedent by risky alternatives for this case in which an alternative's uncertainty profile is expressed in terms of a PBG probability distribution.

We first formalize the above antecedent. Let **R** indicate the payoff associated with the alternative being evaluated. Formally it is a random variable on real line. In order to formalize the antecedent in I we let F be a fuzzy subset of the domain of **R**, this corresponds to a general fuzzy event. In addition we let Q be a fuzzy probability corresponding to what we generically denoted as Large in (I). Using these notations our rule becomes

$$\text{If Prob}(\mathbf{R}\ is\ \text{F})\ is\ \text{Q then} \ldots\ldots.$$

Let us use W to indicate the variable corresponding to the "probability of the event **R** *is* F." Using this notation we can express our rule as

"If W *is* Q then. . . ."

The firing of this rule is determined by the compatibility of the value of W with the fuzzy subset Q.

We now consider a risky alternative whose uncertainty profile is expressed using the PBG probability distribution $K = ((A_i, Q_i), i = 1, \ldots, m)$. Here A_i is a fuzzy subset of X and Q_i is a fuzzy subset corresponding to amount of probability, a fuzzy number in the unit interval.

The task of evaluating the degree to which the risky alternative under consideration satisfies the rule can be formulated as follows. We need to determine the compatibility of the value of W, the probability of the event **R** *is* F with Q, given that all we know about **R** *is* K, $((A_i, Q_i), i = 1, \ldots, m)$.

Consider the firing of the rule "If W *is* Q then ......" If we know that the probability of the event **R** *is* F is precisely equal to the value b, $W = b$, then the degree of firing τ is simply Q(b). More generally, if the value for W is a fuzzy probability B, then using the established procedure in fuzzy systems modeling we obtain as the firing level $\tau = \mathrm{Max}_y[Q(y) \wedge B(y)]$, we take the maximum of the intersection of Q and B.

The situation we are faced with is slightly different than either of these. Instead of knowing the value of W, the probability of **R** *is* F, all we have is the PBG probability distribution K on **R**. In this case our task becomes to calculate the value of W from our information about **R**.

If instead of having a PBG probability distribution we had an ordinary probability distribution $P = [(x_i, p_i)]$, p_i being the probability that $\mathbf{R} = x_i$ then to calculate W, probability that **R** *is* F, we use

$$W = \sum_{i=1}^{n} F(x_i)p_i$$

We must now extend this approach to our situation where we have the PBG probability distribution $K = [(Ai, Q_i), i = 1, \ldots, m]$. With K we have that both A_i and Q_i are fuzzy subsets. The fact that A_i is not crisp conceptually provides more difficulty than the fuzziness of Q_i.

If we temporarily consider the situation in which Q_i is precise, $Q = q_i$ and A_i is an interval we can get some insight into how to proceed. We shall also for simplicity assume that F is a crisp subset. In calculating W we are essentially obtaining the sum of the probabilities of the possible values of **R** that lies in F. When A_i is an interval it is difficult to decide whether the probability is associated with element in F or not. To get around this problem we must obtain upper and lower bounds on W. The actual probability lies between these values.

Using this idea for the more general situation where all the objects are fuzzy we obtain

$$\mathrm{Upper_F} = \sum_{\mathrm{i}=1}^{n} \mathrm{Poss[F/A_i]\ Q_i}$$

$$\mathrm{Lower_F} = \sum_{\mathrm{i}=1}^{n} (1 - \mathrm{Poss}[\bar{\mathrm{F}}/\mathrm{A_i}])\mathrm{Q_i}$$

where $\mathrm{Poss[F/A_i]} = \mathrm{Max_x[F(x) \wedge A_i(x)]}$ and $\mathrm{Poss}[\bar{\mathrm{F}}/\mathrm{A_i}] = \mathrm{Max_x}[(1 - \mathrm{F(x)}) \wedge \mathrm{A_i(x)}]$. Essentially we see that $\mathrm{Poss[F/A_i]}$ is the degree of intersection of $\mathrm{A_i}$ and F while $1 - \mathrm{Poss}[\bar{\mathrm{F}}/\mathrm{A_i}]$ is the degree to which $\mathrm{A_i}$ is included in $\bar{\mathrm{F}}$. There values are closely related to the measures of plausibility and belief in Dempster–Shafer theory [11].

At this point we must draw upon some of results from fuzzy arithmetic [14]. We recall if A and B are two fuzzy numbers then their sum $\mathrm{D} = \mathrm{A} \oplus \mathrm{B}$ is also a fuzzy number such that

$$\mathrm{D(z)} = \underset{\substack{\mathrm{x,\ y\ s.t.} \\ \mathrm{x+y=z}}}{\mathrm{Max}} [\mathrm{A(x)} \wedge \mathrm{B(y)}].$$

We also note that if α is a scalar then α A is a fuzzy number D such that

$$\mathrm{D(z)} = \underset{\substack{\mathrm{x\ s.t.} \\ \alpha\mathrm{x=z}}}{\mathrm{Max}} [\mathrm{A(x)}]$$

More generally if $\mathrm{D_1, \ldots,\ D_n}$ are fuzzy numbers and $\alpha_1, \ldots, \alpha_\mathrm{n}$ are nonnegative scalars then

$$\mathrm{D} = \alpha_1 \mathrm{D_1} \oplus \alpha_2 \mathrm{D_2} \oplus \cdots \oplus \alpha_\mathrm{n} \mathrm{D_n}$$

is a fuzzy number such that

$$\mathrm{D(z)} = \underset{\substack{\mathrm{x_i\ s.t.} \\ \Sigma_\mathrm{i} \alpha_\mathrm{i} \mathrm{x_i = z}}}{\mathrm{Max}} [\mathrm{Ai}(x_i)]$$

The point we can conclude from this digression is that we have available to us the facility to calculate the values $\mathrm{Upper_F}$ or $\mathrm{Lower_F}$. More specifically if we denote $\lambda_\mathrm{i} = \mathrm{Poss[F/A_i]} \in [0, 1]$ then $\mathrm{Upper_F}$ is a fuzzy number H defined on the unit interval such that for all $\mathrm{z} \in [0,\ 1]$

$$\mathrm{H(z)} = \underset{\substack{\mathrm{z_i\ s.t.} \\ \Sigma_\mathrm{i} \lambda_\mathrm{i} \mathrm{Z_i = z}}}{\mathrm{Max}} [\mathrm{Min_i[Q_i(z_i)]}$$

If we denote $\gamma_\mathrm{i} = 1 - \mathrm{Poss}[\bar{\mathrm{F}}/\mathrm{A_i}] \in [0,\ 1]$ then $\mathrm{Lower_F}$ is a fuzzy number L defined on the unit interval such that for all $\mathrm{z} \in [0, 1]$

$$\mathrm{L(z)} = \underset{\substack{\mathrm{z_i\ s.t.} \\ \Sigma_\mathrm{i} \gamma_\mathrm{i} \mathrm{Z_i = z}}}{\mathrm{Max}} [\mathrm{Min_i[Q_i(z_i)]}$$

We must now consider the relationship between the fuzzy subsets H and L. In anticipation of uncovering this we look at the relationship between $\lambda_\mathrm{i} = \mathrm{Poss[F/A_i]}$ and $\gamma = 1 - \mathrm{Poss[F/A_i]}$. Here we use the fact that F and $\mathrm{A_i}$ are normal, they have at least one element with membership grade 1. Assume

$\gamma = \alpha$, then $\mathrm{Max}_x[(1 - F(x)) \wedge A_i(x)] = 1 - \alpha$. Since A_i is normal there exists some x^* where $A_i(x^*) = 1$ and therefore $(1 - F(x^*)) \wedge 1 = (1 - F(x^*)) \leq 1 - \alpha$ hence $F(x^*) \geq \alpha$. Since $\lambda_i = \mathrm{Max}_x[F(x) \wedge A_i(x)] \geq F(x^*) \wedge A_i(x^*) \geq \alpha$. Hence we get $\lambda_i \geq \gamma_i$ for all i. Thus we see that $L = \sum_{j=1}^{n} \gamma_j Q_j$ and $H = \sum_{j=1}^{n} \lambda_j Q_j$ where $\lambda_j \geq \gamma_j$ for all j.

Before preceding we want to introduce a type of relationship between fuzzy numbers

Definition 1. *Let* G_1 *and* G_2 *be two fuzzy numbers such that*

$$\begin{array}{ll} G_j(x) \textit{is non-decreasing} & \text{for } x \leq a_j \\ G_j(x) = 1 & \text{for } x \in [a_j, b_j] \\ G_j(x) \textit{is non-increasing} & \text{for } x \geq b_j \end{array}$$

where $a_1 \leq a_2$ *and* $b_2 \geq b_1$*. If in addition we have*

$$G_1(x) \geq G_2(x) \quad \text{for all } x \leq a_1.$$

$$G_2(x) \geq G_1(x). \quad \text{for all } x \geq a_2$$

we shall say G_2 *is to* **the right of** G_1 *and denote this as* $G_2 \geq_R G_1$

This relationship $G_2 \geq_R G_1$ can be equivalently expressed in terms of level sets. If $G_i(\alpha) = [a_i(\alpha),\ b_i(\alpha)]$ is the α level set of G_i, then the relationship $G_2 \geq_R G_1$ is equivalent to the condition that for each $\alpha \in [0, 1]$ we have $a_1(\alpha) \leq a_2(\alpha)$ and $b_1(\alpha) \leq b_2(\alpha)$.

It can be shown that if $G_2 = \sum_{i=1}^{n} \lambda_i\ Q_i$ and $G_1 = \sum_{i=1}^{n} \gamma_i\ Q_i$ where $0 \leq \gamma_i \leq \lambda_i \leq 1$ for all i and the Q_i are non-negative fuzzy number then $G_2 \geq_R G_1$. From this it follows that $H \geq_R L$, the upper bound is always to the right of the lower bound.

Earlier we indicated that the value of W, the probability that **R** is F, lies between the H and L. In particular, we have the following constraints on the value of W:

W is greater that or equal L

and

W is less than or equal H.

If we let L^* indicate the fuzzy subset *greater than or equal L* and let H^* indicate the fuzzy subset *less than or equal H* then W *is* E where $E = L^* \cap H^*$. It is the intersection of the fuzzy subsets L^* and H^*.

Let us now calculate L^* and H^* from L and H. L^* is obtained as

$$L^*(x) = \mathrm{Max}_y[\mathrm{GTE}(x, y) \wedge L(y)]$$

where GTE is the relationship "greater then or equal" defined on $[0,\ 1] \times [0,\ 1]$ by

$\mathrm{GTE}(x,\ y) = 1$ if $x \geq y$
$\mathrm{GTE}(x,\ y) = 0$ if $x < y$

Here $L(x)$ is non-decreasing for $x \leq a_1$ and $L(x) = 1$ for $x \in [a_1, b_1]$ it is non-increasing for $x \geq b_1$. It is easy to show that in this case that L^* is such that $L^*(x) = L(x)$ for $x \leq a_1$ and $L^*(x) = 1$ for $x \geq a_1$.

Similarly for H^* we have $H^*(x) = \text{Max}_y[\text{LTE}(x, y) \wedge H(y)]$ LTE is the relationship "less then or equal" defined on $[0, 1] \times [0, 1]$ by

$\text{LTE}(x, y) = 1$ if $x \leq y$
$\text{LTE}(x, y) = 0$ if $x > y$

If $H(x)$ is a fuzzy number with value one in the interval $[a_2, b_2]$ then H^* is a fuzzy number such $H^*(x) = 1$ for $x \leq b_2$ and $H^*(x) = H(x)$ for $x > b_2$.

Combining L^* and H^* to get E, the possible values for W, we have $E = H^* \cap L^*$ hence $E(x) = H^*(x) \wedge L^*(x)$. From this we get

$E(x) = L(x)$ for $x \in [0, a_1]$
$E(x) = 1$ for $x \in [a_1, b_2]$
$E(x) = H(x)$ for $x \in [b_2, 1]$

Returning to our concern with determining the firing level of the rule

If W *is* Q then

when our input is W = K we now use this E to calculate the firing level of the rule as

$$\tau = \text{Max}_x[Q(x) \wedge E(x)]$$

6 Cumulative Distribution Functions

Here consider the situation where the information about the uncertainty profile of an alternative is available in terms of a cumulative distribution function and more generally a **P**erception **B**ased **G**ranular **C**umulative **D**istribution function., PBG-CD function.

If **R** is a random variable that takes its value on the real line we recall that a cumulative distribution is a function such that F(x) is the probability that $\mathbf{R} \leq x$. Formally F is a function $F : [-\propto, \propto] \rightarrow [0, 1]$ which is monotonic, $F(x) \geq F(y)$ if $x > y$. We note F is available whether **R** is discrete or continuous. If **R** is discrete then $F(x) = \sum_{\substack{i \text{ s. t.} \\ x_i \leq x}} p_i$. If **R** is continuous with probability density f then $F(x) = \int_{-\infty}^{\infty} f(x)\, dx$. In many real applications we can assume that the domain of F is bounded, there exists some value x_* s.t. such that $F(x) = 0$ for $x \leq x_*$ and some x^* such that. $F(x) = 1$ for all $x \geq x^*$.

With the availability of the CDF we can easily provide the information needed to determine the firing level of a rule of the form

$$\text{If Prob(A) } is \text{ then} \ldots.$$

If A is a crisp subset, $A = \{x/a_1 \leq x \leq a_2]$ then $\text{Prob}(A) = F(a_2) - F(a_1)$ and the firing level is $Q(F(a_2) - F(a_1))$. If A is a fuzzy subset we must look a little more carefully at the situation. Here we shall assume A is a fuzzy number, the fuzzy subset A is of the form

$$
\begin{aligned}
&A(x) = 0 && \text{for } x \le b_1 \\
&A(x) \ge A(y) && \text{for } b_1 \le y < x \le a_1 \\
&A(x) = 1 && \text{for } a_1 < x \le a_2 \\
&A(x) \le A(y) && \text{for } a_2 \le y \le x \le b_2 \\
&A(x) = 0 && \text{for } x \ge b_2
\end{aligned}
$$

We now define a fuzzy subset $\tilde{a}_1$ such that

$$
\begin{aligned}
&\tilde{a}_1(x) = A(x) && \text{for } b_1 \le x \le a_1 \\
&\tilde{a}_1(x) = 0 && \text{elsewhere}
\end{aligned}
$$

We also define the fuzzy subset $\tilde{a}_2$ such that

$$
\begin{aligned}
&\tilde{a}_2(x) = A(x) && \text{for } a_2 \le x \le b_2 \\
&\tilde{a}_2(x) = 0 && \text{elsewhere}
\end{aligned}
$$

$\tilde{a}_1$ and $\tilde{a}_2$ are fuzzy numbers which allow us to express $\text{Prob}(A) = F(\tilde{a}_2) - F(\tilde{a}_1)$. In order to obtain Prob(A) we need to obtain $F(\tilde{a}_2)$ and $F(\tilde{a}_1)$. Since the processes needed to obtain these values are similar we shall only concentrate on $F(\tilde{a}_2)$. Using Zadeh's extension principle [15,16], since $\tilde{a}_2$ is a fuzzy number of real line, then $F(\tilde{a}_2)$ is a fuzzy subset of the unit interval such that $F(\tilde{a}_2) = \bigcup_x \{\frac{\tilde{a}_2(x)}{F(x)}\}$ and since $\tilde{a}_2(x) = A(x)$ for $x \in [a_2,\ b_2]$ and $\tilde{a}_2(x) = 0$ elsewhere then $F(\tilde{a}_2) = \bigcup\limits_{x \in [a_2,\ b_2]} \{\frac{A(x)}{F(x)}\}$. Here $F(\tilde{a}_2)$ is a fuzzy number. In this case the possibility that $F(\tilde{a}_2)$ takes the value z is $\underset{\substack{x \in [a_2,\ b_2] \\ F(x)=z}}{\text{Max}} [A(x)]$. The monotonic nature of the cumulative distribution function F and the special form of $\tilde{a}_2$ results in a form of $F(\tilde{a}_2)$ as shown in Fig. 2. We emphasize that $F(\tilde{a}_2)$ is a fuzzy number of the unit interval such that its membership grade is one at the value $F(a_2)$, and monotonically decreases to zero at the value $F(b_2)$. In the range from zero to $F(a_2)$ and $F(b_2)$ to 1 its membership value is also zero.

Some special situations are worth pointing out. If F is such that it is constant, $F(x) = k$, in the range $x \in [a_2,\ b_2]$ then it can be shown that $F(\tilde{a}_2)$

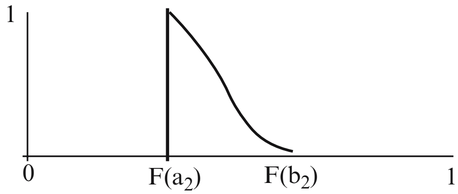

Fig. 2. Fuzzy subset $F(\tilde{a}_2)$

is a singleton set, $F(\tilde{a}_2) = \{\frac{1}{k}\} = \{\frac{1}{F(a_2)}\}$. Another special case occurs if F is a discrete function. Specifically if F is such that within the interval $[a_2, b_2]$ it jumps at the points $a_2 + \delta_1$, $a_2 + \delta_2$, $a_3 + \delta_3$ where the amounts of these jumps are Δ_1, Δ_2, Δ_3. In this special case we get

$$F(\tilde{a}_2) = \left\{\frac{1}{F(a_2)}, \frac{A(a_2+\delta_1)}{F(a_2)+\Delta_1}, \frac{A(a_2+\delta_2)}{F(a_2)+\Delta_1+\Delta_2}, \frac{A(a_3+\delta_3)}{F(a_2)+\Delta_1+\Delta_2+\Delta_3}\right\}$$

The significant point here is that here $F(\tilde{a}_2)$ is a discrete function reflecting the discrete nature of F.

In a similar way we can show generally $F(\tilde{a}_1)$ is a fuzzy number of the unit interval such that $F(\tilde{a}_1) = \bigcup_{x\in[b_1, a_1]} \{\frac{A(x)}{F(x)}\}$, see Fig. 3.

Using these fuzzy values for $F(\tilde{a}_2)$ and $F(\tilde{a}_1)$ we obtain $\text{Prob}(A) = F(\tilde{a}_2) - F(\tilde{a}_1)$ as a fuzzy number of unit interval having nonzero membership grade in the interval $(F(a_2) - F(a_1))$ to $(F(b_2) - F(b_1))$. Here if we let PA be the fuzzy subset denoting the value Prob(A) then

$$\begin{array}{ll}
PA(z) = 0 & z < F(a_2) - F(a_1) \\
PA(z) = 1 & z = F(a_2) - F(a_1) \\
PA(z) \text{ is decreasing} & F(a_2) - F(a_1) < z < F(b_2) - F(b_1) \\
PA(z) = 0 & z > F(b_2) - F(b_1)
\end{array}$$

In some practical situations it may be much more efficient to defuzzify $F(\tilde{a}_1)$ and $F(\tilde{a}_2)$ and use these scalar values to obtain a scalar value for Prob(A).

Let us consider the defuzzification of $F(\tilde{a}_2)$ which we recall was $F(\tilde{a}_2) = \bigcup_{x\in[a_2, b_2]} \{\frac{A(x)}{F(x)}\}$. Letting d_2 denote the defuzzified value of $F(\tilde{a}_2)$ we get

$$d_2 = \frac{\int_{a_2}^{b_2} F(x)\ A(x)\ dx}{\int_{a_2}^{b_2} A(x)dx}.$$

We observed that if F(x) is constant, $F(x) = k$ in the range $[a_2, b_2]$, then $d_2 = k$. Actually as we have already pointed out if $F(x) = k$ in the range a_2 to b_2 then $F(\tilde{a}_2)$ is itself a constant value k, no fuzziness exists.

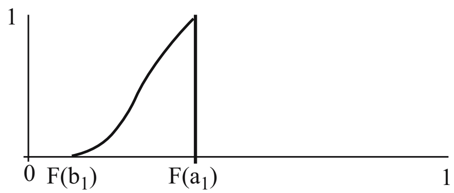

Fig. 3. Fuzzy subset $F(\tilde{a}_1)$

In many real situations it may be difficult for a decision maker to obtain a precise manifestation of the cumulative distribution of the payoff of a risky alternative. In these cases a decision maker may be only able to obtain a imprecise characterization of the underlying cumulative distribution in the form of what we shall call a **P**erception **B**ased **G**ranular **C**umulative **D**istribution function, PBG-CD function. A PBG-CD is a granular description of the cumulative distribution function in a form that is widely used in fuzzy modeling [6]. When using a PBG-CD we partition the range R into fuzzy intervals $B_1, \ldots, B_n$. We then express the value of F in each one of these fuzzy ranges using a fuzzy subset of the unit interval F_i. With PBG-CD function we have a rule based representation of the cumulative distribution function F

If U is B_1 then F is F_1.
....
If U is B_i then F is F_i.
....
If U is B_n then F is F_n.

In working with the fuzzy rule based description of the underlying function we can draw upon the well established literature of fuzzy systems modeling.

In order to find the value of F at some value for U, a, we proceed as follows. We first obtain the firing level of each rule $\tau_i = B_i(a)$. We then calculate $\omega_i = \frac{\tau_i}{\sum_{i=1}^{n} \tau_i}$. Using this we calculate F(a) as the fuzzy subset $\mathbf{F_a} = \sum_{i=1}^{n} \omega_i F_i$. Here we get for F(a) a fuzzy subset of the unit interval such that $\mathbf{F_a}(y)$ is the possibility that F(a) assumes the value y. We can apply a defuzzification operation on $\mathbf{F_a}$ to obtain a scalar value.

In the following example we illustrate the generation of a perception based granular CD function

Example. We consider an investment alternative in which the investor has the following perceptions of the outcome of his investment.

He is certain that he won't lose more then \$500 dollars
He believes his chances of losing more then \$100 is about 10%
He believes his chances of losing any money is 20%
He feels that there is about a 90% chance that he will win at most \$500
He is certain that he won't win more then a \$1,000

We can use this to construct a rule based description of the cumulative distribution function. In particular if $F(U) = \text{Prob}(\mathbf{R} \leq U)$ with $\mathbf{R}$ being the random payoff then the rule base is

If U *is* **less then \$500** then F *is* **zero**
If U *is* "**near −\$100**" then F *is* **about 10%**
If U *is* **zero** then F *is* **about 20%**
If U *is* **about \$500** then F *is* **about 90%**
If U *is* **greater then 1,000** then F *is* **100%**

7 Conclusion

We focused on the issue of decision making in risky situations. We discussed the need for using decision functions to aid in capturing the decision maker's preference among these types of uncertain alternatives. The use of fuzzy rule based formulations to model these functions was investigated. We discussed the role of Zadeh's perception based granular probability distributions as a means of modeling the uncertainty profiles of the alternatives. We look at various properties of this method of describing uncertainty and showed how they induced possibility distributions of the space of probability distributions Tools for evaluating rule based decision functions in the face of perception based uncertainty profiles were presented. We considered the situation in which uncertainty profiles are expressed in terms of a cumulative distribution function. We introduced the idea of a perception based granular cumulative distribution and describe its representation in terms of a fuzzy rule based model.

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Fuzzy Logic Approaches to Consensus Modelling in Group Decision Making

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Summary. The notion of consensus plays a key role in modelling group decisions, and for a long time it was meant as a strict and unanimous agreement, however, since various decision makers have different more or less conflicting opinions the traditional strict meaning of consensus is unrealistic. The human perception of consensus is much "softer", and people are willing to accept that a consensus has been reached when most or the more predominant actors agree on the preferences associated with the most relevant alternatives. The "soft" meaning of consensus, advocated as realistic and humanly consistent, can lead to solve in a more constructive way group decision making situations by using modelling tools based on fuzzy logic.

In this paper we present a review of well known fuzzy logic-based approaches to model flexible consensus reaching dynamics, which constitute a well defined research area in the context of fuzzy GDM. First, the problem of modelling consensus under individual fuzzy preferences is considered, and two different models are synthesized. The first one is static and is based on the algebraic aggregation of the individual preferences aiming to find a consensus defined as the degree to which most of the important individuals agree as to their preferences concerning almost all of the relevant alternatives. The second one is dynamic and it combines a soft measure of collective disagreement with an inertial mechanism of opinion changing aversion. It acts on the network of single preference structures by a combination of a collective process of diffusion and an individual mechanism of inertia. Second, the use of Ordered Weighted Averaging (OWA) Operators to define a linguistic quantifier guided aggregation in the context of GDM is introduced and then generalized to the problem of Multi Expert Multi Criteria Decision Making for which a linguistic approach to define a consensus reaching strategy is presented.

1 Introduction

The construction of models for making decisions when a group of two or more decision makers must aggregate their opinions (individual preferences)

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in order to get a group opinion (collective preference) is a very old problem. The first systematic approaches to the problem were pioneered by Borda [10] and Condorcet [16], who initiated the formal discipline of Social Choice in terms of voting. For an extended review see Nurmi [48].

The subject of Group Decision Making (GDM), traditionally equated with Social Choice, was revived in the twentieth century by Arrow [1, 2], who in his book titled *Social Choice and Individual Values* was concerned with the difficulties of group decisions and the inconsistencies they can generate leading to the well-known Impossibility Theorem.

More specifically, Arrow has proved that in the context of ordinal and symmetric (all decision makers with equal weight) preferences it is not possible to construct a collective preference structure without this being imposed by a single individual, the so-called "Arrow's dictator". In the following 1950s and 1960s many axiomatic variants to Arrow's hypothesis have been proposed, see for instance Fishburn [27, 28] and Kelly [40], but these have not solved the crucial issues and in any case no natural solution to the collective preference aggregation problem has emerged.

The various difficulties highlighted by the strong interest on impossibility theorems have stimulated the development of alternative approaches and, over the last two decades of twentieth century, a number of authors have extended the theory of GDM in various ways to encompass fuzziness in individual and group preferences. Barrett et al. [4, 5] investigated the structure of fuzzy aggregation rules which, for each permissible profile of individual preferences, specify a fuzzy social ordering. Dutta [19], allowing both individual and social preferences to be fuzzy, showed that, under weaker transitivity condition, the fuzzy counterparts of Arrow's condition result in oligarchic and not dictatorial aggregation rules. Montero [47] introduced rationality as a fuzzy property by suggesting a definition of fuzzy opinion different from the classical fuzzy preference relation and showed how to escape from impossibility theorems through the idea of fuzzy rationality. More details and useful references can be found in Nurmi and Kacprzyk [49] and Barrett and Salles [3].

It was in the context of GDM theory that the traditional models of consensus modeling have been addressed, from De Groot [17] classical consensus model to the ones proposed by Chatterjee and Seneta [13], Kelly [41], French [29], Lehrer and Wagner [43], Sen [53] and Loewer [44], mostly in the probabilistic framework.

Almost all of these approaches treat consensus as a strict and unanimous agreement, however, since various decision makers have different more or less conflicting opinions the traditional strict meaning of consensus is unrealistic. The human perception of consensus is much 'softer', and people are willing to accept that a consensus has been reached when most or the more predominant decision makers agree on the preferences associated to the most relevant alternatives.

The problem of consensus reaching modelling in a fuzzy environment was addressed at first in Bezdek et al. (7–9), Ragade [51], Spillman et al. [55], Spillman et al. [56, 57] and then developed in Fedrizzi et al. [24], Kacprzyk and Fedrizzi [34–36], Carlsson et al. [12], Kacprzyk et al. [38], Fedrizzi et al. [21], Kacprzyk et al. [39]. Some authors addressed the problem introducing linguistically-based preference relations, see for instance, among others, Herrera-Viedma et al. [33] and Ben-Arieh and Chen [6].

The 'soft' consensus paradigm developed in Kacprzyk and Fedrizzi [34–36] in the standard framework of numerical fuzzy preferences was extended to a more dynamical context in Fedrizzi et al. [22,23,25] and Marques Pereira [46]. The new model combines a soft measure of collective disagreement with an inertial mechanism of opinion changing aversion. It acts on the network of single preference structures by a combination of a collective process of (nonlinear) diffusion and an individual mechanism of (nonlinear) inertia. The overall effect of the dynamics is to outline and enhance the natural segmentation of the decision makers group into homogeneous preference subgroups. Fedrizzi et al. [26], assuming that the decision makers can express their preferences in a more flexible way, i.e. by using triangular fuzzy numbers, generalized the iterative process of opinion transformation towards consensus via the gradient dynamics of a cost function expressed as a linear combination of the disagreement function and the inertial cost function.

In Chen and Hwang [14] the problem of Multi Expert Multi Criteria decision making is addressed. In their approach, the group decision making strategy requires to each expert to express a performance judgment on each alternative with respect to a set of predefined criteria. In this context the definition of a consensus degree and a consensual alternative ranking requires to work on the 'absolute' experts' evaluations and not on preference relations. More specifically, the reduction of the individual judgments into a representative value (the majority opinion) is usually performed through an aggregation process, introducing aggregation operators associated with linguistic quantifiers (such as most). In particular Ordered Weighted Aggregation Operators [58] have been widely applied to address GDM problems [15]. In Bordogna et al. [11] a linguistic model for Multi Expert Multi Criteria decision problem is defined, the aim of which is to compute a consensual judgement and a consensus degree for a fuzzy majority of the experts on each of the considered alternatives.

In this paper we present some fuzzy approaches to model flexible consensus reaching strategies, and which constitute a well defined research area in the context of fuzzy GDM. In Sect. 2 the problem of modelling consensus under fuzzy preferences is considered, and two different strategies are synthesized. In Sect. 3, the use of Ordered Weighted Averaging Operators to define a linguistic quantifier guided aggregation in the context of GDM is introduced. Finally in Sect. 4 the problem of Multi Expert Multi Criteria Decision Making is considered and a linguistic approach to define a consensus reaching strategy in this context is presented.

2 Consensus Modelling in Group Decision Making under Fuzzy Preferences: Static and Dynamical Approaches

2.1 Soft Consensus in a Static Setting

The basic framework within which most of the GDM processes are modelled can be depicted in the following way. There is a set of decision makers or experts who present their opinions concerning a set of alternatives and these alternatives may initially differ to a large extent. If the individuals are rationally committed to consensus, via some exchange of information, bargaining, etc. the individuals' opinions can be modified and the group may get closer to consensus. Here consensus is not meant as a strict and unanimous agreement, but as the degree to which most of the individuals agree as to their preferences concerning almost all of the relevant opinions. This degree of consensus takes on it values in the unit interval, and it's more realistic and human consistent than conventional degrees, mostly developed in the probabilistic framework.

One of the most widely used approaches proposed in the literature is the one described for first in Kacprzyk and Fedrizzi [34] and then developed in Kacprzyk and Fedrizzi [35,36]. The point of departure is a set of n individual fuzzy preference relations defined on a set $A = \{a_1, \ldots, a_m\}$ of alternatives. The fuzzy preference relation of individual i, R_i, is given by its membership function $\mu_i :\ A \times A \to [0,\ 1]$ and can be represented by a matrix $[r^i_{kl}]$, $r^i_{kl} = \mu_i\ (a_k,\ a_l)$ which is commonly assumed to be reciprocal, that is $r^i_{kl} + r^i_{lk} = 1$. Clearly, this implies $r^i_{kk} = 0.5$ for all $i = 1, \ldots, n$ and $k = 1, \ldots, m$.

Now, a measure of the degree of agreement is introduced, that is derived in three steps. First, for each pair of individuals we derive a degree of agreement as to their preferences between a pair of alternatives, next we pool (aggregate) these degrees to obtain a degree of agreement of each pair of individuals as to their preferences between Q1 (a linguistic quantifier as, e.g., "most", "almost all", "more than 50%", ...) pairs of relevant alternatives, and finally we pool these degrees to obtain a degree of agreement of Q2 (a linguistic quantifier similar to Q1) pairs of individuals as to their preferences between Q1 pairs of relevant alternatives. This is meant to be the degree of agreement sought.

We start with the degree of agreement between individuals i and j as to their preferences between alternatives a_k and a_l,

$$V_{kl}(i,j) = ({r^i}_{kl} - {r^j}_{kl})^2 \in [0,\ 1] \quad \text{where } i,j=1,\ldots,n \text{ and } k,l=1,\ldots,m. \quad (1)$$

Relevance of the alternatives is assumed to be a fuzzy set defined on the set of alternatives A, such that $\mu_{\mathrm{A}}(a_k) \in [0,\ 1]$ is a degree of relevance of alternative a_k: from 0 standing for "definitely irrelevant" to 1 for "definitely relevant", through all intermediate values.

Relevance of a pair of alternatives, $(a_k,\ a_l) \in A \times A$, may be defined in various ways among which

$$p_{kl} = (\mu_A(a_k) + \mu_A(a_l))/2 \tag{2}$$

is certainly the most straightforward; clearly, $p_{kl} = p_{lk}$ and p_{kk} are irrelevant since they concern the same alternative, for all and $k, l = 1, \ldots, m$.

The degree of agreement between individuals i and j as to their preferences between all the relevant pairs of alternatives is

$$V_{\mathrm{P}}(i,j) = \sum_{k=1}^{m-1} \sum_{l=k+1}^{m} p_{kl}\ V_{kl}\ (i,j) \Big/ \sum_{k=1}^{m-1} \sum_{l=k+1}^{m} p_{kl} \tag{3}$$

The degree of agreement between individuals i and j as to their preferences between Q1 relevant pairs of alternatives is then

$$V_{Q1}(i,j) = \mathrm{Q1}\ (V_P(i,j)) \tag{4}$$

In turn, the degree of agreement of all the pairs of individuals as to their preferences between Q1 relevant pairs of alternatives is

$$V_{\mathrm{Q1}} = (2/n(n-1)) \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} V_{\mathrm{Q1}}\ (i,j), \tag{5}$$

and, finally, the degree of agreement of Q2 pairs of individuals as to their preferences between Q1 relevant pairs of alternatives, called the degree of Q1/Q2-consensus, is

$$V_{\mathrm{Q1,Q2}} = \mathrm{Q2}(V_{\mathrm{Q1}}) \tag{6}$$

As far as the quantifiers Q1 and Q2 are concerned, they are of the general form $\mathrm{Q}:\ [0,\ 1] \to [0,\ 1]$ with, for instance,

$$\begin{array}{ll} \mathrm{Q}(x) = 0 & \text{for } x \in [0,\ \mathrm{c}], \\ \mathrm{Q}(x) = (1/(\mathrm{d}-\mathrm{c}))x - (\mathrm{c}/(\mathrm{d}-\mathrm{c})) & \text{for } x \in (\mathrm{c},\ \mathrm{d}), \text{ with } 0 \le \mathrm{c} < \mathrm{d} \le 1 \\ \mathrm{Q}(x) = 1 & \text{for } x \in [\mathrm{d},\ 1], \end{array} \tag{7}$$

such that $x' \le x'' \Rightarrow s(x') \le s(x'')$ for all $x',\ x'' \in [0, 1]$, and $\mathrm{Q}\,(0) = 0$, $\mathrm{Q}\ (1) = 1$. For details on linguistic quantifiers see Zadeh [61].

In Fedrizzi et al. [24] this model was implemented in an interactive user-friendly microcomputer-based decision support system where the consensus reaching process is supervised by a moderator. The moderator, in a multistage session, tries to make the individuals change their preferences by, e.g. rational argument, bargaining, additional knowledge, etc. to eventually get closer to consensus.

A similar approach to consensus modelling was developed by Herrera-Viedma et al. [32], where the novelty basically consists in introducing a degree of consensus between the individuals which depends on two consensus parameters, a consensus measure and a proximity measure. The consensus measure evaluates the agreement of all the experts, while the proximity measure evaluates the agreement between the experts' individual opinions and the group opinion. Individual opinions are represented using fuzzy preference relations derived from preference structures defined on a finite set of alternatives $X = \{x_1, \ldots, x_n\}$.

Two preference structures are considered:

1. Evaluations $\lambda_i{}^k$ associated with each alternative x_i, indicating the performance of that alternative according to a point of view of the selected expert
2. Multiplicative preference relation $A^k = (\boldsymbol{a}_{ij}{}^k)$ (Saaty's).

Individual fuzzy preference relations are derived from each preference structure introducing transformation functions satisfying some consistency properties.

Then, a consensus support system that emulates the moderator's behavior is introduced. The system has a feedback mechanism, based on the proximity measure, to generate recommendations in the group discussion process directed to change the individual opinions (preferences), in order to obtain a higher degree of consensus.

2.2 Soft Consensus in a Dynamical Setting

The soft consensus approach developed by Kacprzyk and Fedrizzi [34] was extended to a dynamical context in Fedrizzi et al. [22, 23, 25] and Marques Pereira [46] combining a measure of collective disagreement with an inertial mechanism of opinion changing aversion. The new model acts on the network of individual preference relations by a combination of a collective process of diffusion and an individual mechanism of inertia. The overall effect of the dynamics is to outline and enhance the natural segmentation of the group of decision makers into homogeneous preference subgroups, according to Bayesian priors from which the model derives. The modelling framework here adopted is essentially that one introduced in the previous section. The only difference consists in simplifying the shape of the quantifiers by eliminating the quantifier Q2 (i.e. by choosing it as the identity function) and by choosing the quantifier Q1 = Q as follows,

$$Q(x) = (f(x) - f(0))/(f(1) - f(0)) \tag{8}$$

where in our soft consensus model the scaling function $f : [0,\ 1] \to \Re$ is defined as,

$$f(x) = -\frac{1}{\beta}\ln\left(1 + e^{-\beta(x-\alpha)}\right) \tag{9}$$

and $\alpha \in (0,\ 1)$ is a threshold parameter and $\beta \in (0,\ \infty)$ is a free parameter which controls the polarization of the sigmoid function f',

$$f'(x) = 1\Big/\left(1 + e^{\beta(x-\alpha)}\right) = \sigma(x) \tag{10}$$

For large values of the parameter β the sigmoid function f' is close to a step function with respect to the threshold value α : $f'(0) \approx 1$, $f'(1) \approx 0$, and $f'(\alpha) = 0.5$. Otherwise, the function f' is smooth and monotonically decreasing with respect to its argument.

Moreover, for sake of simplicity, let us assume that the alternatives available are only two, that is $m = 2$, which means that each (reciprocal) individual preference relation R_i, has only one degree of freedom, denoted by $\mathrm{x}_i = r^i_{12}$. Accordingly, the relevance P is trivial. In such case, we have $V(i,j) = (x_i - x_j)^2 \in [0,\ 1]$ and thus $V_{\mathrm{Q}}\ (i,j) = \mathrm{Q}\ (V(i,\ j)) = \mathrm{Q}\ ((x_i - x_j)^2) \in [0,\ 1]$.

The starting assumption is that each decision maker $i = 1, \ldots, n$ is represented by a pair of connected nodes, a primary node (dynamic) and a secondary node (static). The n primary nodes form a fully connected sub network and each of them encodes the individual opinion of a single decision maker. The n secondary nodes, on the other hand, encode the individual opinions originally declared by the decision makers, denoted $\mathbf{s}_i = [s_i \in [0,\ 1]]$, and each of them is connected only with the associated primary node.

The iterative process of opinion transformation corresponds to the gradient dynamics of a cost function W, depending on both the present and the original network configurations. The value of W combines a measure V of the overall disagreement in the present network configuration and a measure U of the overall change from the original network configuration.

The various interactions involving node i are mediated by interaction coefficients whose role is to quantify the strength of the interaction. The diffusive interaction between primary nodes i and j is mediated by the interaction coefficient $v_{ij} \in (0,1)$, whereas the inertial interaction between primary node i and the associated secondary node is mediated by the interaction coefficient $u_{ij} \in (0,1)$. It turns out that the values of these interaction coefficients are given by the derivative f' of the scaling function.

The diffusive component of the network dynamics results from the consensual interaction between each node x_i and the remaining $n-1$ nodes $x_{j\neq i}$ in the network. The aggregated effect of these $n-1$ interactions can be represented as a single consensual interaction between node x_i and a virtual node $\bar{x}_i$ containing a particular weighted average of the remaining opinion values.

The interaction coefficient $v_i \in (0,1)$ of this aggregated consensual interaction controls the extent to which decision maker i is influenced by the remaining experts in the group. In our soft consensus model the value v_i, as well as the weighting coefficients $v_{ij} \in (0,\ 1)$ in the definition of $\bar{x}_i$ as given below, depend non-linearly on the standard Euclidean distance between the opinions x_i and x_j,

$$v_{ij} = f'((x_i - x_j)^2) \tag{11}$$

$$v_i = \sum_{j\neq i} v_{ij}/(n-1) \tag{12}$$

and the average preference $\bar{x}_i$ is given by

$$\bar{x}_i = \frac{\sum_{j \neq i} v_{ij} x_j}{\sum_{j \neq i} v_{ij}} \tag{13}$$

In the context of these definitions, $f'(x) \in (0,\ 1)$ is the decreasing sigmoid function introduced in the previous section. This sigmoid function plays a crucial role in the network dynamics and is obtained as the derivative of the scaling function $f(x) \in \Re$ which, in turn, enters the construction of the soft consensus cost function from which the network dynamics derives.

The interaction coefficient $u_i \in (0,\ 1)$ of this inertial interaction controls the extent to which the decision maker i resists to opinion changes due to the collective consensual trend. In analogy with the diffusion coefficients, the value u_i in our soft consensus model depends non-linearly on the standard Euclidean distance between the opinions x_i and s_i,

$$u_i = f'((x_i - s_i)^2) \tag{14}$$

where $f'(x)$ is the sigmoid function mentioned earlier.

The individual disagreement cost $V(i)$ is given by

$$V(i) = \sum_{j \neq i} V(i,j)/(n-1) \tag{15}$$

where $V(i,j) = f((x_i - x_j)^2)$ and the individual opinion changing cost $U(i)$ is

$$U(i) = f((x_i - s_i)^2) \tag{16}$$

Summing over the various decision makers we obtain the collective disagreement cost V and inertial cost U,

$$V = \frac{1}{4} \sum_i V(i) \text{ and } U = \frac{1}{2} \sum_i U(i) \tag{17}$$

with conventional multiplicative factors of 1/4 and 1/2.

The full cost function W is then $W = (1-\lambda)V + \lambda U$ with $0 \leq \lambda \leq 1$.

The consensual network dynamics, which can be regarded as an unsupervised learning algorithm, acts on the individual opinion variables x_i through the iterative process

$$x_i \rightarrow x_i' = x_i - \varepsilon \frac{\partial W}{\partial x_i} \tag{18}$$

The effect of the two dynamical components V and U can be analysed separately and it can be proved (see for details Fedrizzi et al. [25]) that

$$x_i' = (1 - \varepsilon(v_i + u_i))x_i + \varepsilon v_i \bar{x}_i + \varepsilon u_i s_i \tag{19}$$

Accordingly, the decision maker i is in dynamical equilibrium, in the sense that $x_i' = x_i$, if the following stability equation holds,

$$x_i = (v_i \bar{x}_i + u_i s_i)/(v_i + u_i) \tag{20}$$

that is, if the present opinion value x_i coincides with an appropriate weighted average of the original opinion s_i and the average opinion value $\bar{x}_i$.

In Fedrizzi et al. [26] the dynamical model was extended assuming that the preferences of the decision makers are expressed by means of fuzzy numbers, in particular by means of triangular fuzzy numbers. Then, in order to measure the differences between the preferences of the decision makers, a distance belonging to a family of distances proposed by Grzegorzewski [31] was introduced.

3 Aggregation Guided by Linguistic Quantifiers expressed as Ordered Weighted Averaging Operators

With the approach to GDM introduced in Sect. 2 each expert compares the alternatives and makes relative judgements of preference among couples of them, thus defining a preference relation. In this section a different approach often used in the literature is introduced, where the experts express an absolute judgement on each alternative to evaluate it. By this approach a numeric or linguistic value (from a set of admissible values) is selected by the expert to indicate the performance of the alternative with respect to her/his opinion. It is not infrequent that the experts are asked to express for each alternative an evaluation with respect to each of a set of predefined criteria. In this case we are in the framework of Multi Expert Multi Criteria decision making [14].

In this absolute evaluation framework, the ultimate aim of the group decision process is to determine for each alternative a consensual judgement (consensual opinion) which synthesizes the experts individual opinions. The consensual judgement is representative of a collective evaluation and is usually computed by means of an aggregation of the individual experts' opinions. Usually also a consensus degree is computed for each alternative, with the consequent problem of comparing the decision makers' opinions to verify the consensus among them. In the case of unanimous consensus, the evaluation process ends with the selection of the best alternative(s).

As outlined in the previous section, in real situations humans rarely come to an unanimous agreement: what is often needed is an overall opinion which synthesizes the opinions of the *majority* of the decision makers. The reduction of the individual values into a representative value (the majority opinion) is usually performed through an aggregation process. As outlined in Sect. 2, within fuzzy set theory the concept of majority can be expressed by a linguistic quantifier (such as *most*), which is formally defined as a fuzzy subset of a numeric domain; the semantics of such a fuzzy subset is described by a membership function which describes the compatibility of a given absolute or percentage quantity to the concept expressed by the linguistic quantifier. By this interpretation a linguistic quantifier is seen as a fuzzy concept referred to the quantity of elements of a considered reference set. In the fuzzy approaches synthetically described in Sect. 2 a full consensus is not necessarily the result of unanimous agreement, but it can be obtained even in case of agreement among a fuzzy majority of the decision makers (Fedrizzi et al. [24], Fedrizzi et al. [21], Kacprzyk and Fedrizzi [35]).

In the fuzzy approaches to group decision making the concept of majority is usually modeled by means of linguistic quantifiers such as *at least* 80% and *most* (monotonic non decreasing linguistic quantifiers). When linguistic quantifiers are used to indicate a fusion strategy to guide the process of aggregating the members' opinions, the formal mathematical definition of the resulting aggregation operator encodes the semantics of the linguistic quantifier. The notion of quantifier guided aggregation has been formally defined by means of Ordered Weighted Averaging operators [58, 59], and by means of the concept of fuzzy integrals (Grabish [30]). An example of linguistic expression which employs a quantifier to guide an aggregation is the following: *Q experts are satisfied by solution a*, where Q denotes a linguistic quantifier, for example *most*, which expresses a majority. To evaluate the satisfaction of this proposition the experts' opinions have to be aggregated using the formal aggregation operator which captures the semantics of the concept expressed by the quantifier Q.

In the applications related to group decision making the use of OWA operators has been extensively experienced [15]. We shortly introduce the formal definition of OWA operators in both cases in which numeric and linguistic values have to be aggregated. For a more extensive definition see Yager [59]. An OWA operator on unit interval is a mapping OWA: $[0,1]^n \to [0,1]$ with an associated weighting vector

$\mathrm{W} = [\mathrm{w}_1, \mathrm{w}_2, \ldots, \mathrm{w}_\mathrm{n}]$ such that $\mathrm{w}_\mathrm{i} \in [0,1]$, and $\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{w}_\mathrm{i} = 1$, and for any arguments $a_1, a_2, \ldots, a_n \in [0,1]$:

$$\mathrm{OWA}(a_1, a_2, \ldots, a_n) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{b}_\mathrm{i}\,\mathrm{w}_\mathrm{i} \tag{21}$$

with b_i being the i^{th} largest element of the a_j [58]. A number of approaches have been suggested for determining the weights used in the OWA operator. Here we present the one that allows to obtain the weights from a functional form of the linguistic quantifier (i.e. from the definition of the linguistic quantifier as a fuzzy subset). Let Q: $[0,1] \to [0,1]$ be a function such that $\mathrm{Q}(0) = 0$, $\mathrm{Q}(1) = 1$ and $\mathrm{Q(x)} \geq \mathrm{Q(y)}$ for $\mathrm{x} > \mathrm{y}$ corresponding to a fuzzy set representation of a proportional monotone quantifier. For a given value $\mathrm{x} \in [0,1]$, the Q(x) is the degree to which the quantity (relative quantity) x satisfies the fuzzy concept being represented by the quantifier. Based on function Q, the OWA vector is determined from Q by defining the weights in the following way:

$$w_i = \mathrm{Q}(i/n) - \mathrm{Q}((i-1)/n). \tag{22}$$

In this case w_i represents the increase of satisfaction in getting i with respect to $i-1$ criteria satisfied. Let us consider now a set of linguistic labels S uniformly distributed on a scale so that an ordering is defined ($s_a, s_b \in S,\ a < b \Leftrightarrow s_a < s_b$) and $s_0,\ s_{max}$ are the lower and the upper elements respectively with $max = |S| - 1$, where |S| denotes the cardinality of S. An Ordered Weighted Average operator OWA on the ordinal scale S is a mapping: $\mathrm{OWA}_Q : S^M \rightarrow S$ with a weighting vector: $\mathrm{W} = [\mathrm{w}_1, \mathrm{w}_2, \ldots, \mathrm{w}_\mathrm{M}]$ in which $w_i \in S,\ w_i \geq w_j$, for $i > j$ and $MAX_i(w_i) = s_{max}$ then:

$$\mathrm{OWA}(a_1, a_2, \ldots, a_M) = \mathrm{Max}(w_i \wedge b_i) \tag{23}$$

where b_i is the i-th highest label a_k in S among the $a_1, a_2, \ldots, a_M$. An ordinal OWA is determined by a relative monotone increasing quantifier Q, by setting $\forall \mathrm{i} \in \{1, M\}$:

$$w_i = Q\left(\frac{i}{M}\right) \in S \tag{24}$$

The value $Q(\frac{i}{M})$ indicates the degree of satisfaction of getting i of the M criteria fulfilled.

In Sect. 4 we synthetically present a linguistic approach to Multi Expert Multi Criteria Decision making entirely based on the use of a majority guided aggregation formalized by OWA operators.

Recently, in Pasi and Yager [50] it was outlined that when aggregating a collection of values by means of an OWA associated with a linguistic quantifier (constructed by applying either formula (22) or formula (24)), the resulting aggregated value may not be representative of the majority of values. To overcome this problem in Pasi and Yager [50] two new and distinct strategies have been proposed aimed at constructing OWA operators which allow to obtain an aggregated value that better reflects a "true" concept of majority. As previously outlined, the weights of the weighting vector of an OWA operator are interpreted as the increase in satisfaction in having i + 1 criteria "fully" satisfied with respect to having "fully" satisfied i criteria. If for example we consider the linguistic quantifier *at least* 80% and we apply the procedure reported in formula (22) to obtain the weights of the OWA weighting vector, the semantics of the obtained aggregated value is like a degree of satisfaction (truth) of the proposition "Q of the values are fully satisfied". This kind of semantics does not naturally model the meaning of the concept of majority as typically used in group decision making applications. In fact an operator aimed at calculating a majority opinion should produce a value which is representative of the 80% of the *most similar values*. In other words what we want to obtain is an aggregation of the most similar opinions held by a quantity of decision makers specified by the linguistic quantifier Q. This situation appears to bring us closer in spirit to interpretation of the OWA operator as averaging operator rather then as a generalized quantifier. In fact what we want is an average of "most of the similar values". This means that we need an aggregation operator that takes an average like aggregation of a majority of values that are similar. The first approach proposed in Pasi and Yager [50] to define such an aggregation operator makes use of Induced Ordered Weighted

Averaging (IOWA) operators (Yager and Filev [60]) to obtain a scalar value for a majority opinion. By IOWA operators the ordering of the elements to be aggregated is determined by an inducing ordering variable. In Pasi and Yager [50] the inducing ordering variable is based on a proximity metric over the elements to be aggregated. The basic idea is that the most similar values must have close positions in the induced ordering in order to appropriately be aggregated. A new strategy for constructing the weighting vector has also been suggested so as to better model the new "majority-based" semantics of the aggregation. This strategy has the aim of emphasizing in the aggregation the most supported values; in other words the values which appear on the right hand side of the vector of values to be aggregated have more influence in the aggregation.

The second approach proposed in Pasi and Yager [50] is based upon the calculation of the concept of the majority opinion as an imprecise value. Under this interpretation a formalization has been proposed of the idea of a fuzzy majority as a fuzzy subset. This approach provides in addition to a value for a majority opinion an indication of the strength of that value as the majority opinion. The goal here is to obtain a value which can be considered as the opinion of a majority, that is, some value that is similar for any large group of people. Both methods require to have both information about the similarity between the experts opinions, and some information about what quantity constitutes the idea of a majority.

4 Consensus Modelling in Linguistic Approaches to Multi Expert Multi Criteria Decision Making

In addressing a decision making problem it is not infrequent that the ratings or performance scores cannot be assessed precisely but in a linguistic form (Herrera-Viedma et al. [33]). The imprecision may come from different sources as pointed out in Chen and Hwang [14]: information may be unquantifiable when the evaluation of a criterion, due to its nature, can be stated only in linguistic terms such as in the case of the evaluation of the *comfort* or *design* of a *car*, terms like *good, fair, poor* can be used. Sometimes precise testimonies cannot be stated because they are unavailable or the cost for their computation is too high and an "approximated estimates" can be tolerated; for example, for the evaluation of a car's speed linguistic terms like *fast, very fast, slow* can be used instead of numeric values.

As an approach representative of consensus modelling in the context of Multi Expert Multi Criteria Decision Making in a linguistic setting, in this section we give a synthesis of the linguistic model proposed by Bordogna et al. [11], as it offers a general approach to group decision making, which is entirely based on the management of information expressed linguistically. A Multi Expert Multi Criteria decision problem is considered, the aim of which is to compute a consensual judgment and a consensus degree for a fuzzy majority of the experts on each of the considered alternatives. The group of experts judges each alternative according to the evaluation of a finite set of predefined criteria. Each expert is asked to linguistically evaluate each alternative in terms of its performance with respect to each criterion. The experts are also allowed to associate a distinct importance to the criteria in a linguistic form as well. This procedure adopts an absolute evaluation of each alternative and is based on the assumption of alternatives' independency. To enable the experts to formulate their judgments in a natural way, a limited set S of linguistic labels is supplied. For example, S can be defined so as its elements are uniformly distributed on a scale on which a total order is defined: $S = [\mathrm{s}_0 = \text{none}, \mathrm{s}_1 = \text{very low}, \mathrm{s}_2 = \text{low}, \mathrm{s}_3 = \text{medium}, \mathrm{s}_4 = \text{high}, \mathrm{s}_5 = \text{very high}, \mathrm{s}_6 = \text{perfect}]$ in which $\mathrm{s_a} < \mathrm{s_b}$ iff $\mathrm{a} < \mathrm{b}$. The cardinality of S must be small enough so as not to impose useless precision to the experts and it must be rich enough in order to allow a discrimination of the performances of each criterion in a limited number of grades.

By allowing the experts to express in a linguistic form the evaluations of both performance and importance of criteria, the burden of quantifying a qualitative concept is eliminated and thus the system-expert interaction is simplified. In Sect. 4.1 the process of reducing, for each expert, the M evaluations expressed for a given alternative (where M is the number of considered criteria) to an overall judgment for the alternative is presented. In Sect. 4.2 the process aimed at computing a consensus degree and a consensual choice among the experts is presented.

4.1 An Overall Performance Judgment for each Alternative and each Expert

Once each expert has expressed a linguistic judgment for each criterion with respect to each alternative, the first phase towards the evaluation of a degree of consensus is aimed at synthesizing an overall performance judgment for each alternative and for each expert. This is done through an aggregation of the linguistic judgments for each alternative with respect to each criterion. To this aim in Bordogna et al. [11] an aggregation function has been proposed which works directly on linguistic labels on an ordinal scale and produces a global linguistic performance label by applying OWA operators.

Formally, the set of alternatives is denoted by: $A = \{A_1, A_2, \ldots, A_N\}$, the set of experts is denoted by: $E = \{E_1, E_2, \ldots, E_K\}$, and the set of criteria is denoted by: $C = \{C_1, C_2, \ldots, C_M\}$. The input to the aggregation phase is represented by a set of K matrixes of dimension $N \times M$, in which K, N and M are the numbers of experts, alternatives and criteria respectively; there is one matrix for each expert, in which each element is a linguistic label $P_{ij} \in \mathrm{S}$ drawn from an ordinal scale and expressing the performance judgment on criterion C_i with respect to the alternative A_j. For each matrix a vector of dimension M is defined in which an element $I_i \in \mathrm{S}$ drawn from the same scale is the importance value associated with criterion C_i by the expert. We omit the index j as the aggregation is performed for a given expert and a given alternative: $P_{ij} \equiv P_i$. The functions aggregating the linguistic performance labels of each alternative have been defined by the relative monotone increasing quantifiers *averagely all, most of* and *more than k%*. For defining these aggregation functions two different formalizations of OWA operators have been proposed. The first approach is more straightforward, as it consists in applying the OWA operators defined on an ordinal scale [59]; in this case, for each quantifier Q the correspondent OWA is defined by specifying the linguistic values of the weighting vector W. These linguistic weights can be defined either by specifying their values directly or by applying formula (24).

When the criteria $C_1, \ldots, C_M$ have the same importance, the OWA_Q operator associated with the quantifier Q is directly applied to the satisfaction values $P_1, \ldots, P_M$ of the criteria. For the l-th expert and the i-th alternative $\mathrm{OWA}_Q(P_{i1}, \ldots, P_{iM})$ will be then evaluated as defined in formula (23).

When differing importance values $I_1, \ldots, I_M \in \mathrm{S}$ are associated with the criteria, one of two possible procedures can be applied to compute the overall performance of an alternative. The procedures are extensively explained in Bordogna et al. [11].

The output of this phase can be summarized in a matrix of dimension $N \times K$, in which an element P_{ij} is the overall performance label of expert E_i with respect to alternative A_j.

4.2 How to Determine a Consensual Opinion

The second phase of a group decision activity is aimed at evaluating the degree of consensus among the experts' overall performance judgments on the alternatives. It is worthwhile to point out that the phase of computation of the consensus degree should be followed by the evaluation of a consensual ranking of alternatives for the specified consensual majority. In other words, the consensual degree refers to a ranking of alternatives which in some way synthesizes the ranking of the considered experts' majority.

In the approach adopted in Bordogna et al. [11] a consensus degree is computed for each alternative, under the assumption of alternative independency on each expert. The novelty of the proposed procedure consists in the direct computation of "soft" linguistic degrees of consensus based on a topological approach [12]; this procedure supported a new definition of consensus referred to a fuzzy majority: the statement "*most of the experts agree of alternative* $\mathrm{A_i}$" is interpreted as "*most of the experts agree with most of the other experts on alternative* $\mathrm{A_i}$".

The starting point is constituted by the matrix of N rows (one for each alternative) and K columns (one for each expert) produced by the phase described in Sect. 4.1. An element on row i and column j of this matrix is a linguistic value in S, which expresses the overall performance judgment of expert j with respect to alternative i. A linguistic degree of consensus among the experts' overall performances is then computed for each alternative. The procedure proposed in Bordogna et al. [11] is aimed at evaluating the consensus degree among Q experts for each alternative, in which Q is a quantifier identifying a fuzzy majority. This procedure is structured in the following phases:

- For each alternative, pair wise comparisons of experts' overall performance labels are made to establish the degree of agreement between all pairs of experts (full agreement = *perfect*, null agreement = *none*). A matrix $K \times K$ is then constructed for each alternative. An element $Ag(E_i, E_j)$ is the linguistic label, which expresses the similarity between the overall performance labels of experts E_i and E_j;
- For each expert E_i (a row of the matrix $K \times K$) the $K-1$ degrees $Ag(E_i, E_j),\ i \neq j$ are pooled to obtain an indication of the agreement $Ag(E_i)$ of expert E_i with respect to Q of the other experts.
- The values $Ag(E_i)$ are finally aggregated to compute the truth of the sentence "Q E_i agree on alternative A_x".

For each alternative A_x, the degrees of agreement between all pairs of experts are first computed, as the complement of a distance between the overall performance labels:

$$Ag(E_i, E_j) = \neg(d(P_{ix}, P_{jx})) \tag{25}$$

in which P_{ix} denotes the linguistic overall performance label of expert E_i on alternative A_x. Provided that the elements in S are uniformly distributed, function d is defined on $S \times S$ and takes values in S; it is applied to the overall performance labels of experts E_i and E_j, and produces a linguistic label indicating the distance between the two arguments. The d function is defined as a difference operator of linguistic labels in the same scale [18]; the labels belong to the totally ordered term set $\mathrm{S} = \{s_i \big| \mathrm{i} \in \{0 \cdots max\}\} : d(s_i, s_j) = \mathrm{s_r}$ with $r = |i-j|$.

The complement operation $\neg$ is defined as: $\neg(s_i) = s_{max-i}$. The evaluation of the complement of the distance between two linguistic labels is a measure of the degree of agreement between the opinions of two experts. The results produced by this phase can be synthesized in N matrixes $K \times K$, one for each alternative.

Once the degrees of agreement between pairs of experts have been computed, they must be pooled to obtain *the degree of consensus among Q experts*, in which Q is a quantifier such as *most of, all, more than k%*. This is done in two subsequent steps. First of all for each expert an overall indication of his/her agreement with respect to Q of the others experts is computed; we indicate this overall degree as $Ag_Q(E_i)$.

Formally, this aggregation is performed by applying to the $Ag(E_i, E_j)$ (with $i \neq j,\ i, j = 1 \cdots K$) on the i-th row of the matrix, the ordinal OWA_Q operator associated with the linguistic quantifier Q, as defined in Sect. 3. At this point it is possible to identify the expert with the highest disagreements versus most of the other experts: this information can be useful in consensus reaching to address the experts who should revise their opinions in order to increase the degree of consensus.

The last step is the determination of consensus among Q experts; to obtain this final consensus degree also the K values $Ag_Q(E_i)$, one for each expert, are aggregated with the OWA_Q operator. The consensual performance judgment of each alternative, defined as the label on which the identified majority of the experts agree, is finally computed. It is obtained by applying the same OWA_Q operator to the overall performance judgments of all the experts on the given alternative.

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Decision Making Based on Fuzzy Data Envelopment Analysis

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Summary. DEA (data envelopment analysis) is a non-parametric technique for measuring and evaluating the relative efficiencies of a set of entities with common crisp inputs and outputs. In fact, in a real evaluation problem input and output data of entities evaluated often fluctuate. These fluctuating data can be represented as linguistic variables characterized by fuzzy numbers for reflecting a kind of general feeling or experience of experts. Based on the fundamental CCR model, a fuzzy DEA model is proposed to deal with the efficiency evaluation problem with the given fuzzy input and output data. Furthermore, a fuzzy aggregation model for integrating multiple attribute fuzzy values of objects is proposed based on the fuzzy DEA model. Using the proposed fuzzy DEA models, the crisp efficiency in CCR model is generalized to be a fuzzy efficiency to reflect the inherent uncertainty in real evaluation problems. Using the proposed fuzzy aggregation models, the objects can be ranked objectively.

1 Introduction

Data envelopment analysis (DEA) initially proposed by Charnes et al. [3] is a non-parametric technique for measuring and evaluating the relative efficiencies of a set of entities, called decision making units (DMUs), with the common inputs and outputs. Examples include school, hospital, library and, more recently, whole economic and society systems, in which outputs and inputs are always multiple in character. Most of DEA papers make an assumption that input and output data are crisp ones without any variation. In fact, inputs and outputs of DMUs are ever-changeful. For example, for evaluating operation efficiencies of airlines, seat-kilometers available, cargo-kilometers available, fuel and labor are regarded as inputs and passenger-kilometers performed as an output [4]. It is common sense that these inputs and output are easy to change because of weather, season, operating state and so on. Because DEA

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is a 'boundary' method sensitive to outliers, it is very difficult to evaluate the efficiency of DMU with varying inputs and outputs by conventional DEA models. Some researchers have proposed several models to challenge how to deal with the variation of data in efficiency evaluation problems by stochastic frontier models [1,9,19]. On the other hand, in more general cases, the data for evaluation are often collected from investigation by polling where the natural language such as *good, medium* and *bad* are used to reflect a kind of general situation of the investigated entities rather than a specific case. In the above example, an expert can make a general conclusion that the airline A is about *200 passenger-kilometers* and fuel cost is *high* based on his rich experience. These fuzzy concepts are used to summarize the general situation of inputs and outputs and reflect the ambiguity of the experts' judgment. The center of a fuzzy number represents the most general case and the spread reflects some possibilities. Some DEA models under uncertainty have been research in papers [5, 6, 10–16, 18, 21, 24].

In this paper, a fuzzy DEA model is proposed which is an extension of CCR model for evaluating the fuzzy efficiency of DMU with the given fuzzy input and output data. The crisp efficiency in CCR model is generalized to be a fuzzy number to reflect the inherent uncertainty in real evaluation problems.

Aggregation operators play an important role in information integration and decision analysis, which offer the synthesized one-dimensional information from the high-dimensional space to facilitate an overall judgment in the decision-making procedure. Several kinds of aggregation operators have been researched in papers [2,7,8,17,20,22,23]. In essence, these methods are sorts of weighted aggregation operators. That is, aggregation is represented as a kind of generalized weighted sum where weight factors of attributes are predetermined by decision-makers to represent their preference or a sort of threshold. It is obvious that different weight factors lead to different aggregation results. Generally speaking, it is very difficult to choose suitable weight factors because of the existence of inherent uncertainty and subjectivity for determining them. In particular, sometimes we need some objective rather than subjective assessment by aggregation operators. In other words, there is no such authority (decision-maker) with the right to determine the weight factors of attributes in advance. Let us give a scenario for explaining this viewpoint. A motorcycle company has designed five kinds of new products and wants to know which is the most popular so that they can make a decision for mass-production. In so doing, a demonstration can be held where the questionnaires on attributes related with sales, such as, price, beauty, comfort and fuel cost etc. are collected from visitors. In this case, it is unimaginable that this company can predetermine the weight factors of attributes because buying or not is completely decided by customers not this company. However, it is certain that the company can give some suggestion on attributes, for example, "the price is the most important attribute for a good sale". Meanwhile, customers also can't determine the weight factors of attributes because producing which kind of motorcycle is completely decided by the company rather than the individual preference of some customer. However, customers can express their comments on the attributes of motorcycles. In a word, there is no authority to determine some specified weight factors of attributes in this example. The weight factors of attributes should objectively reflect the inherent characteristic of the information from customers and the company. This kind of evaluation system is called agent-clients evaluation (ACE) system. In ACE systems the agent (company) can collect some information on the evaluated objects from clients (customers) and decide which action should be taken to meet clients' preference. The ACE systems greatly differ from multi-criteria decision-making systems in the sense that there is an agent rather than an authority that has right to specify weight factors of attributes in advance. An aggregation model for ACE system, called Self-organizing fuzzy aggregation model, is proposed in the paper [11].

In this paper, an aggregation model for integrating multiple attribute fuzzy values of objects is proposed based on the fuzzy DEA model, in which the fuzzy multi-input values of all DMUs become the crisp value 1.

This paper is organized as follows: Section 2 is devoted to a brief introduction of DEA. In Sect. 3, fuzzy DEA models are proposed. In Sect. 4, the methods for evaluating the objects with multiple fuzzy attribute values are proposed. For illustration of our methods, numerical examples are given in Sects. 3 and 4. Section 5 makes some concluding remarks for this paper.

2 Data Envelopment Analysis

DEA (data envelopment analysis) is a non-parametric technique for measuring and evaluating the relative efficiencies of a set of entities with common crisp inputs and outputs. CCR model, a basic DEA model, is a linear programming (LP) based method proposed by Charnes et al. [3]. In CCR model the efficiency of the entity evaluated is obtained as a ratio of its weighted output to its weighted input subject to the condition that the ratio for each entity is not greater than 1. Mathematically, it is described as follows:

$$\begin{aligned} \max_{\mu,\nu} \quad & \frac{\mu^t \mathbf{y}_o}{\nu^t \mathbf{x}_o} \\ \text{s. t.} \quad & \frac{\mu^t \mathbf{y}_j}{\nu^t \mathbf{x}_j} \leq 1 \ (j = 1, \ldots, n), \\ & \mu \geq \mathbf{0}, \\ & \nu \geq \mathbf{0}. \end{aligned} \tag{1}$$

Here the evaluated entities (DMUs) form a reference set and n is the number of DMUs. $\mathbf{y}_j = [y_{j1}, \ldots, y_{jm}]^t$ and $\mathbf{x}_j = [x_{j1}, \ldots, x_{js}]^t$ in (1) are the given positive output and input vectors of the jth DMU, respectively, and m and s are the numbers of outputs and inputs of DMU, respectively. μ and ν in (1) are the coefficient vectors of $\mathbf{y}_j$ and $\mathbf{x}_j$, respectively and the index o indicates the evaluated DMU. $\mu \geq \mathbf{0}$ represents the vector whose elements are not smaller than zero but at least one element is positive value whereas $\mu > \mathbf{0}$ represents the vector with positive elements.

The model (1) is equivalent to the following LP problem.

$$\begin{aligned} \max_{\mu,\nu} \quad & \mu^t \mathbf{y}_o \\ \text{s. t.} \quad & \nu^t \mathbf{x}_o = 1, \\ & \mu^t \mathbf{y}_j \leq \nu^t \mathbf{x}_j \ (j = 1, \ldots, n), \\ & \mu \geq \mathbf{0}, \\ & \nu \geq \mathbf{0}. \end{aligned} \tag{2}$$

It can be seen from (2) that the essence of CCR model is that the DMU evaluated tries to find out its own weight vector to maximize its weighted output with the constraints that its weighted input is fixed as unity and the weighted output is not greater than the weighted input for all DMUs. In other words, each DMU seeks its favorite weight vector to its own advantage.

3 Fuzzy DEA Models

If the input and output data are fuzzy numbers for representing the judgment of persons, let us consider how to evaluate the efficiencies of DMUs. Firstly, the basic concepts of fuzzy sets are introduced in the following section.

3.1 Preliminaries of Fuzzy Sets

Definition 1. *A fuzzy number A is called L–L fuzzy number and denoted as $(a, c, d)_L$ if its membership function is defined by*

$$\Pi_A(x) = \begin{cases} L((a-x)/c), & x \leq a \\ 1, & x = a\,, \\ L((x-a)/d), & x \geq a \end{cases} \tag{3}$$

where $c > 0,\ d > 0$ and reference functions $L : [0, +\infty) \to [0, 1]$ is a strictly decreasing functions with $L(0) = 1$. An L–L fuzzy number $(a, c, d)_L$ with $L(x) = \max(0, 1 - |x|)$ is called triangular fuzzy number, denoted as (a,c,d). A symmetrical L–L fuzzy number is denoted as $(a, c)_L$ for the case of $c = d$.

An n-dimensional vector $\mathbf{x} = [x_1, \ldots, x_n]^t$ can be fuzzified as a symmetrical L–L fuzzy vector $\mathbf{A}$ whose membership function is defined as

$$\Pi_{\mathbf{A}}(\mathbf{x}) = \Pi_{A_1}(x_1) \wedge \ldots \wedge \Pi_{A_n}(x_n), \tag{4}$$

where $\Pi_{A_i}(x_i)$ is the membership function of a symmetrical L–L fuzzy number, denoted as $(a_i, c_i)_L$. An n-dimensional L–L fuzzy vector is denoted as $\mathbf{A} = (\mathbf{a}, \mathbf{c})_L$ with $\mathbf{a} = [a_1, \ldots, a_n]^t$ and $\mathbf{c} = [c_1, \ldots, c_n]^t$.

Consider a fuzzy linear system

$$Y = A_1x_1 + \cdots + A_nx_n = \mathbf{A}^t\mathbf{x}, \tag{5}$$

where x_i is a real number ($i = 1, \ldots, n$) and $\mathbf{A}$ is an n-dimensional symmetrical L–L fuzzy vector whose element is $(a_i, c_i)_L$. From the extension principle, it is known that Y is a symmetrical L–L fuzzy number as follows.

$$Y = \left(\sum_{i=1,\ldots,n} x_i a_i, \sum_{i=1,\ldots,n} |x_i| c_i \right)_L = (\mathbf{a}^t\mathbf{x}, \mathbf{c}^t\,|\mathbf{x}|)_L. \tag{6}$$

Its h-level set, denoted as $[Y]_h$, is as follows.

$$[Y]_h = [\mathbf{a}^t\mathbf{x} - L^{-1}(h)\mathbf{c}^t|\mathbf{x}|, \mathbf{a}^t\mathbf{x} + L^{-1}(h)\mathbf{c}^t|\mathbf{x}|], \tag{7}$$

where $|\mathbf{x}| = [|x_1|, \ldots, |x_n|]^t$ and $0 < h \leq 1$.

3.2 Fuzzy DEA Based on CCR Model

Considering fuzzy input and output data, CCR model (2) can be naturally generalized to be the following fuzzy DEA model.

$$\begin{aligned} \max_{\mu,\gamma} \quad & \mu^t\mathbf{Y}_o \\ \text{s. t.} \quad & \nu^t\mathbf{X_o} \approx \tilde{1}, \\ & \mu^t\mathbf{Y}_j \underset{\sim}{<} \nu^t\mathbf{X}_j \ (j = 1, \ldots, n), \\ & \mu \geq \mathbf{0}, \\ & \nu \geq \mathbf{0}, \end{aligned} \tag{8}$$

where $\mathbf{X}_j = (\mathbf{x}_j, \mathbf{c}_j)_L$ and $\mathbf{Y}_j = (\mathbf{y}_j, \mathbf{d}_j)_L$ are an s-dimensional L–L fuzzy input vector and an m-dimensional fuzzy output vector of the jth DMU, respectively, which generalize crisp input and output vectors in (2). Meanwhile, "equal", "smaller than" and "maximizing crisp output" in (2) are extended to be "almost equal", "almost smaller than" and "maximizing a fuzzy number", respectively. Moreover, 1 in (2) becomes a fuzzy number $\tilde{1} = (1, e)_L$ where $e \leq 1$ is the predefined spread of $\tilde{1}$. In what follows, we interpret the concepts of "$\mu^t\mathbf{Y}_j \lesssim \nu^t\mathbf{X}_j$", "max $\mu^t\mathbf{Y}_o$" and "$\nu^t\mathbf{X_o} \approx \tilde{1}$" in sequence.

Definition 2. *Given two L–L fuzzy numbers $Z_1 = (z_1, w_1)_L$ and $Z_2 = (z_2, w_2)_L$, the relation $Z_1 \tilde{<}_h Z_2$ $(0 < h \leq 1)$ holds if and only if the following inequalities are true for any possibility level $k \in [h, 1]$.*

$$z_1 - L^{-1}(k)w_1 \leq z_2 - L^{-1}(k)w_2, \tag{9}$$

$$z_1 + L^{-1}(k)w_1 \leq z_2 + L^{-1}(k)w_2, \tag{10}$$

where $L^{-1}(\cdot)$ is the inverse function of $L(\cdot)$.

Theorem 1. *The necessary and sufficient conditions that* (9) *and* (10) *hold for any* $k \in [h, 1]$ *are as follows:*

$$z_1 - L^{-1}(h)w_1 \leq z_2 - L^{-1}(h)w_2, \tag{11}$$

$$z_1 + L^{-1}(h)w_1 \leq z_2 + L^{-1}(h)w_2, \tag{12}$$

Proof. It is trivial to prove the necessity. Let us now prove the sufficiency. If $h = 1$, the (11) and (12) are equivalent to (9) and (10), respectively. The sufficiency obviously holds for $h = 1$. Thus, we only consider the case of $h < 1$ in what follows. Taking the sum of (11) and (12) leads to

$$z_2 \geq z_1. \tag{13}$$

(11) is equivalent to

$$z_2 - z_1 \geq L^{-1}(h)(w_2 - w_1). \tag{14}$$

It is straightforward that the relation $0 \leq L^{-1}(k)/L^{-1}(h) \leq 1$ holds for $0 < h \leq k$. Thus,

$$z_2 - z_1 \geq L^{-1}(h)(w_2 - w_1) \geq L^{-1}(k)(w_2 - w_1). \tag{15}$$

(15) is equivalent to

$$z_1 - L^{-1}(k)w_1 \leq z_2 - L^{-1}(k)w_2. \tag{16}$$

Likewise, we can prove that

$$z_1 + L^{-1}(k)w_1 \leq z_2 + L^{-1}(k)w_2. \tag{17}$$

It proves this theorem.

Now, let us consider maximizing a fuzzy number. Referring to Definition 2, "Maximizing an L–L fuzzy number $Z = (z, w)_L$" can be explained as simultaneously maximizing $z - L^{-1}(h)w$ and $z + L^{-1}(h)w$. Here, the following weighted function

$$\lambda_1(z - L^{-1}(h)w) + \lambda_2(z + L^{-1}w), \tag{18}$$

is introduced to obtain some compromise solution where $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$ are the weights of left and right endpoints of the h-level set of Z, respectively, with $\lambda_1 + \lambda_2 = 1$. Taking $\lambda_1 = 1$ is regarded as a pessimistic opinion of maximizing Z because the worst situation is considered, whereas taking $\lambda_2 = 1$ is regarded as an optimistic opinion because the best situation is concerned with.

Next, let us consider the relation $\mathbf{v}^t\mathbf{X}_o \approx \tilde{1}$ in (8) which plays the same role as $\mathbf{v}^t\mathbf{x_o} = 1$ in (2). The crisp input vector $\mathbf{x}_0$ in CCR model becomes a fuzzy vector $\mathbf{X}_0$ so that $\mathbf{v}^t\mathbf{x}_0 = 1$ is generalized to be $\mathbf{v}^t\mathbf{X}_0 \approx \tilde{1}$ where $\tilde{1} = (1, e)_L$ is a fuzzy unity given by decision-makers. Different from the crisp case, that is, $\mathbf{v}^t\mathbf{x_o} = 1$, where the vector $\mathbf{v}$ can be found out to satisfy this equality, the

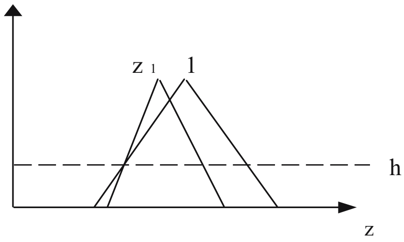

Fig. 1. Explanation of $Z \approx \tilde{1}$

vector ν can not always be found out to make the equality $\nu^t\mathbf{X}_o = \tilde{1}$ hold in the sense that $\nu^t\mathbf{X}_o$ and $\tilde{1}$ have the same membership function. As a result, finding out a vector ν to make $\nu^t\mathbf{X}_o = \tilde{1}$ is translated into finding out ν to make the fuzzy number $\nu^t\mathbf{X}_o$ approach $\tilde{1}$ as much as possible, simply denoted by $\nu^t\mathbf{X}_o \approx \tilde{1}$. Considering Definition 2, the fuzzy number $\nu^t\mathbf{X}_o$ that satisfies $\nu^t\mathbf{X}_o \approx \tilde{1}$ can be regarded as an upper bound subject to $\nu^t\mathbf{X}_o \lesssim \tilde{1}$. It means that the left endpoints of the h-level sets of $\nu^t\mathbf{X}_o$ and $\tilde{1}$ overlap while the right endpoint of $\nu^t\mathbf{X}_o$ expands rightwards as much as possible but is not larger than that of $\tilde{1}$ shown in Fig. 1. Thus, with considering the formulations (5) and (7), the problem for finding out ν such that $\nu^t\mathbf{X}_o \approx \tilde{1}$, i.e., $Z = (\nu^t\mathbf{x}_o, \nu^t\mathbf{c}_o)_L \approx \tilde{1}$, can be converted into the following optimization problem.

$$\begin{aligned} \max_{\nu} \quad & \nu^t\mathbf{c}_o \\ \text{s. t.} \quad & \nu^t\mathbf{x}_o - L^{-1}(h)\nu^t\mathbf{c}_o = 1 - L^{-1}(h)e, \\ & \nu^t\mathbf{x}_o + L^{-1}(h)\nu^t\mathbf{c}_o \leq 1 + L^{-1}(h)e, \\ & \nu \geq \mathbf{0}. \end{aligned} \tag{19}$$

Remarks. The optimization problem (19) is used to find out the maximum $Z = \nu^t\mathbf{X}_o$ constrained by $\nu^t\mathbf{X}_o \leq \tilde{1}$ with the same left endpoint as the one of fuzzy number $\tilde{1}$ in h-level sets. This procedure can be regarded as a generalization of the procedure that seeking a value x such that $x = 1$ is equivalent to finding out the biggest x subject to $x \leq 1$.

Using (9), (10), (18) and (19) and considering (5) and (7), the fuzzy optimization problem (8) can be transformed into the following LP problem with a primary objective function and a secondary objective function.

$$\begin{aligned} \max_{\mu,\nu} \quad & \lambda_1(\mu^t\mathbf{y}_o - L^{-1}(h)\mu^t\mathbf{d}_o) + \lambda_2(\mu^t\mathbf{y}_o + L^{-1}(h)\mu^t\mathbf{d}_o) \\ \text{s. t.} \quad & \max_{\nu} \quad \nu^t\mathbf{c}_o \\ & \text{s. t.} \quad \nu^t\mathbf{x}_o - L^{-1}(h)\nu^t\mathbf{c}_o = 1 - L^{-1}(h)e, \\ & \qquad\quad \nu^t\mathbf{x}_o + L^{-1}(h)\nu^t\mathbf{c}_o \leq 1 + L^{-1}(h)e, \\ & \qquad\quad \nu \geq \mathbf{0}, \end{aligned} \tag{20}$$

$$\boldsymbol{\mu}^t\mathbf{y}_j - L^{-1}(h)\boldsymbol{\mu}^t\mathbf{d}_j \le \boldsymbol{\nu}^t\mathbf{x}_j - L^{-1}(h)\boldsymbol{\nu}^t\mathbf{c}_j \ (j=1,\ldots,n),$$
$$\boldsymbol{\mu}^t\mathbf{y}_j + L^{-1}(h)\boldsymbol{\mu}^t\mathbf{d}_j \le \boldsymbol{\nu}^t\mathbf{x}_j + L^{-1}(h)\boldsymbol{\nu}^t\mathbf{c}_j \ (j=1,\ldots,n),$$
$$\boldsymbol{\mu} \ge \mathbf{0}.$$

It should be noted that the optimization problem (19) is embedded into (20) to obtain $\boldsymbol{\nu}$ such that $\boldsymbol{\nu}^t\mathbf{X}_o \approx \tilde{1}$. The obtained optimal vectors from (20) are denoted as $\boldsymbol{\nu}^*$ and $\boldsymbol{\mu}^*$.

Remarks. It can be seen that when $\mathbf{c}_i = \mathbf{0}$, $\mathbf{d}_i = \mathbf{0}$ and $e = 0$, the fuzzy DEA (8) just becomes CCR model. It means that the model (8) can evaluates the efficiencies of DMUs in more general way, by which the crisp, fuzzy and hybrid inputs and outputs can be handled homogeneously.

Assuming that the optimal value of the objective function of (19) is g_o, the optimization problem (20) can be rewritten as the following LP problem.

$$\begin{aligned}
\max_{\boldsymbol{\mu},\boldsymbol{\nu}} \quad & \lambda_1(\boldsymbol{\mu}^t\mathbf{y}_o - L^{-1}(h)\boldsymbol{\mu}^t\mathbf{d}_o) + \lambda_2(\boldsymbol{\mu}^t\mathbf{y}_o + L^{-1}(h)\boldsymbol{\mu}^t\mathbf{d}_o) \\
\text{s. t.} \quad & \boldsymbol{\nu}^t\mathbf{x}_o \ge g_o \\
& \boldsymbol{\mu}^t\mathbf{y}_j - L^{-1}(h)\boldsymbol{\mu}^t\mathbf{d}_j \le \boldsymbol{\nu}^t\mathbf{x}_j - L^{-1}(h)\boldsymbol{\nu}^t\mathbf{c}_j \ (j=1,\ldots,n), \\
& \boldsymbol{\mu}^t\mathbf{y}_j + L^{-1}(h)\boldsymbol{\mu}^t\mathbf{d}_j \le \boldsymbol{\nu}^t\mathbf{x}_j + L^{-1}(h)\boldsymbol{\nu}^t\mathbf{c}_j \ (j=1,\ldots,n), \\
& \boldsymbol{\mu} \ge \mathbf{0}, \\
& \boldsymbol{\nu} \ge \mathbf{0}.
\end{aligned} \tag{21}$$

Definition 3. *The fuzzy efficiency of an evaluated DMU with the L–L fuzzy input vector $\mathbf{X}_o = (\mathbf{x}_o, \mathbf{c}_o)_L$ and output vector $\mathbf{Y}_0 = (\mathbf{y}_o, \mathbf{d}_o)_L$ is defined as an L–L fuzzy number $E = (w_l, \eta, w_r)_L$ as follows:*

$$\eta = \frac{\boldsymbol{\mu}^{*t}\mathbf{y}_o}{\boldsymbol{\nu}^{*t}\mathbf{x}_o},$$
$$w_l = \eta - \frac{\boldsymbol{\mu}^{*t}(\mathbf{y}_o - \mathbf{d}_o L^{-1}(h))}{\boldsymbol{\nu}^{*t}(\mathbf{x}_o + \mathbf{c}_o L^{-1}(h))},$$
$$w_r = \frac{\boldsymbol{\mu}^{*t}(\mathbf{y}_o + \mathbf{d}_o L^{-1}(h))}{\boldsymbol{\nu}^{*t}(\mathbf{x}_o - \mathbf{c}_o L^{-1}(h))} - \eta.$$

It is obvious that the uncertainty from the inputs and outputs of DMUs characterized by fuzzy numbers is transferred to the uncertainty of the evaluated efficiency, which is very close to human thinking.

Definition 4. *The DMU with $\eta + w_r \ge 1$ for a given possibility level h is called an h-possibilistic D efficient DMU (PD DMU). On the contrary, the DMU with $\eta + w_r < 1$ for a given possibility level h is called an h-possibilistic D inefficient DMU (PDI DMU). The set of all PD DMUs is called the h-possibilistic nondominated set, denoted by S_h.*

It is obvious that the h-possibilistic D efficient DMUs (PD DMUs) and the h-possibilistic D inefficient DMUs (PDI DMUs) in the case of $h = 1$ become the conventional D efficient DMUs and D inefficient DMUs in CCR model.

Theorem 2. *The center of the fuzzy efficiency of any DMU obtained from (20) is not greater than 1.*

Proof. Suppose that μ° and ν° are obtained from (20) for an evaluated DMU. Thus the following inequalities hold.

$$\mu^{ot}\mathbf{y}_j - L^{-1}(h)\mu^{ot}\mathbf{d}_j \leq \nu^{ot}\mathbf{x}_j - L^{-1}(h)\nu^{ot}\mathbf{c}_j \ (j = 1, \ldots, n), \tag{22}$$

$$\mu^{ot}\mathbf{y}_j + L^{-1}(h)\mu^{ot}\mathbf{d}_j \leq \nu^{ot}\mathbf{x}_j + L^{-1}(h)\nu^{ot}\mathbf{c}_j \ (j = 1, \ldots, n). \tag{23}$$

Taking the sum of (22) and (23), the following inequalities hold.

$$\mu^{\circ t}\mathbf{y}_j \leq \nu^{\circ t}\mathbf{x}_j \ (j = 1, \ldots, n). \tag{24}$$

Then,

$$\eta = \frac{\mu^{\circ t}\mathbf{y}_o}{\nu^{\circ t}\mathbf{x}_o} \leq 1, \tag{25}$$

which proves Theorem 2.

The formulation (25) means that evaluating fuzzy efficiencies of DMUs by the model (20) is similar to evaluating crisp efficiencies of DMUs by CCR model. Both of them seek the nondominated one by other DMUs.

Now, we discuss the given possibility level h. If we take a large value for h, it means that we consider a relatively narrow range of input and output data where all of the data considered have high possibilistic grades. Conversely, if we take a small value for h, it means that we investigate the input and output data in relatively wide range.

Let us consider a special case of Definition 1, that is, the symmetrical triangular fuzzy number, denoted as (a, c) where its membership function is defined as follows:

$$\pi_A(x) = \begin{cases} 1 - |x - a|/c, a - c \leq x \leq a + c, c > 0 \\ 0 \qquad\qquad , \qquad otherwise \end{cases} . \tag{26}$$

Assume the given fuzzy inputs and outputs of the ith DMU are symmetrical triangular fuzzy vectors, denoted as $(\mathbf{x}_i,\ \mathbf{c}_i)$ and $(\mathbf{y}_i,\ \mathbf{d}_i)$, respectively, the optimization problem (20) can be rewritten as follows [10]:

$$\begin{aligned}
\max_{\mu,\nu} \quad & \lambda_1(\mu^t\mathbf{y}_o - (1-h)\mu^t\mathbf{d}_o) + \lambda_2(\mu^t\mathbf{y}_o + (1-h)\mu^t\mathbf{d}_o) \\
\text{s. t.} \quad & \max_{\nu} \quad \nu^t\mathbf{c}_o \\
& \text{s. t.} \quad \nu^t\mathbf{x}_o - (1-h)\nu^t\mathbf{c}_o = 1 - (1-h)e, \\
& \qquad\quad \nu^t\mathbf{x}_o + (1-h)\nu^t\mathbf{c}_o \leq 1 + (1-h)e, \\
& \qquad\quad \nu \geq \mathbf{0}, \\
& \mu^t\mathbf{y}_j - (1-h)\mu^t\mathbf{d}_j \leq \nu^t\mathbf{x}_j - (1-h)\nu^t\mathbf{c}_j \ (j = 1, \ldots, n), \\
& \mu^t\mathbf{y}_j + (1-h)\mu^t\mathbf{d}_j \leq \nu^t\mathbf{x}_j + (1-h)\nu^t\mathbf{c}_j \ (j = 1, \ldots, n), \\
& \mu \geq \mathbf{0}.
\end{aligned} \tag{27}$$

The value of e in (27) is take as

$$e = \max_{j=1,\ldots,n} (\max_{k=1,\ldots,s} c_{jk}/x_{jk}). \tag{28}$$

3.3 Numerical Examples

First, a simple numerical example is considered where input and output are symmetrical triangular fuzzy numbers. The data are listed in Table 1.

The fuzzy efficiencies of DMUs (A, B, C, D, E) were obtained by the model (27) with $\lambda_1 = 1, \lambda_2 = 0$ for the different h values and illustrated in Table 2, where $e = 0.25$. Table 2 shows that as the value of h increases, the center of fuzzy efficiency becomes larger and the width of fuzzy efficiency becomes smaller. For the case of $h = 1$, the fuzzy efficiencies of DMUs become crisp values which are the same as the ones obtained from CCR model. From Table 2, we have $S_1 = S_{0.75} = S_{0.5} = \{B\}$ and $S_0 = \{B, D\}$. It means that decreasing the value of h offers more opportunities for PD DMUs in this example. It can be seen from the simulation results that the inherent fuzziness from input and output data has been reflected by fuzzy efficiencies evaluated.

Next, an example with two symmetrical triangular fuzzy inputs and two symmetrical triangular fuzzy outputs illustrated in Table 3 is considered. Fuzzy efficiencies obtained from the model (27) with $\lambda_1 = 1, \lambda_2 = 0$ for different h values are listed in Table 4. The results in Table 4 show that with h being higher the center of fuzzy efficiency almost increases except DMU

Table 1. DMUs with single fuzzy input and single fuzzy output

Branches	A	B	C	D	E
inputs	(2.0,0.5)	(3.0,0.5)	(3.0,0.6)	(5.0,1.0)	(5.0,0.5)
outputs	(1.0,0.3)	(3.0,0.7)	(2.0,0.4)	(4.0,1.0)	(2.0,0.2)

Table 2. Fuzzy efficiencies of DMUs with different h values

h	A	B	C	D	E
0	(0.21,0.47,0.35)	(0.32,0.95,0.45)	(0.21,0.63,0.32)	(0.28,0.76,0.43)	(0.07,0.38,0.08)
0.5	(0.12,0.49,0.15)	(0.18,0.97,0.21)	(0.12,0.65,0.14)	(0.16,0.78,0.19)	(0.04,0.39,0.04)
0.75	(0.06,0.49,0.07)	(0.09,0.98,0.10)	(0.06,0.66,0.07)	(0.08,0.79,0.09)	(0.02,0.39,0.02)
1	(0.0,0.5,0.0)	(0.0,1.0,0.0)	(0.0,0.67,0.0)	(0.0,0.8,0.0)	(0.0,0.4,0.0)

Table 3. DMUs with two fuzzy inputs and two fuzzy outputs

Branches	A	B	C	D	E
x1	(4.0,0.5)	(2.9,0.0)	(4.9,0.5)	(4.1,0.7)	(6.5,0.6)
x2	(2.1,0.2)	(1.5,0.1)	(2.6,0.4)	(2.3,0.1)	(4.1,0.5)
y1	(2.6,0.2)	(2.2,0.0)	(3.2,0.5)	(2.9,0.4)	(5.1,0.7)
y2	(4.1,0.3)	(3.5,0.2)	(5.1,0.8)	(5.7,0.2)	(7.4,0.9)

Table 4. The fuzzy efficiencies of DMUs with different h values

h	A	B	C	D	E
0	(0.15,0.81,0.18)	(0.10,0.98,0.11)	(0.22,0.82,0.3)	(0.22,0.93,0.32)	(0.18,0.79,0.23)
0.5	(0.08,0.83,0.09)	(0.03,0.97,0.03)	(0.12,0.83,0.14)	(0.12,0.97,0.15)	(0.10,0.82,0.11)
0.75	(0.04,0.84,0.04)	(0.03,0.99,0.03)	(0.06,0.83,0.07)	(0.06,0.98,0.07)	(0.05,0.83,0.06)
1	(0.0,0.85,0.0)	(0.0,1.0,0.0)	(0.0,0.86,0.0)	(0.0,1.0,0.0)	(0.0,1.0,0.0)

B in the case of $h = 0.5$ and the width becomes smaller as in the first example. In this example, the nondominated sets with different h values are $S_0 = \{B, C, D, E\}$, $S_{0.5} = \{B, D\}$, $S_{0.75} = \{B, D\}$ and $S_1 = \{B, D, E\}$. It can be seen that $h = 0.0$ gives the most opportunities for PD DMUs and the increasing of the value of h can not always lead to the increasing of the number of PD DMUs. These phenomena indicate that efficiency evaluation via fuzzy DEA models is more complex than the normal DEA because of the inherent fuzziness contained in inputs and outputs.

4 Evaluation of Objects with Multiple Fuzzy Attribute Values

4.1 Fuzzy Aggregation Models Based on Fuzzy DEA

Let us now consider an evaluation system $D = (O, A, Y)$, where $O = \{o_1, \ldots, o_n\}$ is a set of the objects evaluated, $A = \{A_1, \ldots, A_m\}$ is a set of the attributes of o_i $(i = 1, \ldots, n)$ and Y is a mapping defined as:

$$Y : O \times A \to V, \tag{29}$$

where V is a set of all fuzzy numbers defined on the space R^1. $\mathbf{Y}_j$ is an m-dimensional fuzzy vector whose element is a realization of the mapping Y to represent an attribute value of o_j. For the sake of simplicity, the L–L fuzzy vector is used to represent $\mathbf{Y}_j$, denoted as $\mathbf{Y}_j = (\mathbf{y}_j, \mathbf{d}_j)_L$. It should be noted that $\mathbf{Y}_j$ is the evaluation vector rather than the original attribute vector. For example, there are three motorcycles A, B and C, their prices are 5,000\$, 3,000\$ and 1,000\$, respectively. The evaluations of them from an evaluator may be "high", "middle" and "low" instead of "5000\$", "3000\$" and "1000\$".

The problem for evaluating objects with multiple attributes can be regarded as a special case of the FDEA model (8) with unity input shown as follows [11].

$$\begin{aligned} \max_{\mathbf{u}_o} \quad & \boldsymbol{\mu}_o^t \mathbf{Y}_o \\ \text{s. t.} \quad & \boldsymbol{\mu}_o^t \mathbf{Y}_j \underset{\sim}{<} 1 \ (j = 1, \ldots, n), \\ & \mu_{oi} - \mu_{oj} \geq d(i, j) \geq 0 (i \neq j,\ (i, j) \in B \subset \{1, \ldots, m\}^2) \\ & \mu_{oi} \geq \varepsilon \ (i = 1, \ldots, m), \end{aligned} \tag{30}$$

where ε is a positive constant. The constraint $\mu_{oi} - \mu_{oj} \geq d(i,j) \geq 0$ represents some suggestion from an evaluator, namely, the minimum difference of importance degrees between the attributes A_i and A_j. For example, that motorcycle company can make such a suggestion that price is more important than beauty for sale. If no such suggestion, these constraints will disappear. The constraints $\mu_{oi} \geq \varepsilon$ $(i = 1, \ldots, m)$ mean that the weight factors of the attributes are at least larger than ε which plays a crucial role to prevent the dominance effect of some large-valued attribute, which will be explained later. Denote the optimal solution of (30) as $\boldsymbol{\mu}_o^*$. The value of objective function $\boldsymbol{\mu}_o^{*t}\mathbf{Y}_o$ is the aggregated evaluation of the object o. The essential feature of (30) is that each evaluated object tries to find out the weight factors of attributes to its own advantage under the same constraint conditions. Thus the weight factors can be regarded as the results of fair competition rather than the one predetermined by an evaluator.

If an evaluator can suggest a linearly ordered attribute set A_{order} whose ith element is the ith most important attribute in A, we can detail (30) as follows.

$$\begin{aligned} \max_{\mathbf{u}_o} \quad & \boldsymbol{\mu}_o^t \mathbf{Y}_o \\ \text{s. t.} \quad & \boldsymbol{\mu}_o^t \mathbf{Y}_j \lesssim 1, \ (j = 1, \ldots, n), \\ & \mu_{oi} - \mu_{o(i+1)} \geq \varepsilon_i \geq 0 \ (i = 1, \ldots, m-1), \\ & \mu_{om} \geq \varepsilon_m > 0, \end{aligned} \tag{31}$$

where $\mathbf{Y}_j$ is reordered to correspond to A_{order} and ε_i $(i = 1, \ldots, m-1)$ are positive constants reflecting the differences of important degrees between two consecutive attributes in A_{order} and ε_m represents the lowest limit of weight factors.

If "$\lesssim$" is explained by Definition 2, the model (31) can be transformed into the following optimization problem with considering (5), (7), (9), (10) and (18).

$$\begin{aligned} \max_{\mathbf{u}_o} \quad & \lambda_1(\boldsymbol{\mu}_o^t \mathbf{y}_o - L^{-1}(h)\boldsymbol{\mu}_o^t \mathbf{d}_o) + \lambda_2(\boldsymbol{\mu}_o^t \mathbf{y}_o - L^{-1}(h)\boldsymbol{\mu}_o^t \mathbf{d}_o) \\ \text{s. t.} \quad & \boldsymbol{\mu}_o^t \mathbf{y}_j + L^{-1}(h)\boldsymbol{\mu}_o^t \mathbf{d}_j \leq 1 \ (j = 1, \ldots, n), \\ & \mu_{oi} - \mu_{o(i+1)} \geq \varepsilon_i \geq 0 \ (i = 1, \ldots, m-1), \\ & \mu_{om} \geq \varepsilon_m > 0. \end{aligned} \tag{32}$$

In order to clarify the role of the constraints $\mu_{oi} \geq \varepsilon$ $(i = 1, \ldots, m)$ in (31), let us consider the following LP problem.

$$\begin{aligned} \max_{\mathbf{u}_o} \quad & \boldsymbol{\mu}_o^t \mathbf{y}_o \\ \text{s. t.} \quad & \boldsymbol{\mu}_o^t \mathbf{y}_j \leq 1 \ (j = 1, \ldots, n), \\ & \boldsymbol{\mu}_o \geq \mathbf{0}. \end{aligned} \tag{33}$$

It is a special case of (31) for $h = 1$. The constraints $\mu_{oi} - \mu_{o(i+1)} \geq \varepsilon_i \geq 0$ $(i = 1, \ldots, m-1)$ and $\mu_{om} \geq \varepsilon_m > 0$ in (31) are simply replaced by $\boldsymbol{\mu}_o \geq \mathbf{0}$. As a result, some large-valued attribute will dominate the rank so that the result is unacceptable to commonsense. For example, the evaluation of three objects with three attributes are $\{(0.4,\ 0,\ 0),(0.3,\ 0.9,\ 0.9),(0.3,\ 0.5,\ 0.7)\}$. Using (33) the object 1 with (0.4, 0, 0) is in the first rank because the value of attribute 1 of the object 1 dominates the values of the same attribute of other two objects even if other two attribute values of object 1 are very poor. If the weight factor μ_i $(i = 1,\ 2,\ 3)$ are limited to be more than 0.2, then the rank becomes 2, 3, 1 which is harmony with the common feeling.

Theorem 3. **[11]**. *There exits an optimal solution in* (32) *if and only if the constants* ε_i $(i = 1, \ldots, m)$ *satisfy the following inequalities*

$$\mathbf{r}^t(\mathbf{y}_j + L^{-1}(h)\mathbf{d}_j) \leq 1 \ (j = 1, \ldots, n) \tag{34}$$

where

$$r_i = \sum_{j=i,\ldots,m} \varepsilon_j, \tag{35}$$

Proof. Necessary condition: Suppose there is a feasible solution in (32) and μ_{om} satisfies the following relation

$$\mu_{om} = x \geq \varepsilon_m. \tag{36}$$

Thus, the following relations hold.

$$\begin{aligned} &\mu_{o(m-1)} \geq x + \varepsilon_{m-1}, \\ &\mu_{o(m-2)} \geq x + \varepsilon_{m-1} + \varepsilon_{m-2}, \\ &\quad \cdots\cdots \\ &\mu_{o1} \geq x + \sum_{i=1,\ldots,m-1} \varepsilon_i. \end{aligned} \tag{37}$$

Then

$$\boldsymbol{\mu}_o^t\mathbf{y}_j + L^{-1}(h)\boldsymbol{\mu}_o^t\mathbf{d}_j \geq \mathbf{r}^t(\mathbf{y}_j + L^{-1}(h)\mathbf{d}_j), \tag{38}$$

where $\mathbf{r}$ is defined by (35). Considering the constraint $\mathbf{u}_o^t\mathbf{y}_j + L^{-1}(h)\mathbf{u}_o^t\mathbf{d}_j \leq 1$ in (32), the following inequality should hold.

$$\mathbf{r}^t(\mathbf{y}_j + L^{-1}(h)\mathbf{d}_j) \leq 1 \ (j = 1, \ldots, n). \tag{39}$$

It proves the necessity condition.

Sufficient condition: Suppose (34) holds, it is easy to check that there is a feasible solution in the constraint conditions of (32). That is

$$\mu_i = \sum_{j=i,\ldots,m} \varepsilon_j \ (i = 1, \ldots, m). \tag{40}$$

Table 5. Evaluation from an evaluator

Objects	Attribute 1	Attribute 2	Attribute 3	Attribute 4
A	(0.3,0.1)	(0.5,0.2)	(0.7,0.2)	(0.9,0.1)
B	(0.2,0.1)	(0.9,0.1)	(0.7,0.2)	(0.4,0.2)
C	(0.5,0.3)	(0.5,0.2)	(0.9,0.1)	(0.6,0.3)
D	(0.7,0.3)	(0.8,0.1)	(0.8,0.1)	(0.9,0.1)
E	(0.4,0.1)	(0.6,0.2)	(0.3,0.2)	(0.5,0.2)

Moreover, the constraint condition of (32) is a bounded closed set (compact set). Thus, there exists an optimal solution in (32). It proves the sufficiency condition.

Corollary [11]. *If* $\varepsilon_i = a$ $(i = 1, \ldots, m)$, *then* a *satisfies*

$$a \leq 1/(\mathbf{m}^t(\mathbf{y}_j + L^{-1}(h)\mathbf{d}_j)) \ (j = 1, \ldots, n), \tag{41}$$

where $\mathbf{m} = [m, m-1, \ldots, 1]^t$.

4.2 Numerical Example

In Table 5, the evaluations of five objects from an evaluator are given. Symmetrical triangular fuzzy numbers are used for represent the evaluations.

Suppose that from attributes 1 to 4 their important degrees decrease and ε_i $(i = 1, \ldots, 3)$ take 0.001 which offer some difference of weight factors between two consecutive attributes. ε_4 takes 0.001 to give the lowest limit of weight factors. The aggregated evaluations of objects A, B, C, D and E obtained by (32) for $h = 0.6$, $\lambda_1 = 1$ and $\lambda_2 = 0$ are (0.70, 0.17), (0.72, 0.16), (0.76, 0.24), (0.93, 0.17) and (0.60, 0.18), respectively. Let us simply analyze the evaluation results obtained. If only considering the center value, the rank of objects is {D, C, B, A, E}. It is obvious that D is the best one and C is the second one among all objects from Table 5. B is better than A because though B is a litter bit worse than A for the most import attribute 1 and worse than A for the unimportant attribute 4, it is remarkably better than A for the second important attribute and has the same value as A for the third important attribute. Compared with A, E has the almost same values for the first and second important attributes but remarkably small values for the third and fourth important values so that E is inferior to A. It can be concluded that the obtained result is very close to human intuition.

5 Conclusions

In this paper, fuzzy DEA models are proposed for evaluating the efficiencies of DMUs with fuzzy input and output data. The obtained efficiencies are fuzzy numbers to reflect the inherent fuzziness in evaluation problems. It can be concluded that the proposed fuzzy DEA models extend CCR model to more general forms where crisp, fuzzy and hybrid data can be handled easily. Moreover, based on the fuzzy DEA model, an aggregation model for integrating multiple attributes fuzzy value of objects is proposed. Using the proposed fuzzy aggregation models, the objects can be ranked objectively. Because uncertainty always exists in human thinking and judgment, fuzzy DEA models can play an important role in perceptual evaluation problems comprehensively existing in the real world.

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Cognitive Orientation in Business Intelligence Systems

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Summary. With the increasing importance of cognitive aspects in decision making, this research addresses how human cognitive abilities, mainly situation awareness and mental models, can be used to drive the decision process in complex decision situations. Cognitive orientation has long been regarded as an important consideration in the development and application of decision support systems (DSS). Rather than cognitive orientation, a data-driven DSS emphasizes access to and manipulation of a series of company internal and external data, compared to a model-driven DSS underpinned by statistical, financial, optimization or simulation models. A business intelligence (BI) system is essentially a kind of data-driven DSS therefore shares the similar drawbacks with traditional DSS. A framework of cognitive BI system is firstly developed. A model of cognition-driven decision process is then proposed based on the system framework. In this framework and decision model, data retrieval, information filtering and knowledge presentation are based on the tacit knowledge elicited from the decision-maker. The final decision is no longer the direct output of a computer system, but the result of decision-making cycles of human-machine interaction.

1 Introduction

In the decision support system (DSS) community, business intelligence (BI) has been one of the most important research and application areas since its emergence in 1989 by Dresner [29]. BI is a flourishing area and it keeps growing over the past decade despite global information technology downside. International Data Corporation (IDC) reports that in 2005 business analytics market grew by 11.0% to reach US$16.6 billion in revenue and predicts a continuous growth at the same rate in the next 5 years (2006–2010). BI initially referred to decision support systems exclusive to high level management. Today's BI systems are mainly based on data warehouses with inclusion of powerful ad hoc query, reporting and data mining functionality, and the application of BI can spread throughout the organization.

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Essentially BI systems are data-driven DSSs, which focus on the manipulation of large volumes of company data and they carry the same drawbacks as other types of DSS, such as model-driven DSS, communication-driven DSS, document-driven DSS, and knowledge-driven DSS. As computer-based information systems, DSS are designed to aid people to make decisions. DSS are envisioned as "executive mind-support systems" that are able to support decision-making process from human cognitive aspects [5]. Nevertheless the emphasis of today's DSS is falling into either powerful data analysis functionality, or mathematical and statistical models, or efficiency of group communication [2, 5, 23, 26]. Cognitive orientation remains weak although it has long been recognized as an important consideration in DSS research and applications [4, 5, 19, 25, 35].

In the consideration of cognitive orientation, situation awareness (SA) and mental model are receiving increasing attention with the study of naturalistic decision making (NDM). NDM deals with modeling how proficient decision makers behave in their familiar decision situations and this decision process is inspired by the decision-maker's cognitive abilities: situation awareness and mental models. The decision-maker's cognitive abilities play key roles when he/she is dealing with unstructured problems with time pressure, uncertainty and high personal stakes [1, 5, 9, 23]. SA and mental models are thought of as two essential prerequisites for decision making in any dynamic complex systems. Researchers have proven the strong relationship between decision making, SA and mental models. Rich SA and mental models will significantly increase the probability of good decisions and good performance [10, 31].

In order to support and utilize SA and mental models in BI systems, an information system framework of cognitive BI systems is proposed in this chapter. This framework is an extension of current BI systems architecture, however, with cognitive orientation. In this framework, the user is one of the key components interacting with other three components: Thinking Support, Situation Assessment, and Data Warehouse subsystem. Based on this framework, a model of cognition-driven decision process is suggested. Within this model, a complete decision process is made up of several interaction cycles. An interaction cycle consists of a series of eight successive events, each of which represents different interaction or processing. The user's SA, mental models, and experience are represented as information objects and used to drive the occurrence of these events. The final decision, the output of the cognitive BI framework, is directly made by the user and triggered by resource limits, e.g., time, cost, or the user's confidence.

Section 2 of this chapter briefly analyzes the architecture and functionalities of current BI systems and the drawbacks of lack of cognitive support are concluded. Cognitive orientation and its relationship with DSS are detailed in Sect. 3. Section 4 proposes a framework of cognitive BI systems toward cognitive support to managers' work in complex decision situations. Based on the proposed framework, a model and an algorithm of cognition-driven decision process is suggested and analyzed in Sect. 5. Conclusion remarks and further research work are discussed in the last section.

2 Current Business Intelligence

2.1 Architecture

A typical BI system consists of four levels of components (Fig. 1) and metadata management module. These different components cooperate with each other to facilitate the major BI functions: extracting data from company operational environment, storing the extracted data in the center data warehouse, and retrieving stored data for various business analysis applications.

Operational Systems Level

As the data sources of BI systems, business operational systems are mainly on-line transaction processing (OLTP) systems which support the daily business operations. Typical OLTP systems are as customer order processing system, financial system, and human resource management system.

Data Acquisition Level

This level is a pre-process component including three phases: extract, transform, and load (ETL). A company could have different OLTP systems producing huge amounts of data. These data are first extracted from OLTP systems by ETL process and then transformed according to sets of transformation rules. Transformed data are clean, unified, and aggregated and finally loaded into the data warehouse. ETL is the most important component of a BI system

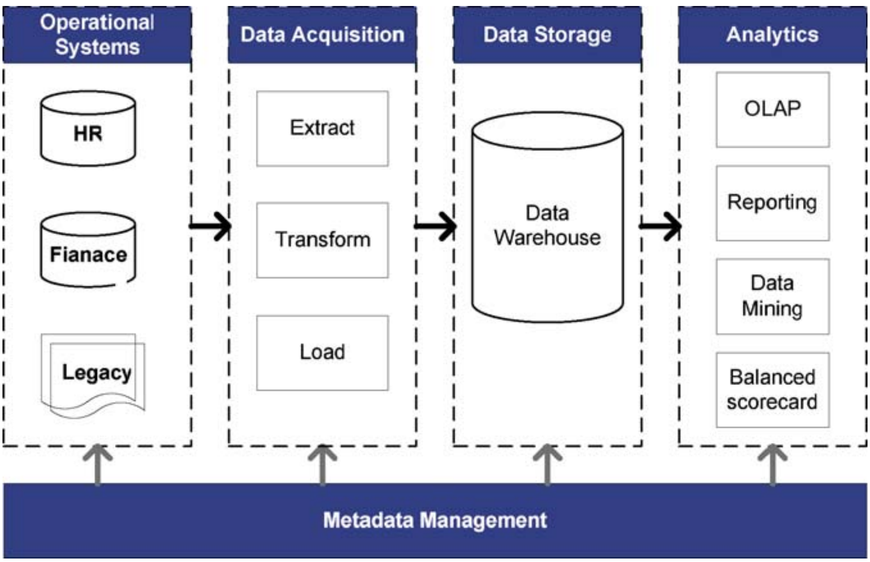

Fig. 1. Current business intelligence architecture

because it provides the basis of the whole systems. In the design and development of ETL, data quality, system flexibility, and the system speed are the major concerns.

Data Storage Level

The data warehouse is the central data storage of the BI system. Data from company OLTP systems are extracted, transformed, and loaded into the data warehouse based on pre-defined schemas. Star schema and snowflake schema are the most popular data warehouse schemas. No matter what kind of schema on which a data warehouse is designed, the data warehouse always includes two types of tables: fact table and dimension table. According data warehouse schemas, data warehouse was initially defined as subject oriented, time-variant, non-volatile and integrated data store. However today's data warehouse systems can be built in company scope and can be updated over time, for instance real-time BI systems.

Analytics Level

Based on the data warehouse, various kinds of applications are developed, which represents the last level: Analytics. The most promising BI application is online analytical processing (OLAP). OLAP application is based on multidimensional data models (known as snow snowflake and star schema) supporting quick ad hoc query and analysis.

Theoretically data mining application is not necessarily build on a data warehouse. However integrating them together is the common practical way because most data mining applications also need a data pre-processing task which can be facilitated by ETL. Other BI applications include conventional reporting, ad hoc reporting, executive dashboards, data mining, customer relationship management, and business performance management.

Metadata Management

Metadata are special data about other data such as data sources, data warehouse storage, business rules, access authorizations, and how it was extracted and transformed. Metadata is crucial for producing accurate, consistent information and system maintenance and it affects the whole process of the designing, developing, testing, deploying and using the BI system.

2.2 Drawbacks of Decision Support

BI is promising to turn 'data' into 'knowledge' and help managers to survive data tsunami and eventually succeed in decision making. A BI system is capable of providing executives with a huge amount of instant data, from internal and external environment of the company, such as operations, marketing, and accounting. However, more data does not equal more valuable information [11]. Current BI systems can only partially support executives' management process [28]. Executives often feel lost when presented with a large body of data concerning decision making. A recent survey, by Economist Intelligence Unit [6], hows 73% of senior managers agreed that it is important to have less but more timely data to improve the quality and speed of decision making. This result corresponds to the research result by Sutcliffe and Weber [32] about the knowledge accuracy. Their research implies that having a lot of facts about a decision situation is less important than having a clear and consistent overview picture. Resnick [23] criticizes current dashboard (one of BI applications) design for emphasizing improvements on data analysis functionality while falling short of cognitive engineering consideration, such as situation assessment and awareness. More recently, an industrial report from InfoWorld Media Group, a division of International Data Group (IDG), shows that 'BI has a reputation for being a resource sink that delivers reports almost no one reads. It doesn't have to be that way. And you can no longer afford to let it be' [14].

BI systems are essentially data-driven decision support systems. OLAP-based ad hoc query and reporting are mainly pre-defined information representation. In the decision process, managers are provided with information in the form of report, ad hoc analysis, or some so called knowledge which is pulled from data warehouse according to pre-defined queries, such as SQL sentences and multidimensional expressions (MDX). The emphasis is the manipulation of large volumes of both internal and external company data in terms of technology, rather than supporting managers' decision making from cognitive perspective.

3 Cognitive Orientation and Decision Support Systems

3.1 Naturalistic Decision Making

In the study of decision making, naturalistic decision making (NDM) has been receiving more interest recently among other theories like classical decision making (CDM), behavioral decision theory (BDT), judgment and decision making (JDM), and organizational decision making (ODM) [16–18]. NDM focuses on investigating how the proficient decision-maker make decisions in his/her familiar decision situations [20].

NDM is a descriptive decision theory. At the other end of the spectrum is normative decision theory, e.g., CDM. In CDM, a typical decision-making process consists of four phrases [27]:

(1) *Intelligence.* In this phrase, the decision situation and related environment are investigated and the decision problem is identified and defined.

(2) *Design*. Based on the results of intelligence phrase, decision model is designed and tested. Consequently alternatives are produced via running the decision model and criteria are set for evaluating different potential alternatives.
(3) *Choice*. The decision-maker is regarded as 'rational' and the decision process is based on "choice model". In the choice model, it is assumed that the decision-maker will not select a course of action, an option that is inferior to some other options. Therefore the final choice made by the decision maker is theoretically optimal and the best solution to the decision problem.
(4) *Implementation*. The choice made is implemented in the decision situation and possible feedback is returned to previous phrases.

Compared to CDM, NDM is based on "matching model" and the decision-maker has only bounded rationality. NDM is shaped by five essentials [20]:

(1) *Proficient Decision Makers*. NDM is attempting to model the behavior of proficient decision makers in real settings familiar to them. Proficient decision makers mean people who have rich relevant knowledge or experience in the decision-making domain. They intuitively rely on their experience when making decisions.
(2) *Situation-Action Matching Decision Rules*. The proficient decision makers make decisions via matching process, not a choice process in CDM. When presented with a decision situation, several options will emerge based on the decision-makers' past experience. The decision makers then quickly screen most of them by comparing them against a standard, rather than with one another. Options are selected or rejected based on their compatibility with the situation. The screening process much more relies on pattern matching and informal reasoning rather than analytical reasoning.
(3) *Context-Bound Informal Modeling*. The decision models created in NDM tend to be informal and context-specific, i.e. closely related to specific application domain.
(4) *Process Orientation*. Rather than the input and output of decision making, NDM is concerned with the process of decision making. This leads to the attention to the information decision makers actually search, understand, and use.
(5) *Empirical-Based Prescription*. Prescriptions are derived from descriptive models of domain expert behavior, which are more feasible than the optimal ones from choice models.

NDM theory is based on human knowledge or experience, particularly decision-makers' SA and mental models. Mental models reflect the past experience which decision makers learn from problem-solving processes or mentoring programs. SA is the concurrent state of personal knowledge regarding current decision situation. NDM theory is effective and efficient in dynamic complex decision situations, especially with time pressure, uncertainty and high personal stakes.

3.2 Situation Awareness

The concept of SA was initiated from military aircraft domain and extended to air traffic control, nuclear power plants, and other tactical and strategic systems [9]. In aviation, SA mainly refers to the pilot's knowledge about the aircraft itself and its environment [8, 15, 33]. Sarter and Woods [24] describe SA as "the accessibility of a comprehensive and coherent situation representation which is continuously being updated in accordance with the results of recurrent situation assessments."

Endsley [9] proposes a model of SA in terms of information processing (Fig. 2). Endsley suggests SA can be divided into three levels of mental representation: perception (level 1 SA), comprehension (level 2 SA), and projection (level 3 SA). This SA model also shows various factors affecting the development of SA.

The development process of SA is called situation assessment. In Endley's SA model, situation assessment is an information processing process within the decision-maker's mind. This process can be enhanced by means of appropriate technologies. For instance, a case study by Endsley and colleagues [11] demonstrates different user interface designs result different degree of situation assessment in aviation control.

SA is believed to be an essential prerequisite for people's decision making in any dynamic complex and dynamic situations [9, 10, 12, 24, 30]. A close

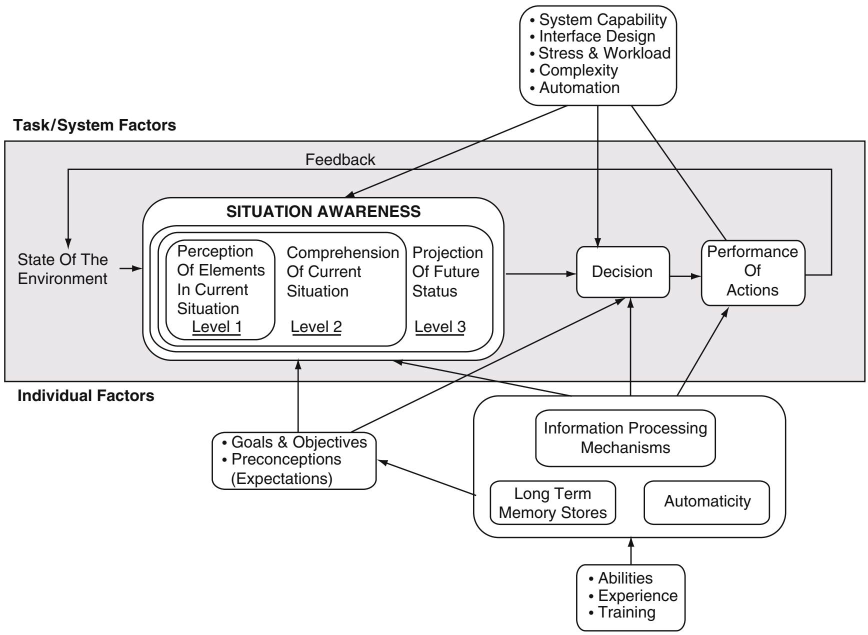

Fig. 2. Endsley's situation awareness model [9]

relationship exists between SA and decision making: richer SA is more likely to lead to good decisions [31].

Simply put, SA is about knowing what is going on around the decision-maker. In business management domain, a manager's SA can be referred to as his/her understanding of the company, e.g., the internal and external environment, the past events, and the current state. SA creates a big picture of the company within the manager's mind and enables the manager to be capable of predicting the future and making decisions.

3.3 Mental Models

Mental models are "psychological representations of real, hypothetical, or imaginary situations" [16]. Mental models are commonly referred to as deeply held assumptions and beliefs that enable individuals to make inferences and predictions [4, 5, 16]. Rouse and Morris [36] define mental models as "mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future states".

Mental models are important for managers to understand business environments and unstructured problems. They provide managers with the ability to simplify the complexity of business environments [22, 25]. Mintzberg [21] categorizes executives' work into ten different roles and connects them with managers' mental models. He finds that managers spend most of their time communicating with other people and thinking, by which their mental models are built based on their past experience. With rich and solid mental models, managers can envision possible future business scenarios that may cause problems or bring opportunities and then make appropriate strategies to respond.

Mental models are about people's past experience which are the basis and guidance for adequate SA development [9, 24]. Managers need both rich SA and mental models to understand the business environment, to anticipate the near future status of the company, and then succeed in decision making.

3.4 Cognitive Orientation in Business Intelligence Applications

Business domain has the characteristics for which the theories of NDM, SA, and mental model can be applied. Today's companies operate in a turbulent business environment where different sectors interact with and affect each other. Walters [34] summarize in six internal business environment sectors (market research, product R&D, basic engineering, financial management, cost controls, and operational efficiency) and six external ones (market, technological, competitive, political/legal, economic, and socio-cultural). For the survival of the company, the manager needs to keep aware of each sector of the environment. Moreover, the speed and quality with which business decisions must be made has increased substantially with the trend of economy globalization. The complexity, uncertainty, dynamics, and time pressure of business decision making show the potential of applying NDM theory to support business decision making. From information system perspective, there is a necessity to make current BI to embrace contemporary cognitive psychology and BI systems should be researched, designed, developed, and applied on cognitive orientation.

4 A Framework of Cognitive Business Intelligence Systems

A conceptual framework (Fig. 3) is proposed with the motivation to empower BI systems to cognitively support managers in ill-defined decision situations. This framework is developed via an extension of the current BI architecture. This framework consists of four major components: (1) User, (2) Thinking Support, (3) Situation assessment, and (4) Data Warehouse subsystem. The input of this framework is a situation presented to the user (decision-maker). A decision corresponding to the situation is the output of the framework as a whole (the user, computer, and situation).

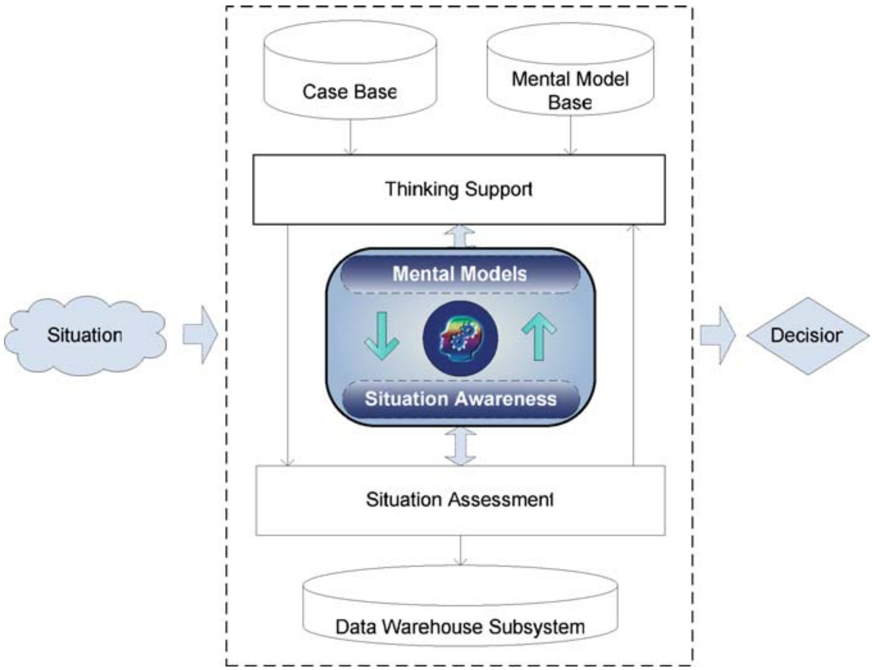

Fig. 3. Cognitive business intelligence system framework

4.1 User Module

In the center of this framework is the user module. This framework incorporates the user as one of its components. The underpinning point of view is that humans are superior to computers when handling with unstructured problems with ill-defined goals, uncertainty, time pressure and high personal stake. Therefore, a decision should be made by humans rather than a computational output of the computer program. The application of a BI system can spread throughout the organization. So the user can be a manager at any management level: executive, middle management, or frontline supervisor.

4.2 Thinking Support Module

Thinking support module is intended to provide the manager with a set of tools for knowledge management and thinking process support. The knowledge base of this subsystem comprises of two parts: case base and mental model base, which represents explicit knowledge and tacit knowledge respectively. Bergmann [3] defines case (also experience) as 'valuable, stored, specific knowledge that was acquired by an agent in a previous problem solving situation.' In the application of cased-based reasoning, a case is described as a problem-solution pair, which can be represented using various methods, such as free-text approach, object-oriented approach, attribute-value approach, and predicate logic approach [3]. An example of case is shown as following:

Problem: *notebook sales up by 5% in 2003 in China*
Solution: *Release a new notebook model based on latest ATI graphic card*
Results: *sales up by 5%*
Key words: *Notebook, sales*
Source: *ABC Company*
Personal notes: *interest rate = 2.01%*

The manager's mental models can be elicited, represented and stored in the mental model base. Mental models can be visualized as graphs: cognitive maps [7]. A cognitive map consists of concepts (nodes) and relationships (linkages). Gnyawali and Tyler [13] discuss a special kind of cognitive map which they called cause map. Compared to general cognitive maps, a cause map reflects the causal relationships between different concepts. Figure 4 is an example of cause map showing how the notebook sales are affected by different factors. The process of producing cause maps is cause mapping. A eight-step cause mapping process is detailed by Gnyawali and Tyler [13].

In our framework, cases and mental models are used to model the user's information need during the interaction between the user and the computer. This interaction is a process of seeking information of interest for decision making. Mental models are acting as mechanism whereby the manager is able to perceive information from the company environment (data warehouse), understand the situation he/she is in (retrieved data), and anticipate the

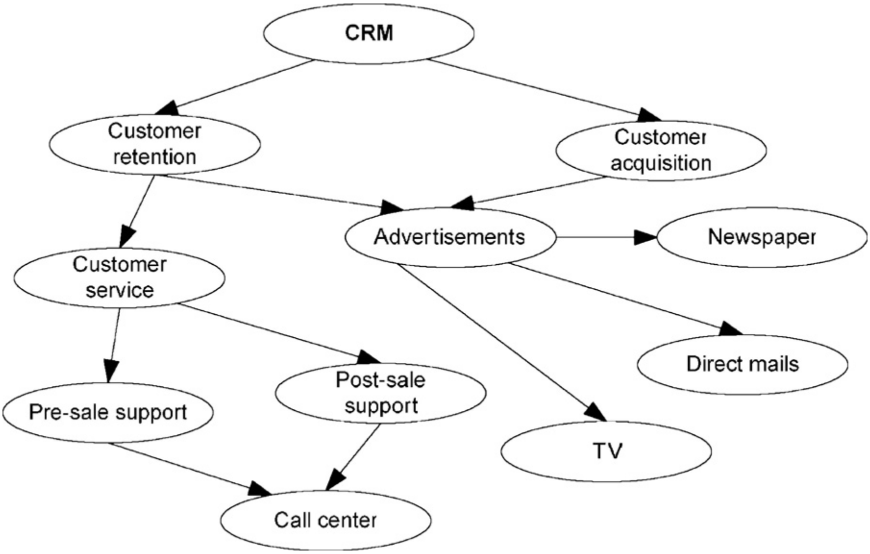

Fig. 4. Cause map

future events (making decision). Therefore, as the representation of mental model, the cause map expose important information or clues to problem-solving. The contents of concepts and relationships within cause maps are used to direct the process of human-computer interaction. Similarly, cases from case base are the manager's past experience of problem-solving and cases are also used to uncover potential aspects of the decision situation.

4.3 Situation Assessment Module

This module is responsible for assessing current decision situation and then aiding managers to develop their SA of the organizational environment. Situation assessment is the process of developing, enriching, and retaining SA [9]. In this chapter, from information system perspective, situation assessment is referred to as a data processing process during which data of interest is retrieved, analyzed, presented, and understood by decision makers (managers).

As a data processing process, situation assessment is accomplished through interaction between human, computer, and environment, which are the basic elements in a cognition-driven decision process (Sect. 5). The data warehouse is the data source of situation assessment, which stores internal and external environment information of the company. Both internal and external data are important for environmental scanning in executives' decision-making process [34]. The functionality of data retrieval and analysis is supported by different data processing techniques: information filtering, SQL reporting, OLAP (online analytical processing), data mining, mathematical modeling, and information fusion. Each of them contributes to situation assessment at different level. Data is extracted from the data warehouse based on the analysis of relevant business cases and the manager's mental models. The result of data retrieval and analysis is presented via data visualization techniques. Common data visualization techniques include charts, plots, maps, 3-D images, translucency, and animation. The manager perceives and understands information from the graphical user interface representing current decision situation and gradually develop his/her SA.

4.4 Data Warehouse Subsystem

The data warehouse forms the factual basis on which decision situations are presented and assessed. The data warehouse subsystem is developed based on current BI system architecture (Fig. 1). According to Fig. 1, this subsystem is made up of company operational systems, data acquisition module, and data storage module. Through the data warehouse subsystem, data from different departments is extracted, transformed, and loaded into central data warehouse.

5 Cognition-Driven Decision Process

5.1 The Model of Cognition-Driven Decision Process

On the basis of the cognitive BI system framework (Fig. 3), a model of cognition-driven decision process (Fig. 5) is proposed to enhance the analytical capability of BI systems.

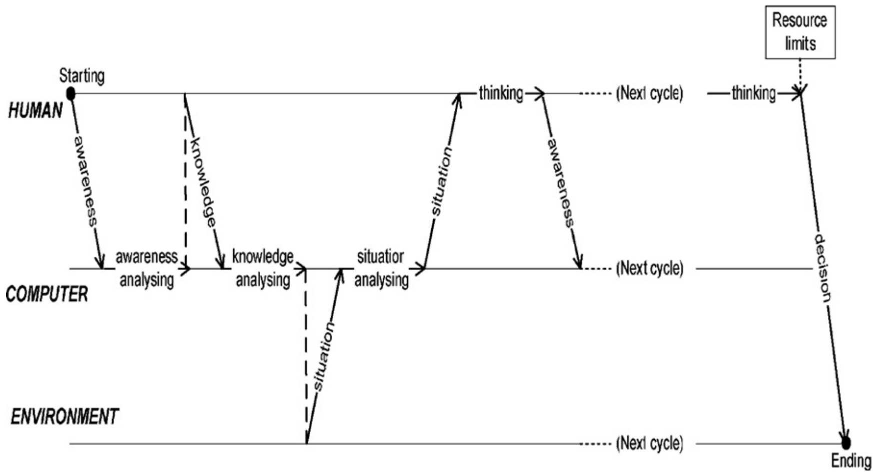

Fig. 5. Cognition-driven decision process model

In this decision model, human, computer, and environment are represented as a horizontal line respectively. The directed lines represent the interaction between human, computer, and environment. The building block concepts in this model are listed as following:

- *Human.* Human represents the user, e.g., the manager of a company. According to NDM theory, the user must be proficient decision-maker. In order for this decision process model to be effective, the user of the cognitive BI system needs to have gained enough experience in business management, i.e., adequate mental models and cases in the databases.
- *Computer.* Computer is the platform where the information system is running.
- *Environment.* Every decision situation is situated in an environment including internal and external environment.
- *Awareness.* The user's SA is represented using the similar approaches to case, e.g., free-text and object-oriented approach.
- *Knowledge.* Knowledge consists of explicit knowledge: cases and tacit knowledge: mental models, which stored in case base and mental model base respectively.
- *Situation.* A situation is the context where the user is situated in with the objective of decision making. In business domain, the manager can have different objectives when presented with a situation, such as finding opportunities, predicting threats, or producing specific solutions to current problems.
- *Analysing.* Computer conducts three kinds of analysis to analyse the corresponding input: awareness analysis, knowledge analysis, and situation analysis.
- *Thinking.* The user conducts retrospective, introspective, and prospective thinking process when presented with the visualized situation.
- *Interaction Cycle.* An interaction cycle is one phrase of the whole decision-making process. The interaction happens between human, computer, and environment. An interaction cycle includes a series of eight successive events which are represented and linked together by eight directed lines (Fig. 5):

  First, awareness is input from human. Awareness is then analysed by computer in order to drive the retrieval of case base and mental model base (happened in Thinking Support module). Case base and mental model base are retrieved according to the result of awareness analysis (Thinking Support Module). Next, via knowledge analysis, the description of information needs of the user is extracted from awareness, cases, and mental models (Thinking Support module). Based on knowledge needs, environment data is retrieved from the data warehouse (Situation Assessment module). The retrieved environment data is analysed using data mining, and mathematical/statistical methods, which produces the possible situation data (Situation Assessment module). Situation data is presented using data visualization techniques (Situation Assessment module). Finally, human conducts the thinking process based on situation presentation.

The result of every interaction cycle is the user's updated SA about decision situation. As interaction cycle loops, the user will gradually acquire and develop richer SA and gain clearer understanding of the decision situation as well as the possible solution.

- *Resource Limit.* The decision process is limited by several resources, such as time, money, and personal satisfaction. Any resource limit can trigger the produce of the final decision.
- *Decision.* The decision as the final output of the human-machine interaction system is directly made by the user under the computer's support.

5.2 The Algorithm of Cognition-Driven Decision Process

An algorithm reflecting the complete decision process based on the proposed model of cognitive decision process in the cognitive BI system framework is manifested in Fig. 6.

The cognitive-driven decision process starts with getting the decision-maker's awareness (situation awareness about current decision situation). The decision-maker's awareness is analyzed and normalized and then used to retrieve case base and mental model base in order to obtain relevant cases and mental models against current decision situation. Information need is the description of information required for seeking information of interest during the retrieval of data warehouse. The information need is built based on analyzing the decision-maker's situation awareness, mental models and cases. The decision-maker's mental models are the mechanism whereby the decision maker is able to interact with and understand the current decision situation. The retrieved cases are the similar situations with current decision situation and thus the attached solutions to the past situations have the potential to be adapted and used to solve current decision situation. The decision maker's awareness is the direct driving force for the formulation of decision for current situation. Therefore the combination of the decision-maker's awareness, cases, and mental models is the treasure trove of information need during the following interaction process; and it has direct implications to the resolution of the current decision situation.

The information need is then parsed into mdXML (Multi-dimensional Extensible Markup Language) elements for retrieving situation data from the data warehouse. mdXML is a kind of markup language developed for accessing multiple-dimensional data (cubes). For more details about mdXML, please refer to http://www.xmlforanalysis.com/.

Using mdXML, data of interest to current decision situation is retrieved from the data warehouse, which is referred to as situation data. The situation data is then analyzed employing such data analysis techniques as data mining, statistical analysis, data fusion and mathematical modeling. The results of

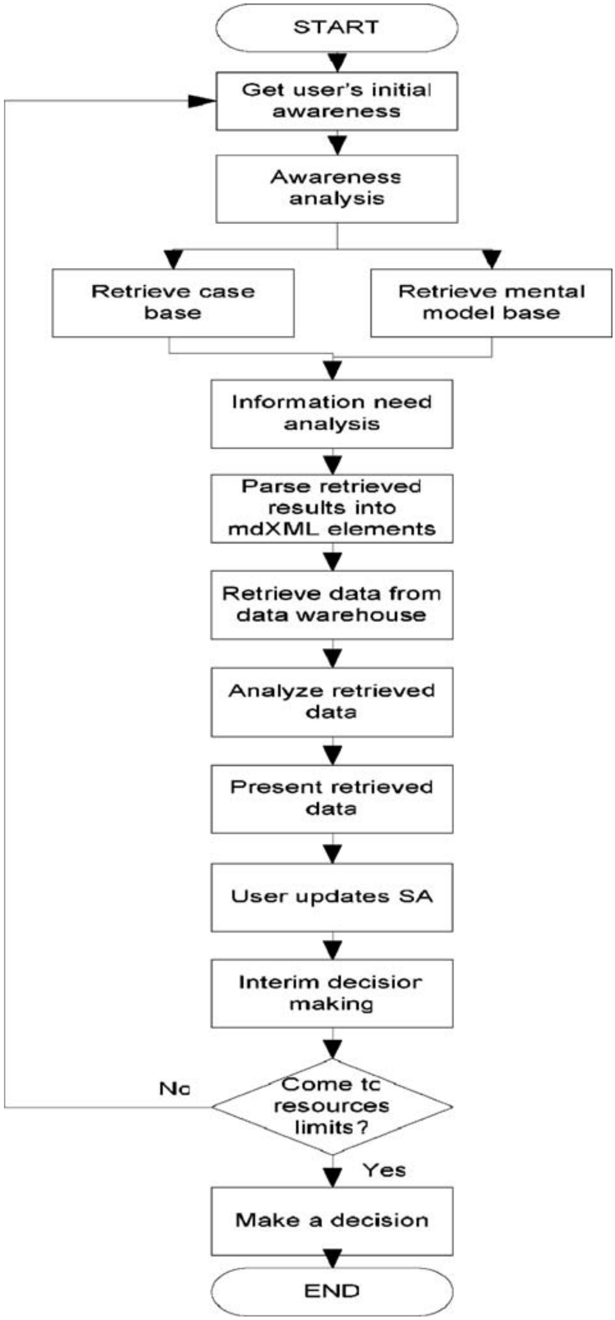

Fig. 6. The algorithm of cognition-driven decision process

data analysis are then visually presented to the decision maker in the forms of graph, chart, plot, isosurfaces and stereopsis.

Visually presented decision situation is then perceived by the decision maker via user interface. The perceived information go through three stages of situation assessment and eventually transformed into the decision-maker's updated awareness. Cognitively the decision maker is capable of make an interim decision based on the updated situation awareness as well as the mental models, which is reflective of the decision process of NDM. The effectiveness and efficiency of the result of a NDM model are not naturally guaranteed by the model itself, which is the empirical characteristic of NDM theory. However the decision can be improved through loops of human-machine interaction until a resource limit comes through the decision process and triggers the output of the final decision.

6 Conclusions

This chapter is an attempt toward achieving high degree of user-centered human-computer interaction for better decision making in complex situations with ill-defined goals, uncertainty, time pressure and high personal stake. The fundamental point of view on decision making, in this research, is that humans are superior to computers when handling some unstructured problems. Consequently a decision (in complex situations) should be made by humans rather than a computational output of computer programs. Following this view, a framework of cognitive business intelligence systems is proposed based on cognitive consideration of human situation awareness, mental models, and experience (case). Both human and computer are incorporated into this framework and become components of the unified decision-making system. Human cognition is represented as information object and used to drive the process of human-computer interaction and eventually facilitate the cognition-driven decision process.

This research is grounded in BI area. Traditional BI systems have drawbacks of lacking cognitive support to unstructured decision-making tasks. With the consideration of cognitive orientation, the proposed decision process model and system framework are expected to be able to improve the performance of current BI systems, particularly the analytical functionality.

Our further study includes implementing and validating the proposed system framework and decision process model through prototype development and case study.

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Personalized Pedestrian Navigation System with Subjective Preference Based Route Selection

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Summary. This chapter describes the pedestrian navigation method reflecting individual preference for route selection, and discusses the validity of the fuzzy measures and integrals model applied to route selection. The presented method selects the route with the highest subjective satisfaction degree which is estimated by a road satisfaction degree evaluation model (RSEM). The RSEM applies fuzzy measures and integrals to calculate the subjective satisfaction degrees of a road. The input to the RSEM is a set of road attributes expressing subjective impression of a road. The road attributes are decided according to the individual preference expressed by fuzzy measures. Experimental results and analyses of the RSEM show that the route selected by the presented method is preferable to other routes and the RSEM is individualized appropriately.

1 Introduction

1.1 Navigation System

An activity to move from one place to the other is called *navigation* [1]. Human beings repeat navigation in their daily life [2]. There are many kinds of navigation in our daily life such as walking from one's home to a near restaurant, traveling overseas by an airplane and so on. One of the main purpose of navigation is to reach a destination [1]. We feel uncomfortable in losing one's way, i.e., failure in navigation. We use a map and ask someone one's way in order to reduce anxiety of navigation.

Computerization of maps and emergence of Global Positioning System (GPS) make our navigation change drastically. It means introduction of a navigation system, i.e., support of the navigation with information technologies. The shortest route from an origin to a destination is shown on computerized

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maps by solving the shortest path problems, i.e., a classical problem in graph theory. The GPS points our present positions in real time on computerized maps. Navigation systems with shortest route selection and positioning provide useful support for navigation in our daily life. Navigation systems for car drivers, which are abbreviated to *Car-Navi* in Japanese, are established by its ability to assist car drivers in navigation.

Expectation for navigation systems makes requirements for ones become sophisticated. Navigation systems are asked to select not only the shortest routes but also the ones from the various viewpoints such as *short time*, *traffic jam avoidance*, *highway use* and so on [3, 4]. Navigation systems, which bring about a great success in navigation support with the shortest route, need to select routes flexibly based on some personal demands as their own next improvements.

1.2 Related Works

Navigation systems are reconsidered as Geographic Information System (GIS) through fusion between its primitive function and other information technologies. Many studies on navigation systems as the GIS are performed from the various viewpoints.

There are improvement in accuracy of positioning technology and increase in speed of route selection algorithm as fundamental research field for realization of navigation systems. Positioning technologies with high accuracy for car navigation systems are realized by combination of the GPS and gyros on board. Positioning technologies for pedestrian navigation systems, however, have less accuracy because pedestrians may move indoors where the GPS is not available. The additional positioning technologies [5,6] are studied in order to complement the GPS.

Dijkstra method [7], i.e., the typical method to solve the shortest path problem, are often used for route selection algorithm in navigation systems. Dijkstra method, however, could not decide routes in actual time if the presented maps become too big or criteria for route selection are too complicated. The route selection algorithms with high speed are studied [4].

Navigation systems as the GIS are applied to many fields by introducing the various criteria to route selection. A tour planning support system for sightseeing [8] are developed in order to meet demands to visit several places in limited time. Attractiveness of each place and the limited time are considered as the criteria for route selection. There is a navigation system for elderly and disabled people, which selects the routes according to *available for wheel chair*, *with braille block (for blind people)* and so on [9].

These studies are similar to the present study in that the routes are selected based on not only distance, i.e., the shortest route, but also the various criteria. The attractiveness of places for sightseeing, however, is fixed among all users, and individuality for each user is not considered. The present study is different from study [8] from the viewpoints that evaluation of roads and the criteria for route selection are personalized based on each user's subjectivity. The present study deals with the subjective information such as *pleasant* and *solitary* which are different from the objective information such as *available for wheel chair*, *with braille block (for blind people)* [9].

1.3 Subjective Preference Based Route Selection

Although the recent navigation systems have selected not only the shortest routes but also the various ones from the viewpoints of *short time*, *traffic jam avoidance*, *highway use* and so on, these routes are selected using objective information such as distance and time [4]. Routes from an origin to a destination are determined independent of each user when a criterion for route selection such as *traffic jam avoidance* is selected. On the other hand human beings may have various demands such as *I would like to take a walk for change of pace* and *I would like to go window-shopping* when they walk in a city. Even if the criteria for route selection such as *I would like to take a walk for change of pace* is determined, users may prefer various routes based on their own subjectivity. The preferable route for all users is not determined because such criteria include subjective information. The navigation systems should select routes based on individual preference even if users have the same demands for the purpose of the route selection considering the subjective demands which human beings may have in a city. We have proposed a new notion of route selection in navigation systems such as the *subjective preference based route selection* and the pedestrian navigation system based on the notion, which provides users satisfactory routes by taking account of their own subjective demands [10–12]. The pedestrian navigation system in these studies selects routes suitable for walking situations such as *I would like to pass the time until an appointment* or *I would like to take a walk with my parents.* Roads are described by road attributes, which express subjective impressions of the roads such as *pleasant* or *crowded.* Users' preference for route selection in a situation, i.e., the importance of each road attribute in route selection, is expressed by fuzzy measures. The routes are selected according to the subjective satisfaction degrees of each road estimated by the fuzzy measures and integrals model constructed for each user. The satisfaction degrees of roads are estimated using four road attributes common among all users in the previous studies [10, 11]. In order to reflect users' own preference for the route selection more than the previous system, study [12] aims at not only obtaining the users' own fuzzy measures but also choosing the road attributes based on users' subjectivity.

We describes in this chapter the method of choosing the road attributes, which are important for expressing users' preference, among many prepared ones by extracting users' preference in the viewpoint of fuzzy measures. The obtained fuzzy measures and road attributes are analyzed in order to confirm whether the valid fuzzy measures and integrals models are constructed by the presented method. Analyses of fuzzy measures and road attributes are performed in the two viewpoints below. One is the error between the satisfaction degrees of roads estimated by the presented preference model and those evaluated by users on questionnaires. The other is correspondence degrees between the road attributes chosen by the presented method and those by users themselves.

Section 2 defines fuzzy measures and integrals used for the evaluation on a road. Section 3 shows the system structure and also explains the route selection part including a road satisfaction degree evaluation model (RSEM), and the route guidance part, which both are components of the system. The RSEM and its construction method are described in Sect. 4. Subject experiments to confirm the validity of the presented system are performed in Sect. 5. Analyses of obtained fuzzy measures and road attributes are conducted in Sect. 6. Conclusions are described in the final section. In this chapter, a *road* means a line segment connecting two intersections, and a *route* means a path with an origin and a destination, which is composed of roads.

2 Fuzzy Measures and Integrals

2.1 Definition

Let $\mathcal{P}(X)$ be a power set of finite set $X = \{x_1, \ldots, x_n\}$, i.e., the set of all subsets in set X. And let us consider a real function as a set function on set X.

Definition 1. *Fuzzy measures g on set X are defined as set function $g : \mathcal{P}(X) \to [0, \infty]$ satisfying (1) and (2) [13].*

$$g(\emptyset) = 0, \tag{1}$$

$$A \subset B \subset X \Rightarrow g(A) \le g(B). \tag{2}$$

Although various types of integrals are proposed as fuzzy integrals with respect to fuzzy measures, Choquet integrals are considered in this chapter.

Definition 2. *Choquet integrals of function f with respect to fuzzy measures g are defined by (3) [13].*

$$(C)\int f\,dg = \sum_{i=1}^{n} \big(f(x_{(i)}) - f(x_{(i-1)})\big) \cdot g(A_{(i)}), \tag{3}$$

$$(A_{(i)} = \{x_{(i)}, \ldots, x_{(n)}\}),$$

where f is a function $f : X \to [0, \infty]$ on set $X = \{x_1, \ldots, x_n\}$, g is fuzzy measures on set X. Let $x_{(i)}$ indicate that $x_1, \ldots, x_n$ are permutated so that the values of function f satisfy $0 = f(x_{(0)}) \le f(x_{(1)}) \le \cdots \le f(x_{(n)})$.

Figure 1 illustrates the Choquet integrals defined by (3). The horizontal axis and the vertical axis show the values of fuzzy measures g and the values of function f, respectively. The area of the shaded part in Fig. 1 is the value of Choquet integrals.

2.2 Evaluation Model with Fuzzy Measures and Integrals

Multiattribute evaluation models [14] are one of the main field that fuzzy measures and integrals are applied to. Fuzzy measures and integrals are interpreted as below when they are employed for the evaluation model of an object with some attributes. Let $\mathcal{O}$ be an evaluation object with n attributes included in attribute set $X = \{x_1, \ldots, x_n\}$. Attribute values $f(x_i)$ $(i = 1, \ldots, n)$ are the evaluation values of object $\mathcal{O}$ from the viewpoint of attributes x_i $(i = 1, \ldots, n)$. Furthermore, fuzzy measures $g(A)$ $(A \subset X)$ defined on set X mean the importance of attribute sets A at the evaluation of object $\mathcal{O}$. The value of Choquet integrals is considered as the total evaluation value of object $\mathcal{O}$, which has attribute values $f(x_i)$ $(i = 1, \ldots, n)$, based on fuzzy measures g. Figure 2 shows the evaluation model with fuzzy measures and integrals.

2.3 Shapley Index

The Shapley index is introduced in order to estimate the importance of attribute $x_i \in X$. Let $A \backslash B$ be a difference set of sets $A, B \subset X$, i.e., $x \in A \backslash B \Leftrightarrow x \in A$ and $x \notin B$.

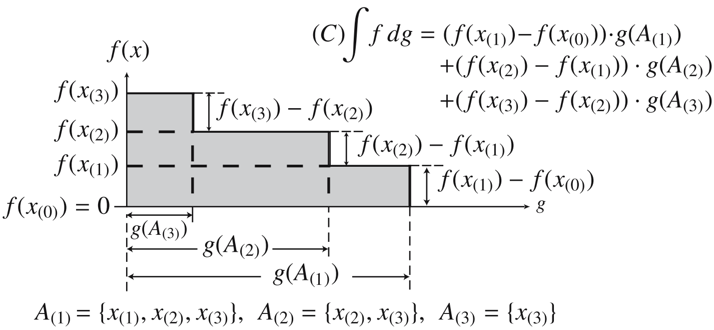


Fig. 1. Choquet integral

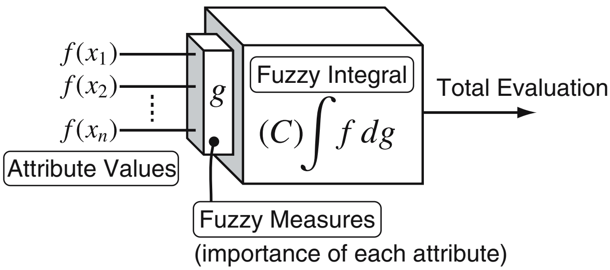


Fig. 2. Evaluation model with fuzzy measures and integrals

Table 1. Example of fuzzy measure

$g(\emptyset) = 0.0$	$g(\{x_1, x_2\}) = 0.6$
$g(\{x_1\}) = 0.3$	$g(\{x_1, x_3\}) = 0.4$
$g(\{x_2\}) = 0.3$	$g(\{x_2, x_3\}) = 0.8$
$g(\{x_3\}) = 0.3$	$g(\{x_1, x_2, x_3\}) = 1.0$

The importance of attribute x_i is not determined only by $g(\{x_i\})$. Considering fuzzy measures g defined on set $X = \{x_1, x_2, x_3\}$ as shown in Table 1, the importance of attribute x_3 are not necessarily assessed at 0.3, despite $g(\{x_3\}) = 0.3$. The incremental importance should be also taken into consideration. For example, the incremental importance degrees by adding $\{x_3\}$ to $\{x_1\}$ and $\{x_3\}$ to $\{x_1, x_2\}$ are 0.1 and 0.4, respectively. It is necessary to consider relation between attribute x_3 and all of attribute sets $D \subset X \setminus \{x_3\}$ at the estimation of the importance of attribute x_3. In this study, the Shapley index [15] is employed for estimating the importance of attributes.

Definition 3. *Let g be fuzzy measures on attribute set $X = \{x_1, \ldots, x_n\}$. The Shapley index $\varphi(g)(x_i)$ for every attribute $x_i \in X$ with respect to g is defined by (4) and (5) [15].*

$$\varphi(g)(x_i) = \sum_{D \subset X \setminus \{x_i\}} \gamma_X(D) \cdot [g(D \cup \{x_i\}) - g(D)] \quad (i = 1, \ldots, n), \tag{4}$$

$$\gamma_X(D) = \frac{(|X| - |D| - 1)! \cdot |D|!}{|X|!}, \tag{5}$$

where $|X|$ denotes the number of elements of set X.

The Shapley index $\varphi(g)(x_i)$ implies the weighted average of the importance of attribute x_i since $g(D \cup \{x_i\}) - g(D)$ $(x_i \notin D)$ represents the incremental importance when $\{x_i\}$ is added to D. That is, the larger the Shapley index $\varphi(g)(x_i)$, the more attribute x_i possesses the importance on the evaluation.

3 System Structure

The presented system as shown in Fig. 3 is composed of two parts such as route selection part and route guidance part.

3.1 User Interface for Traveling

Users move on the map shown in Fig. 4a with the user interface for traveling shown in Fig. 4b. Each road has landmarks or views as shown by dots in Fig. 4a, and the photo of a landmark or a view is presented to users when they move there. Figure 4c shows an example of the landmark photo when users move in front of CAFE shown in Fig. 4b. Users feel impressions of the road by the photos.

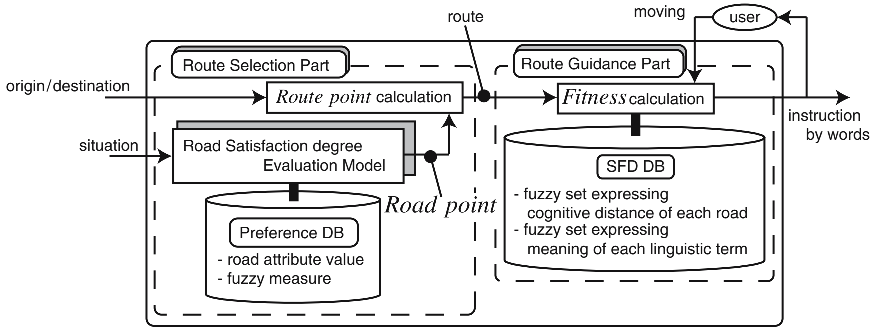


Fig. 3. System structure

(a) Traveling map (b) Interface for traveling (c) Picture of landmark

Fig. 4. Example of user interface

3.2 Route Selection Part

Given an origin, a destination and a situation in which users move on a map, the route selection part selects the route out of many ones from the origin to the destination based on users' own preference for route selection. The route selection part consists of the RSEM and the preference database. The RSEM calculates *Road point*, which expresses users' own satisfaction degree of a road, by using fuzzy measures and integrals. The route selection part selects the route with the highest *Route point*, i.e., the satisfaction degree of a route defined by (6), among all routes from the origin to the destination.

$$Route\ point = \sum_{p=1}^{q} \frac{(Road\ point)_p}{(Road\ length)_p}, \tag{6}$$

where the route consists of q roads, $(Road\ point)_p$ is *Road point* of the pth road and $(Road\ length)_p$ is the distance of the pth road.

3.3 Route Guidance Part

The route guidance part gives users instructions of the route selected by the route selection part. Instructions are expressed in the form of (*the distance* *to the intersection users turn next, the direction users go to after passing the intersection*), e.g., *go straight for a while and turn to the right*. The given instructions reflect users' own sensuous feeling of distance (SFD). The SFD database in the route guidance part has information on users' SFD expressed by two kinds of fuzzy sets. One is the fuzzy set expressing users' cognitive distance of each road and the other is the one that expresses the meaning of linguistic terms expressing users' cognitive distance. These fuzzy sets are obtained by the Sketch Map method [16] mentioned in Sect. 5.3.

In order to express the route with linguistic expressions reflecting users' own SFD, the route guidance part calculates the fitness value of two fuzzy sets defined by (7).

$$Fitness = \frac{1}{2}\Big[\sup\{\mu_{\tilde{A}}(x) \wedge \mu_{\tilde{B}}(x)\} + \inf\{\mu_{\tilde{A}}(x) \vee \mu_{\tilde{B}^{\mathsf{C}}}(x)\}\Big], \tag{7}$$

where $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(x)$ are membership functions of fuzzy sets $\tilde{A}$ and $\tilde{B}$, respectively, $\tilde{B}^{\mathsf{C}}$ denotes the complement of fuzzy set $\tilde{B}$, $\wedge$ and $\vee$ stand for the minimum and the maximum operations, respectively, and sup and inf are the supremum and the infimum operations, respectively. In this study fuzzy set $\tilde{A}$ expresses users' own cognitive distance of each road and fuzzy set $\tilde{B}$ expresses the meaning of linguistic terms expressing users' cognitive distance.

The route guidance part calculates the fitness value and presents instructions by linguistic terms with the largest fitness value. This procedure is repeated every time users turn each intersection until users reach the destination. If users are out of the selected route, this part gives users the instruction to go back and shows the route from the losing point to the destination with linguistic expressions.

4 Road Satisfaction Degree Evaluation Model (RSEM)

The RSEM is composed of road attribute set X and fuzzy measures g on set X. The individual road attribute sets and the individual fuzzy measures are obtained as follows so that users' own preference is reflected directly in the RSEM. HLMS (Heuristic Least Mean Squares) [17] is used for identifying fuzzy measures in the presented study. The HLMS obtains fuzzy measures so that *IE* is minimized, where *IE* is the mean square error between the satisfaction degrees of roads obtained by (3) and those evaluated by users themselves on questionnaire. Here, fuzzy measures and functions are considered as $g : \mathcal{P}(X) \to [0,1],\ g(X) = 1$ and $f : X \to [0,1]$, respectively, for simplicity.

Let $X^{\text{general}} = \{x_1^{\text{general}}, \ldots, x_N^{\text{general}}\}$ denote the general road attribute set, and $X_t^{\text{candidate}}$ $(t = 1, 2, \ldots)$ indicate the subset of set X^{general} satisfying $X_1^{\text{candidate}} = X^{\text{general}}$ and $X_t^{\text{candidate}} \supseteq X_{t+1}^{\text{candidate}}$.

step1: Identifying fuzzy measures of N road attributes in set $X_t^{\text{candidate}}$ $(t = 1)$, i.e., set X^{general}.

step2: Choosing the road attribute(s) with Shapley index values satisfying (8) from set $X_t^{\text{candidate}}$. Adding 1 to t.

$$\varphi(g)(x_i) > \frac{1}{|X_t^{\text{candidate}}|} \quad (i = 1, \ldots, |X_t^{\text{candidate}}|), \tag{8}$$

where $|X_t^{\text{candidate}}|$ is the number of elements of set $X_t^{\text{candidate}}$.

step3: Composing set $X_t^{\text{candidate}}$ of the road attribute(s) chosen in *step2*.

step4: Identifying fuzzy measures of the road attribute(s) in set $X_t^{\text{candidate}}$.

step5: Repeating *step2*, *step3* and *step4* until set $X_t^{\text{candidate}}$ becomes an empty set.

step6: Set $X_t^{\text{candidate}}$ with the smallest *IE* among all sets $X_t^{\text{candidate}}$ $(t = 1, 2, \ldots)$ is considered as set $X^{\text{individual}} = \{x_1^{\text{individual}}, \ldots, x_n^{\text{individual}}\}$ $(\subseteq X^{\text{general}})$, i.e., the individual road attribute set.

step7: Constructing the RSEM with individual road attribute set $X^{\text{individual}}$ and individual fuzzy measures g defined on set $X^{\text{individual}}$.

If all road attributes x_i $(i = 1, \ldots, |X|)$ in set X have the equivalent importance degrees on the evaluation of a road, all the Shapley index values $\varphi(g)(x_i)$ $(i = 1, \ldots, |X|)$ are obtained by (9),

$$\varphi(g)(x_i) = \frac{g(X)}{|X|} = \frac{1}{|X|} \quad (i = 1, \ldots, |X|), \tag{9}$$

since the Shapley index has a property expressed by (10) [15].

$$\sum_{i=1}^{|X|} \varphi(g)(x_i) = g(X) = 1. \tag{10}$$

In this study, the road attribute x_i with the Shapley index values satisfying (8) is regarded as important on the evaluation of a road and chosen in *step2*. Table 2 shows the example of constructing the RSEM by the proposed method. Set $X_2^{\text{candidate}}$ with the smallest *IE* among all sets $X_t^{\text{candidate}}$ $(t = 1, 2, 3)$ is considered to be individual road attribute set $X^{\text{individual}}$.

Table 2. Example of RSEM construction

	$X_1^{\text{candidate}}$ $(= X^{\text{general}})$	$X_2^{\text{candidate}}$ $(= X^{\text{individual}})$	$X_3^{\text{candidate}}$
$x_i,\ \varphi(g)(x_i)$	$x_1,\ 0.08$		
	$x_2,\ 0.30$	$x_2,\ 0.26$	
	$x_3,\ 0.13$		
	$x_4,\ 0.23$	$x_4,\ 0.26$	
	$x_5,\ 0.26$	$x_5,\ 0.48$	$x_5,\ 1.00$
$1\ /\ \lvert X_t^{\text{candidate}}\rvert$	0.2	0.3	1.0
Identifying error *IE*	0.085	0.083	0.11

5 Experiments

The experiments are performed in order to confirm the validity of the present system. There are 11 subjects and three situations $\mathcal{S}_j$ $(j = 1, 2, 3)$. $\mathcal{S}_1$: *They would like to take a walk alone*, $\mathcal{S}_2$: *They would like to take a walk with their parents*, $\mathcal{S}_3$: *They would like to pass the time until an appointment*. Subjects' own RSEMs, preference databases and SFD databases are constructed. The subjects walk along the routes selected by their own RSEMs according to instructions given by the route guidance part, and evaluate the satisfaction degrees of the selected routes. Figure 5 shows the traveling map prepared for the experiments.

5.1 Construction of RSEM

The subjects' own RSEMs are obtained in situations $\mathcal{S}_j$ $(j = 1, 2, 3)$ by the method described in Sect. 4. Thirty roads with some landmarks or views are prepared in order to obtain the RSEMs. These roads are not included in the traveling map as shown in Fig. 5. After the subjects walk along each road, they evaluate the satisfaction degrees of the roads in each situation with a 5-point scale, 1 : *dissatisfied*, 2 : *a little dissatisfied*, 3 : *neutral*, 4 : *a little satisfied*, 5 : *satisfied*. Let $z_j^{k'}$ $(j = 1, 2, 3;\ k' = 1, \ldots, 30)$ be the satisfaction degree of the k'th road in situation $\mathcal{S}_j$. They also evaluate the road from the viewpoints of 8 road attributes, x_1^{general} : *lively*, x_2^{general} : *sophisticated*, x_3^{general}: *solitary*, x_4^{general} : *fancy*, x_5^{general} : *crowded*, x_6^{general} : *calm*, x_7^{general} : *pleasant*, x_8^{general} : *refreshing* with a 5-point scale, 1 : *they don't think so at*

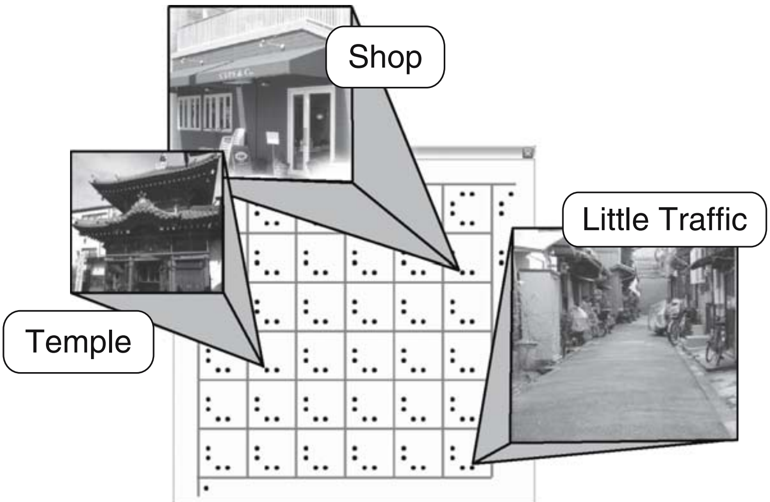


Fig. 5. Prepared map in experiments

all, 2 : *they don't think so very much*, 3 : *neutral*, 4 : *they think so a little*, 5 : *they think so*. Let $X^{\mathrm{general}} = \{x_1^{\mathrm{general}}, \ldots, x_8^{\mathrm{general}}\}$ denote the general road attribute set. Let $f_1^{k'}, \ldots,$ and $f_8^{k'}$ $(k' = 1, \ldots, 30)$ be the road attribute values of the k'th road. The individual RSEMs in situations $\mathcal{S}_j$ $(j = 1, 2, 3)$, which are composed of individual road attribute set $X^{\mathrm{individual}} \subseteq X^{\mathrm{general}}$ and individual fuzzy measures g defined on set $X^{\mathrm{individual}}$, are obtained with the set of 30 data $(f_1^{k'}, \ldots, f_8^{k'}, z_j^{k'}; j = 1, 2, 3,\ k' = 1, \ldots, 30)$ under the following quantifications of questionnaire results; $1 \to 0.0,\ 2 \to 0.25,\ 3 \to 0.5,\ 4 \to 0.75,\ 5 \to 1.0$.

5.2 Construction of Preference Database

The subjects walk along 84 roads which are included in the traveling map as shown in Fig. 5, and evaluate each road from the viewpoints of $x_1^{\mathrm{general}}, \ldots,$ and x_8^{general}. Let $f_1^k, \ldots,$ and f_8^k $(k = 1, \ldots, 84)$ be the road attribute values of the kth road with respect to road attributes $x_1^{\mathrm{general}}, \ldots,$ and x_8^{general}, respectively. Fuzzy measures g in situation $\mathcal{S}_j$ $(j = 1, 2, 3)$ obtained in Sect. 5.1 and road attributes values $f_1^k, \ldots,$ and f_8^k $(k = 1, \ldots, 84)$ of the roads shown in Fig. 5 are preserved in subjects' own preference databases.

5.3 Construction of SFD Database

The Sketch Map method [16], which is used in the field of spatial cognition research, is applied to the acquisition of subjects' own quantitative sensuous feeling of distance. In this method, the subjects move along given routes and keep them in mind. And then the subjects sketch surroundings, landmarks and so on from memory.

In this study, only the user interface as shown in Fig. 4b is presented to the subjects while they walk along routes on a map. Therefore, the subjects perceive only the part of surroundings while walking. They should memorize the relative position between an origin and a destination, and the distance between them. After walking along routes on a map, the subjects draw the route on a computer display according to their SFD from memory. A drawing example of the route from START to GOAL shown in Fig. 6a is illustrated in Fig. 6b.

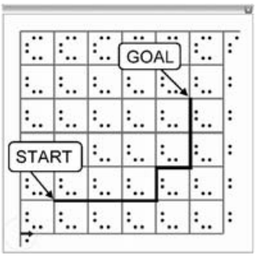
After drawing the route, the subjects express their own SFD of each road with linguistic expressions such as *the distance of walking briefly*, *the distance of walking a little*, *the distance of walking for a while*, *the distance of walking by far*, and *the distance of walking for quite a long time*. Using differences between the drawn route and the route that the subjects move on, two kinds of fuzzy sets are obtained.

5.4 Evaluation

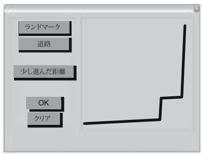
The subjects walk along the routes selected by the present system in each situation, whose origins and destinations are all the same. They also evaluate the satisfaction degrees of the routes in the presented situation from the viewpoint of only impressions effected by the photo of landmarks or views along the routes. Three kinds of routes $\mathcal{R}_j^{\max}, \mathcal{R}_j^{\mathrm{mid}}$ and $\mathcal{R}_j^{\min}$ are considered in situation $\mathcal{S}_j$ $(j = 1, 2, 3)$, which indicate the routes with the highest, middle and the lowest *Route point* among all routes, respectively. After walking along one route, the subjects evaluate the satisfaction degree of the route with a 5-point scale. The subjects walk along nine routes in total and evaluate the satisfaction degrees of each route.

5.5 Experimental Results and Remarks

Figure 7 shows averages of the satisfaction degrees of $\mathcal{R}_j^{\max}, \mathcal{R}_j^{\mathrm{mid}}$ and $\mathcal{R}_j^{\min}$ among all subjects in all situations. The vertical axis indicates the average of the satisfaction degree. Hypotheses that $\mathcal{R}^{\max} = \mathcal{R}^{\mathrm{mid}}$ and $\mathcal{R}^{\max} = \mathcal{R}^{\min}$



(a) Route for moving



(b) Drawn route

Fig. 6. Example of drawing route in sketch map method

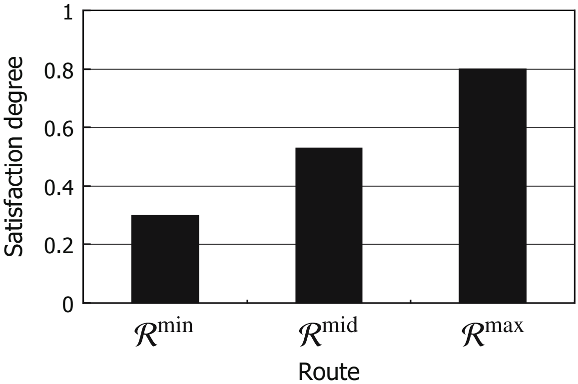
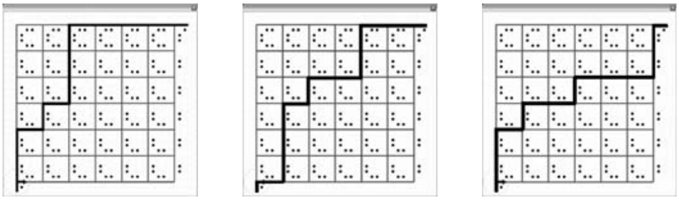
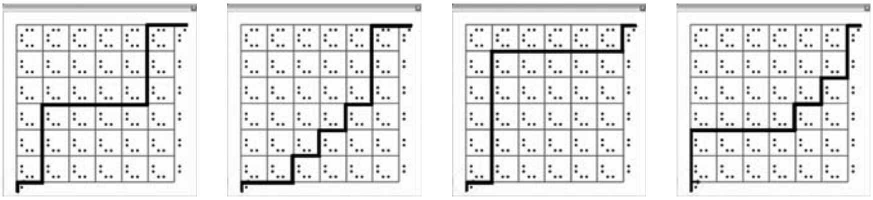


Fig. 7. Satisfaction degrees of routes



(a) Situation $\mathcal{S}_1$ (b) Situation $\mathcal{S}_2$ (c) Situation $\mathcal{S}_3$

Fig. 8. $\mathcal{R}_j^{\max}$ of subject 2 in each situation



(a) Subject 3 (b) Subject 5 (c) Subject 9 (d) Subject 10

Fig. 9. $\mathcal{R}_j^{\max}$ of each subject in situation $\mathcal{S}_2$

in the average of the satisfaction degree are rejected against the alternative hypotheses that $\mathcal{R}^{\max} > \mathcal{R}^{\mathrm{mid}}$ and $\mathcal{R}^{\max} > \mathcal{R}^{\min}$ in the average of the satisfaction degrees, respectively, with a significant difference ($p < .05$). It is found that $\mathcal{R}^{\max}$ reflecting subjective preference for route selection is preferable to other routes such as $\mathcal{R}^{\mathrm{mind}}$ and $\mathcal{R}^{\min}$.

Figure 8 shows $\mathcal{R}_j^{\max}$ presented to subject 2 in each situation. Figure 9 shows $\mathcal{R}_2^{\max}$ presented to each subject in situation $\mathcal{S}_2$. It is found that although the origin and the destination are both the same, various routes are presented to the subjects according to the subjects and the situations.

The subjects turn accurately the instructed intersections at the rate of 79% of all intersections in all selected routes. These results show that the presented system provides the subjects with useful guidance by linguistic expressions fitting their own SFD.

6 Analyses of RSEM

6.1 Verification by Model Error

In RSEM construction mentioned in Sect. 4 road attribute sets used for the RSEM are derived from arbitrary subsets of general road attribute set X^{general}. There are $(2^N - 1)$ road attribute subsets, i.e., possible combination of road attributes when there are N prepared road attributes. The empty set is excluded because the RSEM is not constructed by it. The analysis in this section aims at indicating that road attribute subset necessary for expressing subjects' preference are chosen appropriately from $(2^N - 1)$ possible road attribute subsets. In this section validity of chosen road attributes are evaluated by TE defined by (11), i.e., model error for testing data, which are not used for model construction. The small TE means that road attributes necessary for expressing subjects' preference are chosen appropriately. Eighty four roads included in the map shown by Fig. 5 are used for testing data to calculate TE

$$TE = \frac{1}{84} \sum_{\delta=1}^{84} \sqrt{\left(Road\ point_\delta - z_\delta\right)^2}, \tag{11}$$

where $Road\ point_\delta$ is the satisfaction degrees of road δ $(\delta = 1, \ldots, 84)$ estimated by the RSEM, and z_δ is ones evaluated by the subjects on the questionnaires.

Five kinds of road attribute sets are defined as typical combinations of road attributes as follows, where $k = 1, \ldots, 11$ denotes the subject $1, \ldots, 11$.

- X_{kj}^{general} $(k = 1, \ldots, 11; j = 1, 2, 3)$
  The general road attribute set, composed of eight prepared road attributes. Four kinds of road attribute sets are subset of set X_{kj}^{general} as follows.
- X_{kjm}^{all} $(k = 1, \ldots, 11; j = 1, 2, 3; m = 1, \ldots, 255)$
  Arbitrary subsets of set X_{kj}^{general}, where $m = 1, \ldots, 255$ denotes index of road attribute subset. $255 (= 2^8 - 1)$ road attribute subset are generated because there are eight prepared road attributes.
- $X_{kjt}^{\text{candidate}}$ $(k = 1, \ldots, 11; j = 1, 2, 3; t = 1, \ldots)$
  Road attribute subsets generated in *step1* and *step3* of the RSEM construction method.
- $X_{kj}^{\text{individual}}$ $(k = 1, \ldots, 11; j = 1, 2, 3)$
  Road attribute subset used for the RSEM. The road attribute set with the smallest IE in set $X_{kjt}^{\text{candidate}}$ is chosen as $X_{kj}^{\text{individual}}$.
- $X_{kj}^{\text{complement}}$ $(k = 1, \ldots, 11; j = 1, 2, 3)$
  Set $X_{kj}^{\text{complement}}$ is constructed to exclude $X_{kj}^{\text{individual}}$ used for the RSEM from the general road attribute set X_{kj}^{general}. Set $X_{kj}^{\text{complement}}$ is considered as the road attribute set not necessary for expressing subjects' preference.

The presented method is interpreted as the generation of candidates, i.e., set $X_{kjt}^{\text{candidate}}$ chosen from the general road attribute set X_{kj}^{general} according to the Shapley index, and determination of the final road attribute set, i.e., individual road attribute set $X_{kj}^{\text{individual}}$ with the smallest IE among some candidates $X_{kjt}^{\text{candidate}}$. The RSEMs constructed with X_{kjm}^{all} are regarded as the ones constructed with the road attribute set chosen at random because set X_{kjm}^{all} is the arbitrary subset of set X_{kj}^{general}.

Table 3 shows the average values of model errors TE with the testing data, which are calculated with five kinds of road attribute sets such as X_{kj}^{general},

Table 3. TE : Error of RSEM with testing data

Road attribute set	TE
X^{all}	0.25
$X^{\mathrm{candidate}}$	0.23
$X^{\mathrm{individual}}$	0.20
X^{general}	0.25
$X^{\mathrm{complement}}$	0.28

X^{all}_{kjm}, $X^{\mathrm{candidate}}_{kjt}$, $X^{\mathrm{individual}}_{kj}$, and $X^{\mathrm{complement}}_{kj}$. Hypothesis that TE for set $X^{\mathrm{candidate}}$ is equal to that for set X^{all} is rejected against the alternative hypothesis that the former is smaller than the latter with a significant difference ($p < .05$). Furthermore, hypotheses that TE for set $X^{\mathrm{individual}}$ is equal to that for set X^{general} and TE for set $X^{\mathrm{complement}}$ be that for set X^{general} are rejected against the alternative hypotheses that TE for set $X^{\mathrm{individual}}$ is smaller than that for set X^{general} and TE for set $X^{\mathrm{complement}}$ is larger than that for set X^{general}, respectively, with a significant difference ($p < .05$). The RSEM with road attributes estimated as necessary has small TE. On the other hand the RSEM with road attributes estimated as unnecessary has large TE. Therefore, road attributes chosen by the presented method are seem to be essential for expressing the subjects' preference.

6.2 Verification by Road Attribute Correspondence

The road attributes chosen by the presented method are compared with the ones chosen by the subjects themselves in order to confirm that the former reflects the subjects' preference. The chosen road attributes are compared in the two ways. One is performed with 11 subjects and the other is with seven subjects.

Two descriptions $\mathcal{I}_j$ and $\mathcal{NI}_j$ showing impressions of a route are prepared in situation $\mathcal{S}_j$ ($j = 1, 2, 3$) for the first comparison. The descriptions are composed of two road attributes in general road attribute set X^{general}, for example, a *pleasant* and *lively* route. The description $\mathcal{I}_j$ has the road attributes with the largest and the second largest Shapley index values in individual road attribute set $X^{\mathrm{individual}}$ of the RSEM, and the description $\mathcal{NI}_j$ has the road attributes with the smallest and the second smallest Shapley index values in set $X^{\mathrm{complement}}$. Two descriptions $\mathcal{I}_j$ and $\mathcal{NI}_j$ are presented to the subjects in random order, and the subjects choose the preferable one in situation $\mathcal{S}_j$. There are 33 trials in a total since 11 subjects reply to questionnaire in three situations. If only one road attribute is employed for the RSEM, the road attributes with only the largest and the smallest Shapley index values are included in $\mathcal{I}_j$ and $\mathcal{NI}_j$, respectively.

The subjects reply that $\mathcal{I}_j$ is preferable to $\mathcal{NI}_j$ at the rate of 91% of all trials. This result shows that individual road attribute set $X^{\mathrm{individual}}$ of the RSEM reflects subject's own preference well.

As the second comparison seven subjects choose two road attributes among set X^{general} which he/she thinks as important for route selection in situation $\mathcal{S}_j\,(j = 1, 2, 3)$. Forty-two road attributes (=7 subjects $\times$ 3 situations $\times$ 2 road attributes) are chosen through all trials.

Twenty-five road attributes (60%) are included in set $X^{\text{individual}}$ among 42 road attributes which subjects consider as important for route selection.

The result of the second comparison is inferior to that of the first one. In order to examine its reason, the following discussions are focused on 17 road attributes, which are chosen by subjects themselves and not by the presented method. In the presented method the road attributes are chosen by iteration of elimination of ones with the small Shapley index values. Eleven road attributes, occupied at the rate of 60% of the present 17 road attributes, are eliminated at the first elimination, i.e., *step2* in $t = 1$. Furthermore, 11 road attributes have the Shapley index values 0.11 at the average, which reaches 88% of the threshold of elimination defined by (8), i.e., $0.125(= \frac{1}{8} = \frac{1}{|X_1^{\text{candidate}}|} = \frac{1}{|X^{\text{general}}|})$. This means that 11 road attributes are eliminated despite the high importance degrees, i.e., 88% of the threshold. If the threshold is decreased from $\frac{1}{|X_t^{\text{candidate}}|}$ to $0.8 \times \frac{1}{|X_t^{\text{candidate}}|}$, eight road attributes at the rate of 73% of 11 road attributes are chosen for the RSEM. Under the same condition as the decreased threshold 35 road attributes at the rate of 83% of 42 road attributes chosen by subjects are used for RSEM construction. These results show that there are some cases where the threshold defined by (8) does not reflect subjective evaluation on choice of important road attributes well because the threshold is determined by the strict mathematical property of the Shapley index defined by (10). It is considered as the future works that the threshold should be adjusted according to each subject as well as determined by the mathematical property of the Shapley index.

6.3 Qualitative Verification by Impressions of Roads

The qualitative verification is performed by showing that the estimated satisfaction degrees of the same roads are dependent on the road attributes chosen by the RSEM. Three trials such as subject 1 in situation $\mathcal{S}_3$, subject 2 in situation $\mathcal{S}_3$ and subject 9 in situation $\mathcal{S}_2$ are used for analyses. The $\text{RSEM}_{k,\mathcal{S}_j}$ denotes the RSEM of subject k $(k = 1, \ldots, 11)$ in situation $\mathcal{S}_j$ $(j = 1, 2, 3)$.

Table 4 shows the chosen road attributes in each trial and its Shapley index values. The symbol $*$ indicates two road attributes chosen by subjects themselves in Sect. 6.2. Road attributes x_4 and x_7 are chosen for both of subject 1 and subject 2 but the road attributes chosen for them are all different from ones for subject 9. Next, five roads with the large difference between the satisfaction degrees estimated by $\text{RSEM}_{1,\mathcal{S}_3}$ and $\text{RSEM}_{2,\mathcal{S}_3}$, and that by $\text{RSEM}_{9,\mathcal{S}_2}$ are derived from the map as shown in Fig. 5. Table 5 shows the index of these five derived roads, their pictures and the satisfaction degrees of each road. The values in parentheses are the satisfaction degrees of each road

Table 4. Chosen road attributes and its shapley index values

Subject/situation	$1/\mathcal{S}_3$	$2/\mathcal{S}_3$	$9/\mathcal{S}_2$
x_1:lively	$*$ 0.36		
x_2:sophisticated		$*$	
x_3:solitary			0.36
x_4:fancy	0.31	0.35	
x_5:crowded		0.34	
x_6:calm			$*$ 0.32
x_7:pleasant	$*$ 0.33	$*$ 0.31	
x_8:refreshing			$*$ 0.32

Table 5. Impressions of roads and estimated satisfaction degrees

Road			$1\ /\ \mathcal{S}_3$	$2\ /\ \mathcal{S}_3$	$9\ /\ \mathcal{S}_2$
05			0.75 (1.00)	0.91 (0.75)	0.08 (0.25)
26			0.73 (1.00)	0.67 (0.75)	0.16 (0.50)
60			0.39 (0.50)	0.40 (0.00)	1.00 (0.75)
69			0.24 (0.50)	0.33 (0.25)	1.00 (1.00)
49			0.58 (1.00)	0.74 (0.75)	0.08 (0.00)

evaluated by the subjects on questionnaires. Correlation coefficient between the satisfaction degrees of roads estimated by the RSEM and that on questionnaire is 0.76. It is considered that the RSEM estimates the satisfaction degrees of roads so as the subjects do.

Road 05 and road 26 are considered as preferable by subject 1 and subject 2 but not so by subject 9. Differences of satisfaction degrees of roads among the subjects seem to be caused by differences of impression of roads expressed by road attributes used for each subject's RSEM. The impressions expressed by the road attributes such as x_4: *fancy* or x_7: *pleasant*, which are used for $\mathrm{RSEM}_{1,\mathcal{S}_3}$ and $\mathrm{RSEM}_{2,\mathcal{S}_3}$, correspond to the impressions of shop windows or cafes as shown in road 05 and road 26, respectively, but ones expressed by the road attributes used for $\mathrm{RSEM}_{9,\mathcal{S}_2}$ do not.

The trial of road 60 and road 69 is explained by the same discussion as above. Road 60 and road 69 are evaluated as satisfactory by subject 9 but not so by subject 1 and subject 2 because the impressions expressed by road attributes such as x_3: *solitary* or x_6: *calm* in $\mathrm{RSEM}_{9,\mathcal{S}_2}$ would reflect more directly impressions of clear coasts and historic houses along road 60 and road 69, respectively, than those expressed by road attributes in $\mathrm{RSEM}_{1,\mathcal{S}_3}$ or $\mathrm{RSEM}_{2,\mathcal{S}_3}$ do so.

Evaluation of road 49 is in a different condition from two kinds of trials mentioned above in that the satisfaction degrees of it estimated by $\mathrm{RSEM}_{1,\mathcal{S}_3}$ and $\mathrm{RSEM}_{2,\mathcal{S}_3}$ do not correspond each other. Road attribute x_5: *crowded* included in $\mathrm{RSEM}_{2,\mathcal{S}_3}$ but not in $\mathrm{RSEM}_{1,\mathcal{S}_3}$ would have much influence on evaluation of road 49 because the impressions of road 49 with crowds could be expressed well by road attribute x_5: *crowded*. It is considered that $\mathrm{RSEM}_{2,\mathcal{S}_3}$ with road attribute x_5 brings higher satisfaction degree of road 49 than $\mathrm{RSEM}_{1,\mathcal{S}_3}$ without it does.

From these results, it is found that the satisfaction degrees of same roads would change according to the road attributes used for the RSEM. Furthermore, roads with the impressions similar to the road attributes used for the RSEM would have the high satisfaction degrees.

7 Conclusions

This chapter describes the pedestrian navigation system that selects routes based on users' own preference for routes. The system has the route selection part and the route guidance part. The route selection part consists of the RSEM and the preference database. The RSEM applies fuzzy measures and integrals to estimate the satisfaction degree of a road, and is constructed based on users' own preference for route selection. The route guidance part has the SFD database, and fuzzy sets are applied to generate instructions with linguistic expressions reflecting users' own SFD. The experimental results show that various routes are selected according to the subjects and the situations and that satisfaction degrees of the routes selected by the present system are higher than those of other routes. The analysis results of experimental data show that the RSEMs reflect subjects' own preference in road attributes.

There are some problems to be solved in a future. The presented method should be applied in the real world. As the first step of application to the real world, a vast park is considered, where there are some roads with various subjective impressions such as lively or refreshing.

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A Knowledge Based Recommender System Based on Consistent Preference Relations

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Summary. E-commerce companies have developed many methods and tools in order to personalize their web sites and services according to users' necessities and tastes. The most successful and widespread are the recommender systems. The aim of these systems is to lead people to interesting items through recommendations. Sometimes, these systems face situations in which there is a lack of information and this implies unsuccessful results. In this chapter we propose a knowledge based recommender system designed to overcome these situations. The proposed system is able to compute recommendations from scarce information. Our proposal will consist in gathering user's preference information over several examples using an incomplete preference relation. The system will complete this relation and exploit it in order to obtain a user profile that will be utilized to generate good recommendations.

1 Introduction

In the last years Internet development has grown beyond all expectations. New services have arisen in order to meet the users' necessities. As a consequence of this development nowadays people can accomplish a great number of activities such as watching films, buying books or flowers, chatting with other people, etc.

Usually these services are designed to offer a wide range of items and/or activities in order to be able to cater for the necessities or requirements of millions of potential users [14, 15, 19]. For instance, Amazon (http://www.amazon.com) sells over eight millions of books of any genre: scientific, business, or historical books as well as comics, novels or mystery books. iTunes Store (http://www.apple.com/itunes/store/) offers over three and a half millions of songs of a wide variety of artist such as The Killers, Bob Dylan, U2, or Sheryl Crow.

Although these services are designed to offer interesting items or services that fulfil the necessities or requirements of millions of potential users, many of them have problems to identify, and therefore, satisfy the necessities of a particular user. An e-bookshop can offer a wide range of mystery books in

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order to offer interesting ones for any user who likes this genre. However, it is not easy for this shop gets to know or finds out which particular books or kind of books each user likes. In such cases, the user has to search among all the books in order to find those ones that are more interesting for him/her. Due to the fact that the e-shops offer a huge variety of books, the search processes could be tedious and the user could waste much time exploring alternatives that he/she will never like and it is possible that the user gives it up and tries to find what he/she wants in a traditional shop where he/she can receive some pieces of advice from the shop assistant.

As a consequence of these problems, many tools have arisen to assist people in their searches. The most famous and successful ones are the Recommender Systems. These systems were first developed in the e-commerce area. Quite often e-commerce customers have to face situations in which the web site offers them a huge range of items that potentially could meet their requests, however only a small set of them really fulfil their necessities and many times they are hard to find out. These systems were developed with the aim of leading these customers towards interesting items by means of recommendations, limiting the offered items or sorting them according to the customers' necessities or tastes.

In the literature we can find different techniques to generate recommendations. Essentially, all these techniques have the same aim and accomplish the same phases to make the recommendations. First of all, before any recommendation process begins, they need a data set stored. The sources of information and its nature can be very varied. Such information is provided by customers, users, experts and it is related to their opinions, preferences, descriptions... The recommendation process starts when a user wants to find out a new item and the Recommender System has already stored the previous dataset with information regarding the user him/herself and/or other users. Then, an algorithm combines the information provided by the user about his/her necessities and the information stored in the Recommender System to generate recommendations about which items are the most suitable for him/her. Depending on the algorithm used to generate the recommendations we can classify them into:

- *Demographic Recommender Systems [12].* In this type of systems, the recommendations are based on demographic information. A specific customer will receive recommendations according to the information they have about the people who belong to the same demographic group.
- *Content-Based Recommender Systems [15].* They gather information about the features of the items user has liked in the past and use this information to find other items that the user could like.
- *Collaborative Recommender Systems [7].* These systems predict the users' preferences as a weighted aggregation of other users' preferences, in which the weights are proportional to the similarity between users on the basis of their ratings.

- *Knowledge Based Recommender Systems [4].* These systems infer the recommendations using the knowledge they have about the users, the items and how the features of these items fulfil the users' expectations.
- *Utility Based Recommender Systems [8].* They make recommendations based on the computation of the utility of each item for the user.
- *Hybrid Recommender Systems [3, 5].* The aforementioned Recommender Systems present some problems and drawbacks. Some authors have proposed to combine these techniques to smooth out these disadvantages and therefore improve the accuracy of the recommendations.

To choose the most suitable items for a user, these systems use information about the items, the users, their necessities, tastes... Sometimes this information is scarce and insufficient. Classical Recommender Systems, Collaborative and Content-based, are unable to make accurate recommendations in such cases. For instance, both of them need historical information about which items the user has liked in the past. If this information is not available (for example, it is a new customer) then, they cannot find out which items could be recommended. To smooth out these drawbacks some proposals have been presented. One of them is the Knowledge Based Recommender Systems. In these systems users state their preferences choosing an example that represent their preferences. The system defines a user profile based on the description of the example, and then, the system finds out which items are the most suitable one according to the user profile.

In this chapter we shall propose a Knowledge Based Recommender model that tries to improve the gathering process and the recommendations of the classical Knowledge Based Recommender Systems by using more examples and employing preference relations. To accomplish the gathering process, the user provides his/her preferences over a small set of items. This set contains examples that the user has chosen to represent his/her necessities. The user's preferences are expressed by means of an incomplete preference relation in which the user only supplies a row (or a column) of the relation. This incomplete preference relation will be completed by means of a method based on a consistency property, and from this relation, the system will compute a user profile that will be used to generate the recommendations. Thus, the gathering process is easier for users since they do not have to provide much information, given that the system can compute and complete by itself.

2 Preliminaries

In this section we shall review some preliminaries needed to understand the model that will be presented in the following section. First of all, we shall study the lack of information in Recommender Systems. Secondly we shall present a brief review of Knowledge Based Recommender Systems. Thirdly, we shall describe the preference relations. And finally we shall show a method to complete an incomplete preference relation by using the consistency property.

2.1 Problems in Classical Recommendater System Models

In the real world these systems face situations in which the information about user's necessities and tastes is not available or is scarce. For instance, some recommender systems ground their recomendations in the historical information about the user. If they are dealing with a new user, they will not be able to generate any recomendations. Even though, if they have historical information about the user, it may not be useful or enough for the current search, i.e., the user is looking for something that is neither related to his/her necessities in the past nor the necessities of other users. Moreover, the border that differentiates when the recommender system has enough information to generate recomendations and when it needs more information is incredibly blurry [5].

These problems particularly concern Classical Recommender Systems, both the Collaborative and the Content-based ones, which require historical information about their users. Some of the most common problems are [5]:

- *The new user ramp-up problem.* If the user has few ratings, Recommender Systems may not be able to make recommendations. This problem is presented in both Collaborative and Content-based Recommender Systems.
- *New item ramp-up problem.* In Collaborative Recommender Systems, items with few ratings are unlikely recommended, even though, they could be interesting for the users.
- *Grey sheep problem.* We can find this problem in Collaborative Recommender Systems. There might exists users whose ratings are not consistently similar with any group of users, and for this reason, they will rarely receive any accurate recommendation.
- *Quality dependent of large historical data set.* Many times, to obtain acceptable recommendations, a good and large historical dataset is needed.

These problems can cause recommender systems to lead the user towards false positives (items that are not truly interesting for him/her). If the user purchases the recommended item and finds out that he/she does not like it, the user will be unlikely to use the recommender system again [17] and this can cause a loss of money and customers. To sort out these problems some solutions have been presented, such as the Hybrid Recommender Systems [5] or the Knowledge Based Recommender Systems [4]. The aim of the first ones is to overcome the drawbacks of these Recommender Systems combining them to smooth out the above problems. The most usual combination is between the Collaborative and the Content-Based Recommender Systems. For instance, this kind of Hybrid Recommender Systems does not suffer from the new item ramp-up problem. However, the Knowledge Based Recommender Systems face the problem of lack of information from another point of view. These systems exploit the information provided by the user about their necessities and the knowledge that the system has about the items that can be recommended, to find out which items match the user real expectations.

In this chapter we develope a variation of a Knowledge Based Recommender Systems. In the next subsection we shall explain in further detail the working of a classical knowledge based recommender system.

2.2 Knowledge Based Recommender Systems

These Recommender Systems attempt to arise recommendations by exploiting the knowledge they have gathered about the items, the users, ... The algorithms used to infer these recommendations are usually based on case based reasoning [11]. These algorithms deal with three types of knowledge:

- *Catalog knowledge.* Knowledge that the Recommender System has about the items and their features.
- *Functional knowledge.* These systems need to know how items might meet the user's necessities.
- *User's knowledge.* The system needs to gather information about the user's necessities in order to find which items satisfy his/her necessities.

The acquisition of user's knowledge is the most challenging and important process in Knowledge Based Recommender System. For instance, this knowledge can be gathered through general demographic information, but the better and more knowledge we have about his/her necessities, the more accurate recommendation will be made. That is the reason why the most usual way to obtain this knowledge is directly requiring an example of the user's necessities. With this example the system is able to define a user profile that describes user's necessities. Then, it can find which items satisfy these necessities and they are returned as recommendations.

The main advantage of this kind of Recommender Systems is that they do not suffer from problems such as, the *new user* or *new item ramp-up problem* or those ones that are related to historical data about the users. As a consequence of this fact they are suitable in situations where there is no historical information (or it is very scarce) about the user.

Even though, these systems are easy to use, they present some drawbacks in the gathering process users' preferences, i.e., the user's knowledge. First of all, in some contexts users can find thousands and thousands of items related to their necessities. Many times it could be so difficult to find an example of what the user needs as to find directly what he or she really needs. And secondly, although the user can find an example of his/her necessities, it is possible that this example does not match exactly with his/her real expectations. The user profile defined from this example will not faithfully represent his/her necessities and therefore, he/she will not obtain a suitable recommendation. In order to solve this problem, this type of Recommender Systems let the user refines his/her user profile modifying, removing, or adding some features. Nevertheless, this process could be hard, time-consuming and not all the users can be willing to do so.

2.3 Incomplete Preference Relations

The numerical preference relations have been widely use to model preferences for problems such as decision-making problems [6,10,16]. In this representation the intensity of preference between any two alternatives of a set of feasible ones, $X = \{x_1, \ldots, x_n\}$ $(n \geq 2)$, is measured with a scale $[0, 1]$.

Definition 1. *[2] A numerical preference relation P on a set of alternatives X is a function on the alternative set $X \times X$ that is defined as following:*

$$\mu_P : X \times X \rightarrow [0, 1] \,.$$

Every value in the matrix P represents the preference degree or intensity of preference of the alternative x_i over x_j:

- $p_{ij} = 1/2$ indicates the maximum grade of indifference between x_i and x_j $(x_i \sim x_j)$.
- $p_{ij} = 1$ indicates that x_i is absolutely preferred to x_j
- $p_{ij} > 1/2$ indicates that x_i is preferred to x_j $(x_i \succ x_j)$

based on this representation we also know that $p_{ii} = \frac{1}{2} \forall i \in \{1, \ldots, n\} \, (x_i \sim x_i)$.

In an ideal situation the information provided by the user should be consistent and complete, however, many times in real situations this is not possible or suitable. For instance, users could be under time pressure or some alternatives could be unknown. In these situations, it would be more suitable to represent his/her preferences by means of an incomplete preference relation.

In our case, we know that time is a key issue in the gathering process of Knowledge Based Recommender Systems. Therefore, we shall propose that the users of our recommender system will provide preferences about different examples by using a preference relation that is a structure easy to exploit in order to obtain a user profile. However, to avoid a time-consuming process, instead of expecting the user provides a complete preference relation, the system will require an incomplete one, just a row (or a column) of the preference relation.

From the incomplete preference relation the system extracts as much information as it can. To do so, the system will fill it up by using a method that ensures that the resulting relation is not only complete, but also consistent. In the following section we shall review a method to complete this kind of relations.

2.4 A Method for Filling Preference Relation Based on the Consistency Property

The concept of consistency is usually characterized by the idea of transitivity. Transitivity represents the idea that the preference value obtained by comparing directly two alternatives should be equal to or greater than the preference value between those alternatives obtained using an indirect chain of alternatives [13, 18]. Some of the suggested transitivity properties that we can find in the literature are the *Triangle condition* [13], the *Weak transitivity* or the *Additive transitivity* [18].

The last one seems a suitable property to characterize consistency in numerical preference relations and has been used successfully to construct consistent numerical relations from incomplete ones [1, 9].

Definition 2. *[1, 9] A numerical preference relation is "additive consistent" when for every three options on the problem $x_i, x_j, x_k \in X$ their associated preference degrees p_{ij}, p_{jk}, p_{ik} fulfil the following expression [9]:*

$$(p_{ij} - 0.5) + (p_{jk} - 0.5) = (p_{ik} - 0.5)\,\forall i, j, k.$$

A simple and practical method for filling a complete preference relation from an incomplete one that only has got the values of a row (or a columnn) is the following one [1, 9]:

Step 1. Let $X = \{x_1, \dots, x_n\}$ be a discrete set of alternatives. The expert must provide a row (or a column) of the preference relation

Step 2. To utilize the known elements in P to determine all the unknown elements, and thus get a consistent preference relation, P', using the following expressions obtained from definition 2:

1. $p_{ij} + p_{jk} + p_{ki} = \frac{3}{2}$
2. $p_{i(i+1)} + p_{(i+1)(i+2)} + \cdots + p_{(j-1)j} + p_{ji} = \frac{j-i+1}{2} \forall i < j$

Step 3. End.

Example. Let's Suppose that we have a set of four alternatives $\{x_1, x_2, x_3, x_4\}$. If we know that $\{p_{12} = 0.55, p_{13} = 0.7, p_{14} = 0.95\}$, we shall have the following preference relation:

$$P = \begin{pmatrix} 0.5 & 0.55 & 0.7 & 0.95 \\ & 0.5 & & \\ & & 0.5 & \\ & & & 0.5 \end{pmatrix}.$$

If we use the previous algorithm we obtain:
$p_{21} = \frac{3}{2} - p_{12} - p_{22} = \frac{3}{2} - 0.55 - 0.5 = 0.45,$
$p_{31} = \frac{3}{2} - p_{13} - p_{33} = \frac{3}{2} - 0.7 - 0.5 = 0.3,$
...
therefore:

$$P' = \begin{pmatrix} 0.5 & 0.55 & 0.7 & 0.95 \\ 0.45 & 0.5 & 0.65 & 0.9 \\ 0.3 & 0.35 & 0.5 & 0.75 \\ 0.05 & 0.1 & 0.25 & 0.5 \end{pmatrix}.r$$

3 A Knowledge Based Recommender System Based on Numerical Consistent Preference Relations

Here, we will present our model for a Knowledge Based Recommender System that employs incomplete preference relations in order to build the user profile.

The main advantage of this kind of Recommender Systems is that they are suitable for casual exploration, i.e., they do not require to have any historical information (for instance, the items that the user has liked in the past) to make suitable recommendations. However, in this type of Recommender System the processes for building the user profile are usually more complex than in other kind of recommender systems such as the Collaborative or the Content-based ones. Besides, this user profile plays a key role in order to obtain an accurate recommendation. The more accurate it is gathered, the better recommentions are obtained.

Taking into account that the Knowledge Based Recommender System will deal with user's preferences and descriptions of the items, in our proposal both of them are modelled by means of numerical values. In future works we will study other types of preference modelling that can be more appropriate such as intervals, linguistic assessments and so on.

The Knowledge Based Recommender System that we propose has three phases (see Fig. 1):

(a) *Gathering user preference information.* The target of this phase is to obtain the preference information from the user. For this purpose, we need a small number of preferred items (4 or 5) that represents user's necessities and an incomplete preference relation provided over them.
(b) *Building the user profile.* The preference relation and the items' descriptions are used to build the user profile. First of all, the system fills up the incomplete preference relation and obtains partial profiles. These profiles express the user's preferences related to a specific item. Afterwards, they are aggregated to obtain the user profile.
(c) *Recommendation.* Eventually, the system recommends the items that are the closest to the user profile, i.e., the items that are the best to fulfil the user's real expectations.

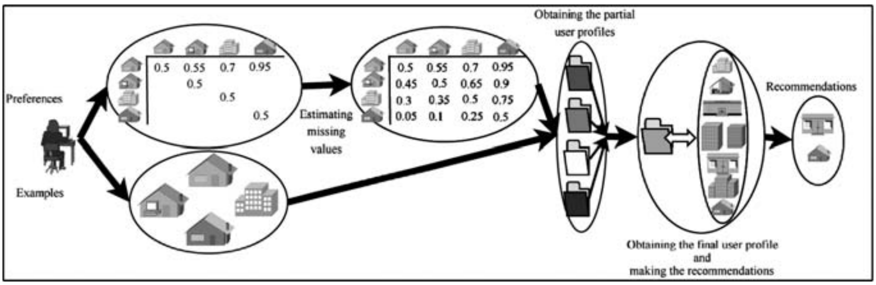

Fig. 1. Recommendation Model

3.1 Gathering User Preference Information

Initially, the user, u, chooses four or five items as examples of his/her preferences or necessities. Moreover, this process would be as difficult as (or more) finding directly the item(s) he/she likes. In order to make easier this choice, the system suggests a subset of representative items in which the user must select the examples of his/her necessities. This subset should be big enough to have items that represent any kind of user's necessities, these items ought to be "well-known" for almost everybody, but not too big because users could find this task too teadious. If he/she had to choose these examples from all the item database, he/she would waste much time exploring useless alternatives. We must remark that there is not any correlation between "well-known" and "preferred", i.e., in this set of well-known items we will find preferred items as well as items which the users do not like.

Let $X = \{x_1, x_2, \ldots, x_m\}$ be the set of items to be recommended and each one is described by a vector of features $x_i = \left\{c_i^1, \ldots, c_i^t\right\}$, the system offers a subset $X_r = \{x_1^r, x_2^r, \ldots, x_{m'}^r\}$ ($m' \leq m$) that contains the most representative or well-known items of X ($X_r \subseteq X$). The aim of this step is to obtain the user preference information. To do so, it must accomplish these two steps:

1. *Acquiring an incomplete preference relation.* The user provides it over the set of examples that represents his/her necessities.
2. *Filling the preference relation.* To exploit the above preference relation and define the user profile it is required that the system fills it up in order to build a complete and consistent preference relation.

Now, we shall present these steps in depth.

Acquiring an Incomplete Preference Relation

Once the user, u, selects from the subset of X_r four or five items, $X_u = \{x_1^u, \ldots, x_n^u\}$, as examples of his/her preferences, he/she has to choose one of them as the closest example to his/her necessities. Then, the user compares this example with the other ones assessing his/her preferences in a numerical value belonging to the interval $[0, 1]$.

Although, the user is only required to give a row of the preference relation $(p_{11}, \ldots, p_{1n})$, the system needs a complete preference relation to generate better recommendations. Therefore, the system will complete a consistent one by using the algorithm presented in Sect. 2.4. This way of computing the user preferences provides us two advantages:

(a) The user only provides the minimum and necessary information (a row or a column of a preference relation).
(b) The preference relation has not got inconsistent values because the algorithm will build a consistent preference relation from the incomplete preference relation.

Filling Up the Preference Relation

After the user has provided one row (or column) of the preference relation, the system can fill up the relation applying the properties presented in [1]. The result is:

$$P' = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p^*_{21} & p^*_{22} & \cdots & p^*_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p^*_{n1} & p^*_{n2} & \cdots & p^*_{nn} \end{pmatrix},$$

where p_{1j} is a value that the user has provided about the preference of example x^u_1 over the example x^u_j, and p^*_{ij} is an estimated value for the preference of the example x^u_i over x^u_j. By definition, p_{ii} has the value 0.5 (that means indifference).

3.2 Building the User Profile

The next phase of this model is to build the user profile. To accomplish this task the system will build a set of partial profiles, one for each item. Then, the partial user profiles will be combined to obtain the final user profile that will be used to compute the recommendations. This phase consists of two steps (see Fig. 2):

1. *Building partial user profiles.* The system will compute the partial user profiles from user's preference.
2. *Computing the user profile.* This user profile represents the knowledge about the user's necessities and it will be utilized to obtain the most suitable items for the user.

Now, we shall explain these steps in further detail.

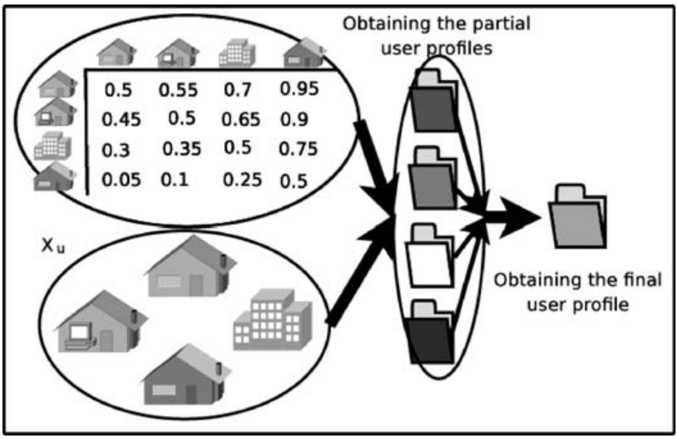

Fig. 2. Building the user profile

Building Partial User Profiles

Before building the user profile, the system will obtain partial profiles for each item that was chosen as example of the user's necessities. This partial profile will represent the user's preference regarding each item. For a given item, x_j^u, the system will build a partial profile, pp_j, related to this item aggregating the vectors of features of the other items different from x_j^u. That way, for the item x_j^u, the system will combine the description of the items $\{x_i^u, \forall i \neq j\}$. Our aim is to build a partial user profile that take into account that some items are closer to the user needs or tastes than others. To measure the importance of each item the system will use the filled preference relation, so that, for the partial user profile for the item x_j^u, the importance of the item $\{x_i^u, i \neq j\}$ is p_{ji}. To aggregate the vector of features of each item (its description) the system will use the IOWA operator (Induced OWA operator) proposed in [21].

The IOWA operator is used to aggregate tuples of the form (v_i, a_i). Within these pairs, v_i is called the order inducing value and a_i is called the argument value. The following procedure for performing the IOWA aggregation was suggested:

$$F_W\left(\langle v_1, a_1\rangle, \ldots, \langle v_l, a_l\rangle\right) = W^T B_v,$$

where $B_v = (b_1, \ldots, b_l)$ is the result of ordering the vector $A = (a_1, \ldots, a_l)$ according to the value of the order inducing variables, v_i, and W^T is the column vector of weights which satisfies:

$$W = (w_1, \ldots, w_l)$$
$$w_i \in [0,1] \quad \forall i \sum_{i=1}^{l} w_i = 1.$$

Our goal in this step is to obtain partial profiles $\left\{pp_j = \left(c_{pp_j}^1, \ldots, c_{pp_j}^t\right)\right\}$, one for each item x_j^u, aggregating the vectors $\left\{(c_i^1, \ldots, c_i^t), \forall i \neq j\right\}$ that describe the item $\{x_i^u, \forall i \neq j\}$. Each element $c_{pp_j}^k$ is obtained by aggregation of the $n-1$ elements $\left\{c_i^k, \forall i \neq j\right\}$. In this process, we need to choose order inducing variables, such as the IOWA operator suggest. For this purpose, we will take the column j of the preference relation $(p_{1j}, p_{2j}, \ldots, p_{nj})$. So, for every attribute we apply the following function:

$$c_{pp_j}^k = F_W\left(\left\langle p_{1j}, c_1^k\right\rangle, \ldots, \left\langle p_{nj}, c_n^k\right\rangle\right) = W^T B_v.$$

Then, the vector $B_v = (b_1, \ldots, b_{n-1})$ is given by an ordering, from the greatest to the smallest value, of the elements of the set $\left\{c_i^k, \forall i \neq j\right\}$ according to such order inducing variables, $(p_{1j}, \ldots, p_{nj})$ where p_{ij} represents the preferences of the example x_i^u over the example x_j^u.

In the literature there are different methods to compute the weighting vector $W = (w_1, \ldots, w_{n-1})$. For instance, We could associate it with a linguistic quantifier [21]. The selection of the quantifier will depend on the type of problem, items, etc.

Computing the Final User Profile

Now, we have a set of partial user profiles, $\{pp_1, \ldots, pp_n\}$, the system will aggregate them in order to obtain an unique and final user profile that state the user's preferences and tastes (see Fig. 3). This aggregation process is very similar to the previous one and the system will also use the IOWA operator. For every attribute the system will apply the following function:

$$c_{fp}^{k} = F'_W \left(\langle p_1, c_{pp_1}^{k} \rangle, \ldots, \langle p_n, c_{pp_n}^{k} \rangle \right) = W'^T B'_v,$$

where the vector $B'_v = (b'_1, \ldots, b'_n)$ is given by an ordering, from greatest to smallest value, of the elements of the set $\left\{ c_{pp_i}^{k} \right\}$ according to the order inducing variables, $(p_1, \ldots, p_n)$ and the weighting vector $W' = (w'_1, \ldots, w'_n)$.

The inducing variables $(p_1, \ldots, p_n)$ represents the importance of each alternative. The most important alternative, which is the closest to the user's needs, will have the greatest value and the furthest alternative, the smallest value. To obtain these values we need to compute the importance of each partial user profile. The importance of the partial user profile, pp_i, is computed by using the following function:

$$p_i = \frac{1}{n-1} \sum_{j=1|j \neq i}^{n} p_{ji}.$$

This function computes the importance, p_i, as a mean of the preferences provided by the user over the item x_i. These preferences are obtained from the preference relation that was filled up in Sect. 3.1.

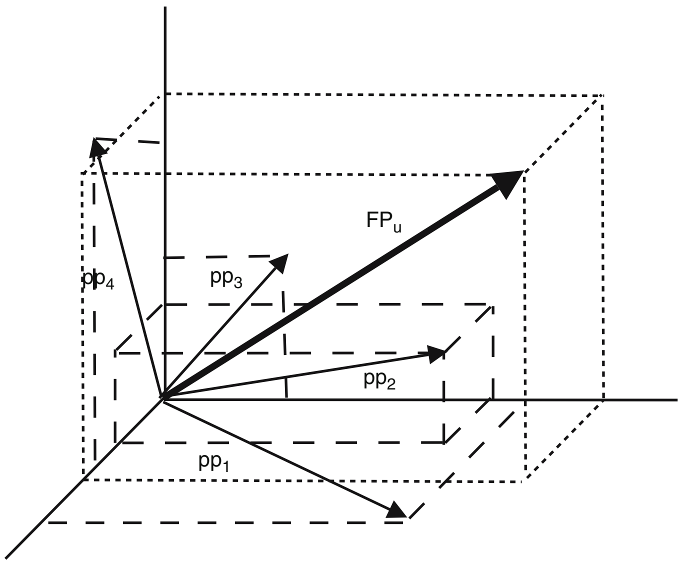

Fig. 3. Final User Profile. Vector representation

Finally, the system obtains the user profile, FP_u, for the user, u, that will be used in the recommendation phase:

$$FP_u = \{c^1_{fp}, \ldots, c^t_{fp}\}.$$

3.3 Recommendation

Once the user profile $FP_u = \left\{c^1_{fp}, \ldots, c^t_{fp}\right\}$ has been computed, the system will recommend the most suitable items to the user's necessities and tastes. The system has a item database $X = \{x_1, x_2, \ldots, x_m\}$ in which the system keeps all the items that can be recommended. Each item $x_i \in X$ is described by a set of features $x_i = \{c^1_i, \ldots, c^t_i\}$. To compute a score that measures the similarity between an item, x_i, and the user profile we shall used a similarity function based on the cosine of two vectors [22]. To acomplish these computations we shall deal with the user profile and the descriptions of items as vectors composed by t features defined in a t-dimensional space. Then, we shall define the similarity function based on the cosine of two vectors (see Fig. 4):

Definition 3. *The similarity between the user profile, FP_u and the item x_i is obtained as*

$$Similarity\,(FP_u, x_i) = cos\left(\overrightarrow{FP_u}, \overrightarrow{x_i}\right) = \frac{\overrightarrow{FP_u} \cdot \overrightarrow{x_i}}{||FP_u|| \cdot ||x_i||}.$$

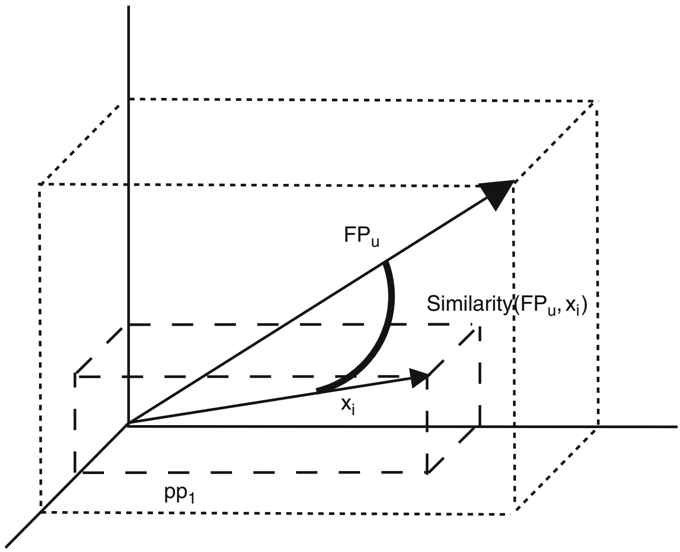

Fig. 4. Similarity between the final user profile and an item

The final recommendation(s) will be those items that are closest to the final user profile, FP_u, i.e., its overall similarity is greater. It is very likely that among the closest items the user could find the items that were chosen as examples of his/her necessities. These items must be left out from the final solution because their aim was to represent something close to what the user really needs, not to fulfil his/her necessities.

4 Example

In this section, we shall apply our model to a specific problem where a user wants to obtain some recommendations. The items that can be recommended are stored in a database $X = \{x_1, x_2, \ldots, x_m\}$. Each item is described by a vector of features, $x_i = \left\{c_i^1, \ldots, c_i^t\right\}$, in which each feature is assessed in the interval $[0, 1]$ (see Table 1).

The system will show the set X_r of the most "well-known" examples of the system, and the user will select the four closest examples of his/her necessities (see Table 2):

The examples chosen by the user are $X_u = \{Product\ 11, Product\ 15, Product\ 23, Product\ 24\}$. Moreover, the user provides his/her preferences about these examples. In our case, he/she provides the preference of the first item over the other ones:

Table 1. Item database

Item ID	Description
Product 1	(0.74, 0.37, 0.26, 0.41, 0.39, 0.86, 0.22, 0.050, 0.62, 0.62)
Product 2	(0.36, 0.52, 0.74, 0.28, 0.42, 0.14, 0.76, 0.12, 0.36, 0.59)
Product 3	(0.55, 0.012, 0.81, 0.88, 0.45, 0.97, 0.13, 0.60, 0.88, 0.49)
Product 4	(0.20, 0.18, 0.61, 0.93, 0.28, 0.49, 0.78, 0.88, 0.49, 0.67)
...	...
Product 11	(1.0, 0.2, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0)
...	...
Product 15	(1.0, 0.3, 1.0, 1.0, 0, 0, 1.0, 0, 1.0, 1.0)
...	...
Product 21	(0.82, 0.30, 0.89, 0.46, 0.38, 0.12, 0.26, 0.27, 0.57, 0.49)
...	...
Product 23	(0.5, 0.1, 0.4, 0.8, 1.0, 1.0, 1.0, 0.4, 0.9, 0.9)
Product 24	(0.1, 0.3, 0.3, 0.9, 1.0, 0, 0.78, 0, 0.85, 0.95)
...	...
Product m	...

Table 2. Given examples

Item	Description
...	...
Product 11	$(1.0, 0.2, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0)$
...	...
Product 15	$(1.0, 0.3, 1.0, 1.0, 0, 0, 1.0, 0, 1.0, 1.0)$
...	...
Product 23	$(0.5, 0.1, 0.4, 0.8, 1.0, 1.0, 1.0, 0.4, 0.9, 0.9)$
Product 24	$(0.1, 0.3, 0.3, 0.9, 1.0, 0, 0.78, 0, 0.85, 0.95)$
...	...
Product m'	...

$$P = \begin{pmatrix} 0.5 & 0.25 & 0.4 & 0.65 \\ & 0.5 & & \\ & & 0.5 & \\ & & & 0.5 \end{pmatrix}.$$

Now, with these preference values the system must find and recommend the most suitable items among all the items of its items database (see Table 1).

First of all, the system fills up the user's preference relation using the algorithm reviewed in Sect. 2.4 and obtains a complete and consistent preference relation:

$$P' = \begin{pmatrix} 0.5 & 0.25 & 0.4 & 0.65 \\ 0.75 & 0.5 & 0.65 & 0.9 \\ 0.6 & 0.35 & 0.5 & 0.75 \\ 0.35 & 0.1 & 0.25 & 0.5 \end{pmatrix}.$$

In the next phase the system will compute the user profile, but before, it must compute the weights that will be used to obtain the partial profiles and the final user profile. To obtain these weights we shall use the following function based on the use of a non-decreasing linguistic quantifier, Q [20]:

$$w_i = Q\left(\frac{i}{m}\right) - Q\left(\frac{i-1}{m}\right), \quad i = 1, \dots, m,$$

where m is the number of values we are going to aggregate, and Q is the linguistic quantifier "*at least half*" [20]:

$$Q(x) = \begin{cases} 0 & si\ x < a \\ \frac{x-a}{b-a} & si\ a \le x \le b \\ 1 & si\ x > b \end{cases} \quad with\ a = 0,\ b = 0.5.$$

The above function obtains the weighting vectors, W and W', that will be utilized to obtain the partial user profiles and the final user profile respectively.

Table 3. Partial profiles

Partial profile	Description
$pp_{Product\,11}$	$(0.83, 0.23, 0.8, 0.93, 0.33, 0.33, 1, 0.13, 0.97, 0.97)$
$pp_{Product\,15}$	$(0.67, 0.13, 0.6, 0.87, 1, 1, 1, 0.6, 0.93, 0.93)$
$pp_{Product\,23}$	$(1, 0.27, 1, 1, 0.33, 0.33, 1, 0.33, 1, 1)$
$pp_{Product\,24}$	$(0.83, 0.23, 0.8, 0.93, 0.33, 0.33, 1, 0.13, 0.97, 0.97)$

The values obtained for the first vector are $W = \{0.67, 0.33, 0\}$ and for the second one $W' = \{0.5, 0.5, 0, 0\}$.

With these weights and using the complete and consistent preference relation the system aggregates the items descriptions to obtain the partial profiles. For example, to obtain the first value of partial profile related to the first example, $pp_{Product\,11}$, the system shall compute:

$$c^1_{pp_{Product\,11}} = F_W\left(\langle 0.75, 1\rangle, \langle 0.6, 0.5\rangle, \langle 0.35, 0.1\rangle\right) = 0.83.$$

We can see the partial profiles in Table 3.

To obtain the final user profile we shall aggregate the partial profiles using the weights W'. For instance, to obtain the first value of the final user profile the system shall compute:

$$c^1_{fp} = F'_W(\langle 0.57, 0.83\rangle, \langle 0.23, 0.67\rangle, \langle 0.43, 1\rangle, \langle 0.77, 0.83\rangle) = 0.83.$$

Where the inducing variables $\{p_1, \ldots, p_4\}$ are calculated, from the preference relation, as follows:

$$p_1 = \frac{1}{3}\sum_{j=1|j\neq 1}^{n} p_{ji} = \frac{1}{3}(0.75 + 0.6 + 0.35) = 0.57,$$

$$p_2 = \frac{1}{3}\sum_{j=1|j\neq 2}^{n} p_{ji} = \frac{1}{3}(0.25 + 0.35 + 0.1) = 0.23,$$

$$p_3 = \frac{1}{3}\sum_{j=1|j\neq 3}^{n} p_{ji} = \frac{1}{3}(0.4 + 0.65 + 0.25) = 0.43,$$

$$p_4 = \frac{1}{3}\sum_{j=1|j\neq 4}^{n} p_{ji} = \frac{1}{3}(0.65 + 0.9 + 0.75) = 0.77.$$

If we compute all the values we shall obtain the following final user profile (see Table 4).

The last step in our model is the recommendation phase. In this phase the system will compute the similarity of the final user profile with the description

Table 4. Final user profile

Final profile
(0.83, 0.23, 0.8, 0.93, 0.33, 0.33, 1., 0.13, 0.97, 0.97)

Table 5. Recommendations

Item	Similarity
Product 4	0.914
Product 21	0.897
Product 3	0.895
...	...

of each item of the item database and it will recommend those items that are the closest to the user's necessities. The system will use the function defined in Sect. 3.3 that is based on a cosine measure. The results of this comparisons can be seen in Table 5.

Therefore, according to these results the closest item to the user necessities is the item *Product* 4, the second one is the *Product* 21, the next one is the *Product* 8 and so on.

5 Conclusions

When people visit an e-shop, they usually can find thousands of items related to their necessities, but only a few of them can fulfil their real expectations and sometimes it is hard to find them. The Recommender Systems assist them in finding these items among all of them. There are different types of Recommender Systems, such as the Content-based and the Collaborative ones. These kind of Recommender Systems make good recommendations as long as they have enough information about the users, their necessities or the items. However, when this information is scarce or not available, they are unable to make recommendations.

In this chapter we have presented a model for Knowledge Based Recommender System that provides a technology to avoid this problem. It gathers the information from the users using a numerical preference relation structure that only requires to be filled with a small number of values and then, using the consistency property the system will complete the preference relation in order to exploit it and to obtain better recommendations but without forcing the users to spend much time in the generation of his/her profile.

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An Intelligent Recommender System for Web Resource Discovery and Selection

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Summary. The Web is now evolving from information sharing to resource provisioning as the emerging Web services and Grid technologies are widely accepted and practiced. Soon the Web will be populated with abundant resources that can be accessed, shared and reused, which will inevitably lead to resource overflow. This chapter introduces a semantic-enabled, knowledge-based intelligent recommender system for Web resource discovery, selection and effective use. The system is based on a novel hybrid approach, which draws on the functionality of Semantic Web Services to represent, expose and discover available resources, and exploits domain knowledge to guide resource selection and use. We propose an integrated system architecture and describe the underpinning semantic- and knowledge-based recommending mechanisms. A number of technologies and tools are developed, and further applied to a real world application – the UK e-Science GEODISE project, to demonstrate the system's applicability and benefits.

1 Introduction

1.1 Background

The Web has made information sharing on a global scale become true. It is currently evolving towards the sharing and coordinated use of diverse resources for collaborative real-world problem solving where resources are referred to as capabilities, applications, storages, computation and knowledge, etc. This trend has led to the emergence of service-oriented computing architecture (SOA[1]) and Grid technologies [1]. Web service technologies have been designed to wrap and expose resources and provide interoperability among diverse applications. Hereafter resource and service are used interchangeably in this paper. The Grid has been conceived to provide an enabling infrastructure

[1] http://www.w3.org/2002/ws

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for “flexible, secure and coordinated resource sharing and problem solving in dynamic, multi-institutional virtual organizations” [2]. The convergence and combination of these technologies has seen the advent of Web Service Resource Framework (WSRF[2]), which regards the Web/Grid as providing an extensible set of resources that virtual organizations can aggregate in a high-level of automation in various ways to solve domain specific problems.

With the wide acceptance of the SOA paradigm in real world applications such as e-Science [3] and the increasing population of Web resources, resource overflow is becoming an acute problem and leading to a number of core challenges for resource discovery and use. Firstly, users are spending more and more time to discover the “right” resources by sifting and filtering large-scale, distributed, heterogeneous resources. In particular, when a function can be performed by a number of resources, users have to decide which resource to be chosen. Given that Web resources are provided by different organizations and most probably in different models and terminologies, making such a decision is not an easy task. Secondly, real world applications are usually knowledge intensive. Problem solving requires dedicated domain knowledge and expertise. As different domains have different problems, each dependent on different aspects of domain-specific knowledge, it is hard, if not impossible, for a user to know every details for all Web resources provided by a third party in order to use them. Thirdly, problem solving is usually a dynamic process, the required resources often changes as the process proceeds. This means resource discovery should be context aware and dynamic.

Current resource discovery, selection and use are handled by a stack of Web service protocols, e.g. WSDL[3], UDDI[4] and SOAP[5]. However, none of these standards defines the meaning of services and their parameters in a way that transcends the tendency of agents to use their own terms and frame of reference. These protocols also do not address the need of domain knowledge to coordinate the sequencing and execution of resources as part of some larger problem solving tasks. Some industry initiatives have been developed to address this issue, such as WSFL[6], XLANG[7] and BPEL4WS[8]; however, such initiatives generally focus on representing service compositions where the flow of the process and the bindings between the services are known a priori. For many real-world problems the knowledge required to select and coordinate the activity of available services is usually specific to the application domain. It is often the case that resource selection cannot be specified in advance of the execution of individual resources of the more global workflow specification.

[2] http://www.globus.org/wsrf
[3] http://www.w3.org/TR/wsdl12/
[4] http://www.uddi.org/
[5] http://www.w3c.org/TR/2001/WD-soap12-part0-20011217/
[6] http://www-3.ibm.com/software/solutions/webservices/pdf/WSFL.pdf
[7] http://www.gotdotnet.com/team/xml_wsspecs/xlang-c/default.htm
[8] http://www-106.ibm.com/developerworks/webservices/library/ws-bpel/

As such it is apparent that pre-defined service sequencing and binding is not sufficient in most real-world applications; domain knowledge needs to come into play.

We believe that an intelligent recommender system is indispensable for the success of the SOA computing paradigm. The system should provide context-based just-in-time recommendations of Web resources for concerned tasks and help make choices among recommended resources from all kinds of sources without the users needing to have sufficient personal experience of all these alternatives.

We argue that both semantic service descriptions and domain-specific knowledge-based decision support are essential ingredients for resource discovery and effective use in Web/Grid based applications. Matchmaking based on semantic service descriptions supports effective service discovery, seamless resource integration and reuse. Knowledge-based decision-making support systems can suggest what should be done next during a service composition process and which service should be chosen once a number of services are discovered. All decisions can be made dynamically by taking into consideration the problem characteristics, previous computation results and expected resources Furthermore, once a service is selected, knowledge support can be further provided for the configuration of that service. As such we contend that Web-based service-oriented applications, both e-commerce and e-Science, ought to exploit semantic service descriptions and domain knowledge in order to solve complex problems through automatic, seamless resource synthesis on the Web/Grid.

1.2 Related Work

Recommender systems have been widely advocated as a way of coping with the problem of information overload. Major recommendation techniques include the content based approach [4], the collaborative filtering approach [5], the hybrid approach [6] and a market-based approach [7]. These approaches help identify desirable information items or textual articles from web sites in one or another way, each with some advantages and disadvantages. As information overflow and resource overflow have a substantial different nature in the way that information and resources are created, published, stored, searched and used, we recognize that these techniques are enlightening and inspiring; but they are not directly applicable to and suitable for recommending Web resources.

The Semantic Web technologies [8] have been used to facilitate Web resource discovery and composition through the Semantic Web Service (SWS) initiatives such as OWL-S[9] and WSMO[10] [9]. SWSs provide more explicit and expressive descriptions for Web resources by means of ontologies, thus

[9] http://www.daml.org/services/owl-s/

[10] http://www.w3.org/Submission/WSMO/

enabling content-based service discovery and composition based on semantic matchmaking [10–13]. While this approach can retrieve multiple semantically compatible resources, it fails to identify which resource is the best for the work at hands. In the case of multiple choices of resources available for an individual task, resource selection can only be done manually.

In recent years, research on using recommender systems for Web resource discovery and use is emerging. In [14], a resource recommendation system is developed based on the collaborative filtering approach. The system allows users to rate resources and provides facilities such as similarity computation, prediction and evolution algorithms for recommending resources. As the collaborative filtering approach the system inherits the "cold start" problem. In [15], a conversational case-based recommender system is developed based on case-based reasoning. The system provides semantic descriptions for both problems and their solutions. Cases are problem and solution pairs. Problem descriptions are used for similarity computation. In essence, the system is underpinned by semantic metadata descriptions – an extension of the SWS approach with case based reasoning techniques.

Our approach is similar to the above practices in that it is also built upon the semantic metadata descriptions, but different in that it makes heavy use of domain knowledge for resource selection and configuration. We agree that semantic matchmaking is able to return coarse-grained resources that are semantically compatible with query criteria. However, as the selection and configuration of a resource for a specific task are usually dependent on rich nexuses of domain knowledge, semantic metadata is not enough because they do not model and incorporate sufficient fine-grained domain knowledge. Our approach uses AI techniques, i.e. rule based knowledge modeling and reasoning, for recommending Web resources.

The paper is organized as follows: Section 2 introduces a system architecture for the proposed recommender system and briefly describes a use case for such an approach. Section 3 describes the resource discovery sub-system; and Sect. 4 discusses the resource selection sub-system. We describe the application of the approach in the context of the GEODISE[11] project in Sect. 5. We conclude the paper in Sect. 6 by discussing some initial findings and possible future work.

2 The System Architecture

We propose a hybrid approach that combines semantic matchmaking and knowledge based decision support for resource discovery, selection and composition. The system architecture, as shown in Fig. 1, is functionally composed of three subsystems: Resource Discovery System, Resource Selection System

[11] Grid enabled optimization and design search in engineering (Geodise) project: http://www.geodise.org/

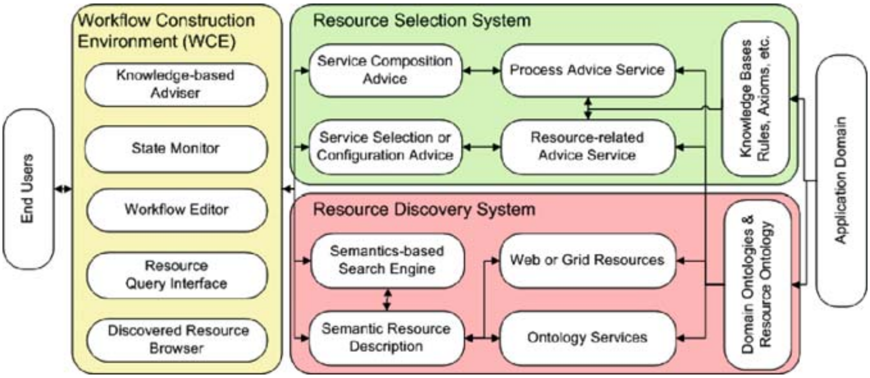

Fig. 1. The system architecture

and an application dependent resource consumption environment such as a Workflow Construction Environment. The Resource Discovery System aims to discover available resources on the Web/Grid for collaborative problem solving such as workflow specification. It uses semantically-enriched resource descriptions, to assist in the process of resource discovery via semantic matchmaking. Semantic matchmaking allows for automated search, enhances the interoperability of resources in heterogeneous environments and enables accurate resource discovery. This ability to exploit semantic resource descriptions facilitates the workflow specification process with respect to existing descriptions of Web/Grid resources. Detailed descriptions for resource discovery will be presented in Sect. 3.

However, discovering resources is only one aspect of a problem solving process. As in real life, for a given task multiple resources might be returned from semantic discovery processes and each of them can accomplish the task. To decide on which resource is selected for a specific task, deep domain knowledge is required in order to choose the most appropriate resource. The Resource Selection System intends to provide well-informed advice and guidance with respect to the selection, sequencing and correct configuration of resources in the process of problem solving. It is built upon the approach of traditional knowledge based system, but adopts the latest Web-oriented knowledge management technologies such as ontological knowledge models and service-oriented knowledge provision. Detailed descriptions for resource selection will be given in Sect. 4.

Whilst resources on the Web/Grid could be consumed by any domain related applications, the most common way of using Web/Grid resources for problem solving is to compose resources into a workflow. Upon execution a workflow will produce a result for the corresponding problem. In this use case, the WCE consists of five graphical tools to assist workflow specification. Each of them presents relevant structures and information via a control panel. The Resource Query Interface is an ontology-driven front-end graphical user interface. It is used to specify query criteria for resource discovery. Discovered resources from a search process are displayed in the Discovered Resource Browser. The Workflow Editor is a resource composition workspace with a number of editing functions such as Add, Delete, Connect, etc. Users can choose resources from the Discovered Resource Browser and edit it in the Workflow Editor based on the advice given for a particular workflow composition.

The novelty of the architecture lies in the exploitation of domain-specific knowledge for resource selection and use. These knowledge bases consist of concepts, axioms and rules captured through knowledge acquisition, which formally conceptualize the target domain and resource knowledge. Advice services are actually knowledge-based systems that are implemented as Web services [16] such as the Service Composition and Selection Advice Services. They provide advice based on service requests. Users can obtain advice in two ways. First, a user may request advice according to his/her epistemic needs and requirements during the workflow construction process. Secondly, a software agent can be used to monitor the service composition process as it unfolds, and provide advice and/or recommendations along the way. To be context aware, both approaches will collect process states and resource parameters at the particular time point when advice is requested. A component called State Monitor is used to monitor the progress of resource composition process and capture all relevant states. These states are then fed into the reasoning engine to retrieve context-sensitive advice as with traditional knowledge-based systems. Advice can be provided at multiple levels of granularity, for example the process level – what to do next, and the resource level – which resource should be used, dependent on the availability of knowledge in the underlying knowledge bases.

3 The Resource Discovery System

Web/Grid resources refer to not only information but also assets (data storage and specialized experimental facilities), capabilities (computational systems) and knowledge (recommendation and advice). Such resources are geographically distributed in heterogeneous platforms, environments and often in different formats and interfaces. To enable their sharing and interoperability, they are currently modeled as Web/Grid services, which are described in WSDL, published through UDDI and invoked by SOAP. However, all these technologies provide limited support for resource metadata and semantics. For example, WSDL uses XML[12] to describe services as a set of endpoints operating on messages. The implementation of WSDL during service design is usually more concerned with the signature of a service, i.e. the identifiers of the service and its parameters. Based on this description, it is usually

[12] http://www.w3.org/XML/

impossible for software agents to figure out the precise meaning of a service's identifiers and functionalities provided by the service. The lack of semantics in the abstract functionality description of the service, i.e. the capabilities of the service, makes it difficult for machines to discover and use the service at the right time.

The Resource Discovery System aims to leverage the emerging ontology and metadata infrastructure found in the semantic web community to work with heterogeneous resources across multiple domains so as to facilitate accurate and automatic resource discovery and enhance interoperability of resource use. It consists of a number of components, which interact with each other and operate in coordination. Details are described below.

3.1 Managing Resources' Semantic Descriptions

Modeling Metadata and Context with Ontologies

Ontologies are explicit shared specifications of conceptualizations in a problem domain. They contain commonly agreed knowledge structures, i.e. domain concepts and the relations among them, and also shared terminology for describing these knowledge structures. The Domain Ontologies and Resource Ontology component contains domain ontologies and resource ontology, which capture and formally model metadata of Web/Grid resources and the concepts related to the domain in which these resources operate. Domain ontologies provide the context in which metadata can be interpreted by both humans and machines whereas the resource ontology provides a conceptual model for describing resources by which semantic resource descriptions can be generated.

The resource ontology is based on OWL-S upper ontology that partitions a semantic description of a Web/Grid service into three components: the Service Profile, Process Model and Grounding. The Service Profile describes what a service does by specifying its inputs, outputs, preconditions, effects and other properties. The Process Model describes how a service works; each service is either an Atomic Process that is executed directly or a Composite Process that is a combination of other sub-processes. The Grounding contains the details of how an agent can access a service by specifying the details of the communication protocol, i.e. the parameters to be used in the protocol and the serialization techniques to be employed for the communication. OWL-S allows the definition of classes of related services and can establish links to other concepts that describe specific service types and their properties. This makes service discovery much easier in terms of the built-in links, thus facilitating resource reuse.

Ontologies are developed through ontological engineering and exposed through the Ontology Services component. The Ontology Services provide complete access to any OWL ontologies available over the Internet. Users can perform common ontological operations, such as subsumption checking, class and/or property retrieval and navigation of concept hierarchies through a set of ontology service APIs in conjunction with an ontology reasoner such as the FaCT reasoner [17].

Generating Resources' Semantic Descriptions

Ontology-based metadata models are conceptual templates. To generate semantic descriptions for a resource, it is necessary to bind metadata models with the concrete information of the concerned resources. This incurs two tasks – metadata collection and metadata instantiation with metadata models (ontologies). Two approaches are identified for capturing resources' metadata: the human-centered approach and information extraction based approach. In the first approach, a person (either a resource provider or a domain expert or a knowledge engineer) analyzes resource domain, obtains all metadata values and prepares them in accordance with the metadata model. This approach requires that the person should have domain background knowledge. The latter approach is to extract metadata values using information extraction techniques. It tries to acquire metadata automatically by parsing and recognizing designated entities and their values. The problems with this approach are that different resource providers may use different terminology for their resources. An information extraction algorithm that works for one domain may not work for others. Furthermore, some resources, in particular those legacy resources, may not have enough information.

Semantic descriptions can be generated through metadata instantiation and semantic enrichment. Metadata instantiation is to assign values to metadata, also known as binding semantic enrichment is to establish links between the services (concepts), metadata (properties) and metadata assignments (fillers). By following ontological links metadata and their assignment can be explicitly defined in terms of ontological concepts, properties, values and relations. These links allow both humans and machines to track down the exact meaning of metadata and their assignments based on the ontology – context model. This guarantees metadata can be interpreted unambiguously.

Semantic Description Representation

Semantic description representation needs to fulfill several requirements. First it should have appropriate expressive capabilities, thus being able to model and convey all explicit meaning of metadata without any ambiguity and fidelity loss. Second it should be easily distributed and accessed on the Web/Grid so that as many Web/Grid users as possible can get hold on it. Third semantic description representation should allow for high degree interoperability and machine understandability in order to facilitate semantic description processing and semantic consumption for end users' applications.

Many languages have been designed to express the ontology and semantic information. Among them, the most recent is the Web Ontology Language

```xml
<?xml version="1.0" encoding="ISO-8859-1" ?>
- <rdf:RDF xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#" xmlns:rdfs="http://www.w3.org/2000/01/rdf-
   schema#" xmlns:owl="http://www.w3.org/2002/07/owl#"
   xmlns="http://www.ecs.soton.ac.uk/~ft/ontology/function2.owl#">
 - <owl:Ontology rdf:about="">
     <rdfs:comment>Ontology designed for semantically describing grid-related resources such as functions,
      workflows, etc.</rdfs:comment>
   </owl:Ontology>
 - <owl:Class rdf:ID="Function">
     <rdfs:comment>This is the function concept in the context of GEODISE. in particular, it refers to the MAtLab
      functions.</rdfs:comment>
   </owl:Class>
 - <owl:Class rdf:ID="VariableType">
     <rdfs:comment>This class can only have two direct sub-classes representing complex type and primary type.
      (this assumtion is used in the semantic advisor java code.)</rdfs:comment>
   </owl:Class>
 - <owl:Class rdf:ID="OptionsMatlabFunction">
```

Fig. 2. An example OWL representation of the function ontology

(OWL[13]), which has evolved from RDF[14] to provide more expressive power. OWL is based on the knowledge representation formalism of Description Logic (DL), which gives OWL a solid foundation on which semantics can be explicitly expressed and reasoned.

Figure 2 shows a segment of the OWL representation of the GEODISE Function ontology.

Which language to use for semantic description representation is actually a question of choice, depending on application characteristics, users' preferences and the way semantic description is used. For applications that involve large amount of ontological concepts, thus requiring consistency check and classification, OWL might be a better choice. OWL is also appropriate for applications that need description-logic based reasoning.

Semantic Description Storage

So far we have not defined what exactly a resource's semantic description is in terms of formal metadata models and representation. In ontology terminology, the semantic description of a resource is the instance of the ontological concept of the resource. Alternatively we can say a resource's semantic description is the semantic description of the resource using metadata and context models. Concretely a resource's semantic description is a number of instantiated schema interconnected via ontological links with each schema filled of concrete values.

The semantic resource description component is responsible for storing resources' semantic descriptions. There are different mechanisms for the storage of resources' semantic descriptions. The key issue is scalability with regards to the size of the repository, the response time, etc. Currently there are two mainstream technologies for semantic description storage, retrieval and reasoning, which are mainly categorized in terms of semantic description representation. The first one is based on the RDF formalism. Systems using this technology include Sesame [18] and 3Store [19]. The second one

[13] www.w3.org/2004/OWL
[14] www.w3.org/RDF/

focuses on DL-based descriptions represented by OWL. Such systems include RACER [20] and Instance Store (IS) [17]. The common approach of these systems is to use database technologies for semantic instance indexing, search optimization, and semantic inference mechanisms for the classification of ontological concepts. By replacing reasoning over semantic description instances with reasoning against concepts and optimized database search, the retrieval and query performance can be significantly improved.

While further extensions and formal experiments and evaluations are needed for semantic repository technologies, nevertheless these systems, in particular, the 3Store and Instance Store, provide a starting point for semantic description management. Once again the development and/or the selection of semantic description repository technology would depend on the nature of the application and the use of semantic metadata.

3.2 Resource Discovery Through Semantic Matchmaking

Once the Semantic Resource Description repositories are populated with semantic descriptions, resource consumers can make use of the semantic information for many purposes. The semantics-based search engine is responsible for providing consumption mechanisms and tools to facilitate the use of resources' semantic information. Generally speaking, semantic descriptions can be used in the following ways: Firstly consumers can browse and navigate resources (through the Discovered Resource Browser) in the repository in terms of semantic descriptions. Resources and metadata are classified into different categories when they are formally modeled using ontologies. By referencing the associated ontology users can obtain all resources under a specific resource category (a concept and/or a property) and their semantic metadata. These resources can be presented in a hierarchical structure that shows their inter-relations and also facilitates selection.

While it is desirable to construct a resource hierarchy for users to navigate and select the required resources, in reality it is not practically viable given that distributed resources on the Web/Grid are dynamically evolving and the size of the set of such resources could grow to thousands or millions. Therefore, the main usage of semantic descriptions is to support semantics-based resource discovery.

Semantics-based search is different from traditional keyword-based search mechanism in that it is not based on textual parsing and statistical analysis, instead on meaning of resources' signatures and metadata. Given a semantic resource repository with all semantic resource descriptions as $\boldsymbol{A}$ (also known as assertions in description logic (DL)) and all ontological service concepts as $\boldsymbol{T}$ (also known as Terminology in DL), for a retrieval query concept $\boldsymbol{Q}$, the semantic matchmaking algorithm to retrieve the instances of $\boldsymbol{Q}$ can be described as follows:

(a) Use a DL terminology reasoner to compute the location of $\boldsymbol{Q}$ in the class hierarchy of service ontologies;

(b) Compute the set of atomic concepts, denoted as $\boldsymbol{SAT}$, in $\boldsymbol{T}$ subsumed by $\boldsymbol{Q}$; these are the equivalents and descendants of $\boldsymbol{Q}$ in $\boldsymbol{T}$;
(c) Find the set of individuals, denoted as $\boldsymbol{I1}$, in $\boldsymbol{A}$ that realise some concepts in $\boldsymbol{SAT}$;
(d) Use the reasoner to check whether $\boldsymbol{Q}$ is equivalent to any atomic concept in $\boldsymbol{T}$; if that is the case then $\boldsymbol{I1}$ will be the query results;
(e) Otherwise, use the reasoner to compute the set of most specific atomic concepts, denoted as $\boldsymbol{MSAT}$, in $\boldsymbol{T}$ subsuming $\boldsymbol{Q}$;
(f) Compute the set of individuals, denoted as $\boldsymbol{I2}$, in $\boldsymbol{A}$ that realise every concept in $\boldsymbol{MSAT}$;
(g) Compute the set of individuals, denoted as $\boldsymbol{I3}$, in which each individual belongs to $\boldsymbol{I2}$, and is an instance of concept $\boldsymbol{C}$, and $\boldsymbol{C}$ is subsumed by $\boldsymbol{Q}$;
(h) Return the union of $\boldsymbol{I2}$ and $\boldsymbol{I3}$ as the query results.

To perform semantics based resource discovery, users can specify the required resource's category that is equivalent to the concept of the service ontology and its properties that are actually the attribute-value pairs of the corresponding instantiated concept (using the Resource Query Interface – an ontology-driven graphical user interface). The underlying semantics enabled reasoners such as DL-based reasoner can then match the framed query specification with all instances of resources' semantic descriptions. The resources that have these semantic metadata will be discovered (displayed in the Discovered Resource Browser).

The use of semantic matchmaking has several benefits: Firstly, it increases the accuracy of resource discovery. Secondly it enhances interoperability as both resource providers and consumers can communicate and understand each other using the common terms. Finally ontology based modeling enables software agents and machines to understand and interpret semantic descriptions, thus facilitating automated and automatic processing.

Depending on the richness of knowledge captured through metadata modeling, semantic descriptions can be exploited to different extent for application specific purposes. An example is to use semantic descriptions for resource composition and aggregation. Resources can only be joined together to form a valid workflow when their interface semantics matches each other, i.e. one resource's inputs/outputs are semantically compatible with another resource's outputs/inputs. Based on the semantic matching of resource interface the Resource Discovery System can suggest all resources that fit into the workflow at a specific point during a workflow construction process. The recommendation can also be given at resource level for resource configuration such as what are the types and default values of a variable, what and where the alternative similar functions are and so on.

The extent to which semantic descriptions can be used for Web/Grid applications is dependant on how many semantic descriptions are available on the Web/Grid and how much knowledge the semantic descriptions hold. The more knowledge semantic descriptions hold, there will be more semantic description usage. The more semantic descriptions there are available on the Web/Grid, the closer it is for the Web/Grid to move to the so-called Semantic Web/Grid. To facilitate Web/Grid resource consumers to access and retrieve resources in terms of semantic description, APIs and tools are needed.

4 The Resource Selection System

Real world applications often involve discovering, selecting and aggregating distributed resources appropriately in a Problem Solving Environment (PSE). An example is to construct a workflow either manually or automatically (according to pre-configured criteria) to realize a particular experiment or series of business activities. In service-oriented computing paradigm, this process amounts to discovering services on the Web/Grid and composing those services into a workflow. Some domains such as a supermarket demand-supply chain have a fixed flow of process and stationery bindings between services. However, for most applications a workflow is both domain-specific and problem-dependent. The appropriate selection of services at each point in the workflow often depends on the results of executing the preceding steps. Moreover, the selection of a service from a set of competing services with similar capabilities is usually determined by the exact nature of the problem as well as the performances of the services available. As a result, it is not practical to specify, a priori, the precise sequence of steps for a problem goal. The successful selection, configuration and orchestration of component services into a valid workflow specification are heavily dependent on bodies of domain knowledge applied on the current runtime state of the system.

Semantics based matchmaking assesses the potential fit of each service to a particular role in a workflow specification based on a resource's semantic descriptions. It enables a suitable reasoning engine to automatically retrieve services that match the required semantic descriptions. External agents can use the outcome of semantic discovery to select a service commensurate with their information processing goals. Often, however, such systems are limited with respect to the appropriate selection of services suited for a specific task or with respect to the appropriate configuration of service parameters. For example, in the domain of engineering design search and optimization there are over a hundred different optimization methods, each of which is geared to solving a specific type of engineering problem. Even with a single method, different configurations of control parameters may produce very different results. Knowledge about the correct method to choose in a particular situation as well as the appropriate configuration of method parameters is an important feature of expert-level performance and a vital ingredient of problem-solving success. Any system concerned with the appropriate selection of optimization methods, therefore requires access to an exquisitely detailed representation of the knowledge contingencies relating problem characteristics and design goals with the appropriate selection and configuration of available methods.

To facilitate service selection and configuration, we have proposed a knowledge-based Resource Selection System for resource selection. This approach builds on the classical model of knowledge-based decision support systems that make extensive use of domain knowledge. Therefore, it relies heavily on the techniques of knowledge engineering [21]. The development of knowledge-based systems usually involves (1) the identification of knowledge-intensive task areas, and the gaining of a detailed insight into the ways in which knowledge is used to yield favorable decision outcomes, (2) the elicitation or indirect acquisition of domain knowledge using knowledge acquisition (KA) techniques, (3) The modeling of human-level knowledge in formal, symbolic structures and the representation of that knowledge using a range of representational formalisms, (4) The use and reuse of knowledge in the knowledge-based system to meet the user requirements, and finally (5) The update and maintenance of both the formalized knowledge and knowledge-based systems.

In order to deploy and re-use knowledge-based resource selection systems for multiple applications in distributed environments, the system has been developed with three important innovations. Firstly, ontologies are used as knowledge models for capturing and representing knowledge. Second, ontologies are exploited to conceptualize knowledge systems with commonly accepted vocabulary, thus facilitating knowledge sharing and re-use. Third, knowledge based systems themselves are exposed as services within a service-oriented framework. The system is described in details below.

4.1 Resource Selection Framework

Traditionally, knowledge intensive systems are constructed anew for each knowledge project. There is often little reuse of existing knowledge structures and problem-solving elements. The reasons for this are legion, including the diversity of domain knowledge, the close coupling of domain knowledge with reasoning processes and the different terminologies and modeling views adopted by different users for a single domain. It is obvious that the exploitation of knowledge technologies on the Web/Grid requires that these obstacles be successfully surmounted, an insight that has led to a variety of new tools, techniques and research agendas [22–24].

Based on the above consideration we have developed a generic framework for knowledge-based resource selection that is intended to operate on the Web/Grid (see Fig. 3) [16]. The system framework has three distinguishing features. The first is that it separates domain knowledge and reasoning functions into the Application Side and Knowledge Service Side respectively. The Application Side concerns with the acquisition, modeling (knowledge engineer's work) and usage (end users' requirements) of domain knowledge. Knowledge services on the Service Side provide reasoning mechanisms, recommendation representation and communication. This feature enables the effective re-use of domain-specific knowledge across different problem-solving

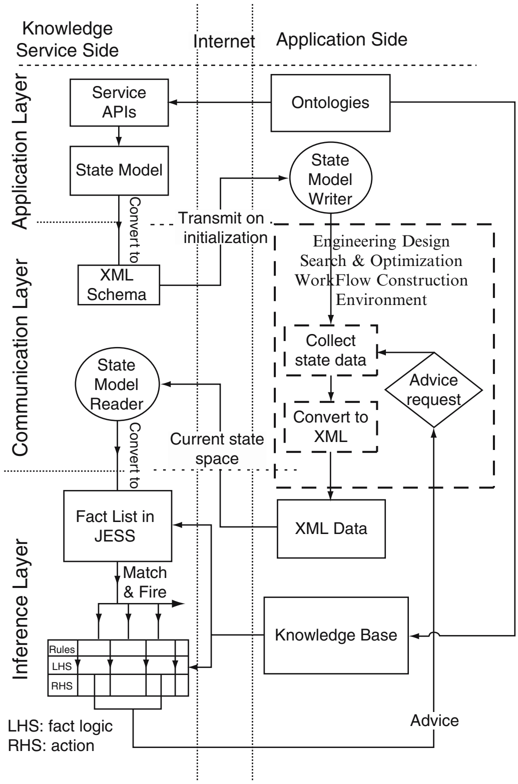

Fig. 3. The resource selection framework

contexts and the application of common reasoning processes to diverse domain-specific problems. Such an approach has many advantages in terms of ease of maintenance and re-use of knowledge components.

The second feature of the framework is its use of multiple layers. These layers enable the effective separation of reasoning, communication and representation components into the Inference, Communication and the Application Layers. The Application Layer uses domain ontologies from the Application Side to define an application-dependent state model. This model is then converted to a frame-like XML schema used as a placeholder for state variables. A state model contains the description of all possible factors that can potentially affect the recommender delivered by the knowledge service. It holds the state space of an application on the Application Side and uses the state information as the input to the reasoning engine in the Inference Layer. The Communication Layer deals with the transmission protocols and serialization of messages between the Application Side and the Knowledge Service Side, i.e. transmission of the XML schema of the state model and the state information requests. The Inference Layer provides a domain-independent inference capability via a reasoning engine. The availability of a domain-specific knowledge base enables the reasoning engine to drive inferential processes that operate on the state information.

The third feature regards its use of OWL for representing machine processable knowledge models on the Web. Not only are the state variables of an application denoted using ontology vocabularies, as discussed above, but also the axioms, facts and rules of the knowledge base are all formalized with respect to the shared repository of common terms. The use of ontology enables different users and machines to share and reuse conceptulisation of domain-specific knowledge. These features make the proposed resource selection system different from traditional standalone knowledge-based systems, and contribute to the interoperability requirement in a boarder computing environment on the Web/Grid.

The generic knowledge-based resource selection system is actually a web service, which operates as follows. The service user in the Application Side supplies domain knowledge, i.e. ontologies and knowledge bases. The knowledge service in the Knowledge Service Side creates the state model and corresponding XML schema. The state XML schema is passed onto the Application Side during knowledge service initialization. The State Model Writer in the Application Side monitors the progress of the application and collects relevant states to fill in the state XML schema. Whenever the application requests recommendation for resource selection, the state information in the state model, i.e. an instantiated XML schema, will be sent to the knowledge service. Once the state information of the application reaches the Knowledge Service Side, it will be parsed and converted to facts. The reasoning engine in the Inference Layer will reason against these facts to provide domain-specific, context-sensitive decision support.

Fig. 3 illustrates the proposed framework in the context of Engineering Design Search and Optimization (EDSO). In this scenario, the Application Side (the user) is concerned with recommendation on EDSO resource selection. Domain knowledge in this example application assumes the form of EDSO ontologies and knowledge-rich contingencies represented in a production rule-like format. The reasoning of the Inference Layer is based on Java Expert System Shell (JESS[15]). Outside of this domain, the aforementioned system rationale is applicable to any area of domain, providing that a suitable characterization of the domain-specific knowledge is available.

4.2 State Panel Ontology

Knowledge engineers have recognized the importance of context in which domain experts act, i.e. an expert's experience only applies in the context of a real problem solving situation. Context can be modeled as a State Panel (SP) representing the environment's working memory. It should contain most key

[15] http://herzberg.ca.sandia.gov/jess/

factors from which experts make their decisions. The SP ontology is designed using Protégé[16] where each concept is modeled as a class with slots that resemble its properties. Furthermore, some constraints can be applied on the slot so that they can only be assigned pre-declared values.

The SP ontology captures three key elements that can be used to represent actionable knowledge:

(a) *Users' skill and expertise level*
This state indicates whether a user is highly skilled and infers the appropriate level of recommendation to be given. Skill levels can be set as either "high", "medium" or "low" where in the first case, recommendation is not necessary. If it is the later case, then rigorous advice will be provided.
(b) *Resources*
This state denotes returned resources discovered through semantic matchmaking. The type "Resource" is a general place holder that can be instantiated into different resource types. Which resource (optimization algorithms in this example) is selected to perform a certain task will depend on the recommendation from the recommender system based on problem characteristics, and resource performance.
(c) *Tasks*
This state denotes the tasks that have already been accomplished. Users can obtain a job's running context based on executed tasks. The context will then be used for the Resource Selection System to decide resources for a specific task. The state is modeled as "depend_on" slot in the workflow task concept. The slot value is the instance of a workflow task.

Fig. 4 shows the visualization of the SP ontology in EDSO domain. As can be seen from the SP ontology, slots always take values from a pre-defined enumeration. For example, in the "workflow_task" concept, the "task_name" is constrained to a single selection from a list of symbols. The "available_resources" slot takes only multiple instances of Resource type, where the resource name is again constrained to an enumeration of declared symbols. This modeling feature guarantees that each symbol will be recognized and matched precisely in a reference engine, which we will describe later.

While the SP models context, i.e. the current situation, as the states at a specific time point, usually in a short-term memory (working memory), a rule base contains the long term memory of accumulated experience in form of production rules [25]. The rules are formulated in the form of the CLIPS[17] language which is then manipulated through a JESS rule engine. The basic elements of rules are concepts and pre-defined knowledge models upon which forward chain reasoning can be performed to infer a solution. In certain circumstances, recommendation can be actions that change the

[16] http://protege.stanford.edu/index.html
[17] http://www.ghg.net/clips/WhatIsCLIPS.html

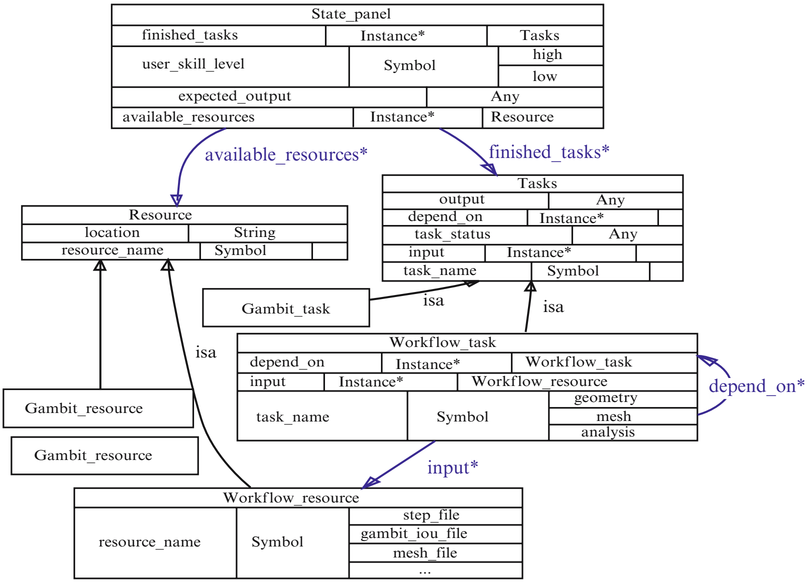

Fig. 4. The state panel ontology

state panel so that forward chaining happens. An inference engine can use a rule base to generate a prioritized list of actions appropriate to the current situation based upon the condition of a state panel.

4.3 Working Memory

We use frame-like schema to model facts, assertions and constraints. Table 1 lists several example templates defined in the context of EDSO using JESS. For example, a resource can be described using name, inputs, output, the task it can perform, the problems it is suitable and its performance. The "working memory", i.e. the state space at a particular time, is actually a set of instantiated templates representing the values of each state variable. When the knowledge-based system starts, a set of facts are asserted. Each of them conforms to its corresponding template. On overall they form a contextual state space or say, the "working memory".

Table 2 lists some fact assertions of a working memory in the context of EDSO domain. For different domains, both the knowledge models and asserted facts may look different but the underlying approaches are same. While knowledge can be used for many purposes, the Resource Selection System focuses on suggesting what resource among a number of discovered resources should be used to perform the task at hands.

Table 1. Knowledge models

(deftemplate workflow_task	(deftemplate resource	(deftemplate state_panel
(slot name)	(slot name)	(multislot finished_tasks)
(multislot input)	(multislot input)	(slot user_skill_level)
(slot output)	(slot output)	(multislot available_resources)
(relevant_commands)	(slot task)	
(slot finished?)	(multislot problems)	(slot expected_output))
(slot constrains)	(multislot performance))	(deftemplate problem
(multislot dependance)		(slot name)
(multislot usedResource))		(slot variableNo)
		(slot type), and etc.

Table 2. Example asserted facts in the working memory

. . . . . .
f-6 (MAIN::resource (name “Genetic_algorithm”) (input “population_num” “variable_num” “tolerance_”) (output “objective_fun”) (task “optimization”) (problem “unstructured_system”) (performance “good”))
f-7 (MAIN::resource (name “Hill_climbing_algorithm”) (input “variable_num” “tolerance_value”) (output “objective_fun”) (task “optimization”) (problem “structured_system”)(performance “good”))
f-8 (MAIN::problem (name “aero_wing”) (variableNo “8”) (type “structured”))
f-9 (MAIN::workflow_task (name “optimization”) (input nil) (output “avs_file”) (relevant_commands nil) (finished? nil) (constrains “run time not very high”)(dependance) (usedResource “Genetic_algorithm”))
f-10 (MAIN::workflow_task (name “analysis”) (input “mesh_file” “fluent_jou_file”) (output nil) (relevant_commands nil) (finished? nil) (constrains nil) (dependance) (usedResource “Hill_climbing_algorithm”))
f-11 (MAIN::state_panel (finished_tasks “geometry”) (user_skill_level “low”) (available_resources “fluent_jou_file”) (expected_output nil))
. . . . . .

4.4 Reasoning Strategies

In order for the Resource Selection System to provide knowledge based recommendation based on application context and available discovered resources, rules are needed. These rules encode domain knowledge about resources, tasks, problems and resource configuration. Table 3 shows a fragment of some rules in CLIPS in the context of EDSO. For example, rule1 claims that if the problem type is unstructured, and the “working memory” does not have the state “population_num”, then eliminate the algorithm.

There are many reasoning mechanisms that have been used in rule-based knowledge systems. Here we simply describe an elimination strategy to demonstrate our recommendation approach. This strategy designs and deploys rules

Table 3. Rules designed for elimination strategy

```
......
(defrule rule1
    (not (state_panel (available_resources $?x "Genetic_algorithm" $?y)))
    ?algorithmID<-(algorithm(input $?a "population_num" $?b))
    ?problemID<-(problem(type $?c "structured" $?d))
    =>
    (retract ?algorithmID)
    (printout t ?algorithmID "Retract this algorithm because it needs population_
num as input, which is not available according to the state panel." crlf))
(defrule rule2
    (not (state_panel (available_resources $?x "Hill_climbing_algorithm" $?y)))
    ?algorithmID<-(workflow_task(input $?a "tolerance_value" $?b))
    =>
    (retract ?algorithmID)
    (printout t ?algorithmID "Retract this algorithm because it needs tolerance_
value as input, which is not available according to the state panel." crlf))
......
(defrule algorithm-answer-1
    (declare (salience -10))
    (algorithm (name ?n))
    =>
    (printout t "In term of this task, the algorithm recommended is:" ?n crlf))
```

in a way that allows algorithms to be eliminated from the candidate list if any of its attributes conflicts to the problem characteristics as described in the state panel. After the elimination process, those remaining are algorithms that satisfy the current system state. The elimination strategy guarantees that any algorithm survived has a full compatibility to the problem characteristics indicated in the state panel.

Table 3 lists part of the rules coded in CLIPS. These rules are loaded into the JESS reasoning engine and their LHS are matched with the state panel and workflow task facts. The logic is quite simple: firstly, all algorithms are asserted into the working memory as possible candidates. Then for each available algorithm that is NOT satisfied with input declared available in the state panel fact, if there is an algorithm fact whose input property includes that resource, then this rule is fired with the action of retracting (eliminating) that algorithm from the working memory ("$?x "Genetic_algorithm" $?y" expresses a pattern that matches to a list of literals that include "Genetic_algorithm", $?x is a JESS expression of multifields). The default salience of rules is 0 which makes sure that these rules are checked first before checking rule "algorithm-answer-1", which has a lower salience of -10. After all the "retracting" rules have been checked (some of them may be executed), the "answer_rule" simply prints out all facts of algorithm that haven't been retracted yet. In other

Table 4. Reasoning result using elimination strategy

Facts	Reasoning results
. . . . . .	
(MAIN::algorithm (name "Genetic_algorithm") (input "population_num" "variable_num") (output "objective_fun") (task "optimization") (problem "unstructured_system") (performance "good"))	Found state panel with user_skill_level low in fact list. So Switching ON Advisor. . .
(MAIN::algorithm (name "Hill_climbing_algorithm") (input "variable_num" "tolerance_value") (output "objective_fun") (task "optimization") (problem "structured_system") (performance "good"))	<Fact-16> Retract this algorithm because it needs population_num as input, which is not available according to the state panel.
	In term of this task, the algorithm recommended is: Hill_climbing_algorithm
(MAIN::state_panel (finished_tasks "geometry") (user_skill_level "low") (available_resources "step_file" "gambit_jou_file") (expected_output nil))	
. . . . . .	

words, these algorithms are recommended according to the current resource availability. Table 4 shows the reasoning result when applying the fact list to the rule set in Table 3.

4.5 A Ranking Algorithm for Resource Selection

Now that we have a set of recommended candidates (Tasks, Algorithms) to carry out in the next step of the workflow, a ranking mechanism can be applied to sort these candidates in the order of their suitability according to some pre-defined criteria. We adopted a method called Semantic Ranking (***SR***) which allows the user to assign different weights for a set of semantic attributes that are pre-defined in the resource ontology. The ***SR*** exploits weighting attributes specified in the ontology and apply them in calculating their Euclidean distance to an Ideal Candidate (***IC***). The ***IC*** can be a virtual candidate which does not exist, or it can be one of the recommended candidates that the engineers think the best for the context. The ***SR*** algorithm then calculates the Euclidean distance between the recommended candidate and the ***IC*** using the following formula:

$$Dis(C,\ iC) = \sqrt{\sum_{i=1}^{n}(C_i - IC_i)^2}$$

Where $\boldsymbol{n}$ is the number of pre-defined weighting attributes. $\boldsymbol{Ci}$ is the $\boldsymbol{i}$th weight value in the weighting attribute of the candidate $\boldsymbol{C}$. In this way, each candidate can be assigned with a distance to the $\boldsymbol{IC}$ and be ranked higher if it is closer to the $\boldsymbol{IC}$.

5 Recommending Resources for Workflow Construction

Engineering design search and optimization (EDSO) is the process whereby engineering modeling and analysis are exploited to yield improved designs. An EDSO process usually comprises many different tasks. Consider the design optimization of a typical aero-engine or wing. It is necessary: (1) to specify the wing geometry in a parametric form which specifies the permitted operations and constraints for the optimization process, (2) to generate a mesh for the problem, (3) decide which analysis code to use and carry out the analysis, (4) decide the optimization schedule, and finally (5) execute the optimization run coupled to the analysis code. Apparently a problem solving process in EDSO is a process of constructing and executing a workflow.

Grid enabled engineering design search and optimization (GEODISE) aims to aid engineers in the EDSO process by providing a range of Internet-accessible resources comprising a suite of design optimization and search tools, computation packages, data, analysis and knowledge resources. A desirable feature of GEODISE is that it allows for users to compose a suite of EDSO algorithms (Web/Grid resources) into a workflow, i.e. to create a design solution to a specific EDSO problem. To provide such a capability we have applied our approach and the corresponding framework in GEODISE. The detailed work is described below.

We have undertaken extensive knowledge and ontological engineering using CommonKADS methodology in the domain of EDSO. A substantial amount of domain knowledge has been acquired and modeled [26]. Fig. 5 displays examples of EDSO tasks, optimization algorithms and the description of an individual algorithm.

We have developed a number of ontologies, including EDSO domain ontology, task ontology, SP ontology and the OWL-S based service ontology. To facilitate the access and use of ontologies, we also developed ontology services to provide a set of Java APIs for common ontological operations. We have developed knowledge bases that characterize EDSO design process and relationships among tasks, resources and problem types, as can be seen in Table 1.

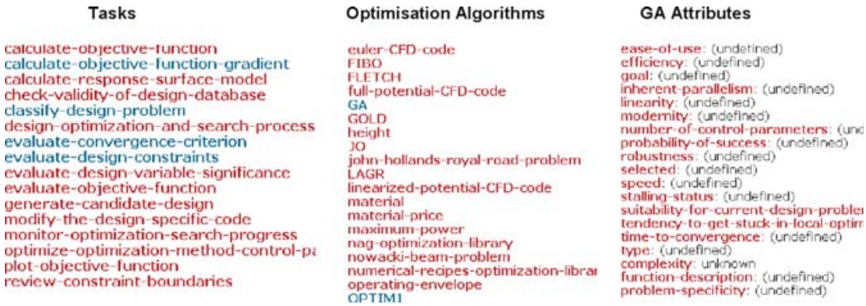

Fig. 5. Example representation of EDSO domain knowledge

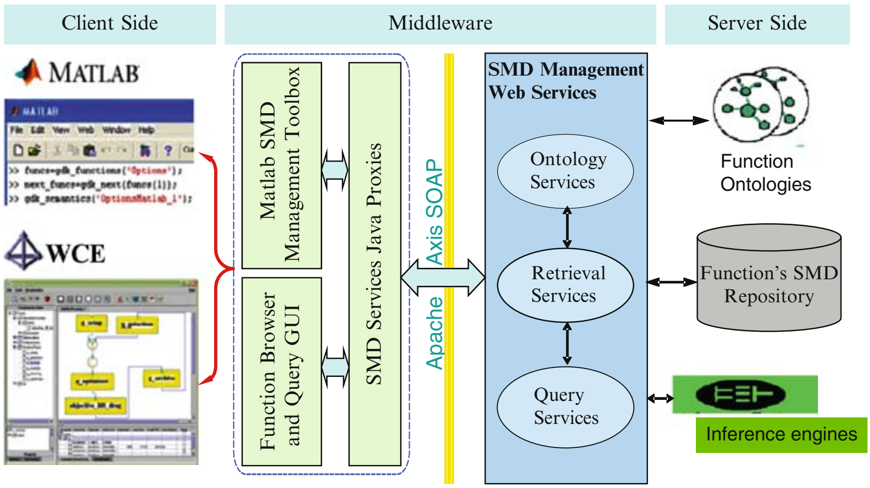

Fig. 6. Resource discovery system deployment

5.1 Semantic-Enabled Resource Discovery

We have implemented the Resource Discovery System and integrated it into GEODISE PSE to facilitate resource discovery. Figure 6 shows the deployment of GEODISE resource discovery system. As can be seen, the Server Side hosts the resource (function) ontologies, functions' semantic metadata (SMD) repository and a DL-based reasoning engine. The Client Side includes the script-based Matlab execution environment and the GEODISE Workflow Construction Environment (WCE). Client-side applications access and manipulate function's semantic descriptions through GEODISE SMD management middleware that comprises client-side tools, APIs and a number of SMD Management Web Services.

SMD Management Web Services are responsible for interacting with underlying SMD repositories, reasoning components and performing actions. For instance, Query Service performs resource discovery based on semantic matchmaking. Applications can use either client-side tools such as Function Browser or Query GUI to explore Grid resources directly or APIs to build such functionality in their systems for more complex functions. In GEODISE, services are implemented using Apache Axis framework (http://ws.apache.org/axis). Client-side tools and APIs interact with knowledge services through KB Service Java Proxies that in turn communicate with knowledge services via SOAP messages. Further implementation details about Resource Discovery System can be found in [27].

5.2 Knowledge-Based Resource Selection

We have integrated both the Resource Discovery System and the Resource Selection System into GEODISE WCE for assisting workflow construction, as shown in Fig. 7. The left hand panel displays EDSO task hierarchy in the Ontology Concept Browser, which is driven by the task ontology. The right hand panel is the Component Editor. Its lower part is used to specify the properties of a resource required for the task; its upper part is used to search for such resources that match the semantic description defined in the lower part. Once a query is framed and fired, a list of reusable resources (components) will be discovered and displayed in the upper part of the right hand panel. The middle panel is the Workflow Editor where resources are composed and edited. The bottom panel is the State Monitor while the right top panel is used to display knowledge-based recommendation on resource selection. The knowledge-based recommender system has not yet been wrapped up as a set of resources. It currently runs as a standalone knowledge-based system, which is directly integrated with the WCE. Despite this difference from the architectural specification detailed in Sect. 2, the decision support provided for resource composition is the same.

5.3 Workflow Construction Using the Recommender System

A workflow specification represents a design solution to a specific EDSO problem. The general procedure for composing resources as a workflow using the WCE is described step by step below. This process is also illustrated in Fig. 7.

(a) Load the EDSO task ontology via ontology services into the left hand panel. All EDSO tasks will be presented in a hierarchy in the Ontology Concept Browser.

 To start a workflow construction process, users need to provide an initial description of the problem at hand, e.g. the problem type and its characteristics. The knowledge-based recommender system can then give advice on what to do first to solve the problem via the advice panel. Alternatively a static knowledge support system will suggest to users what should be done first.

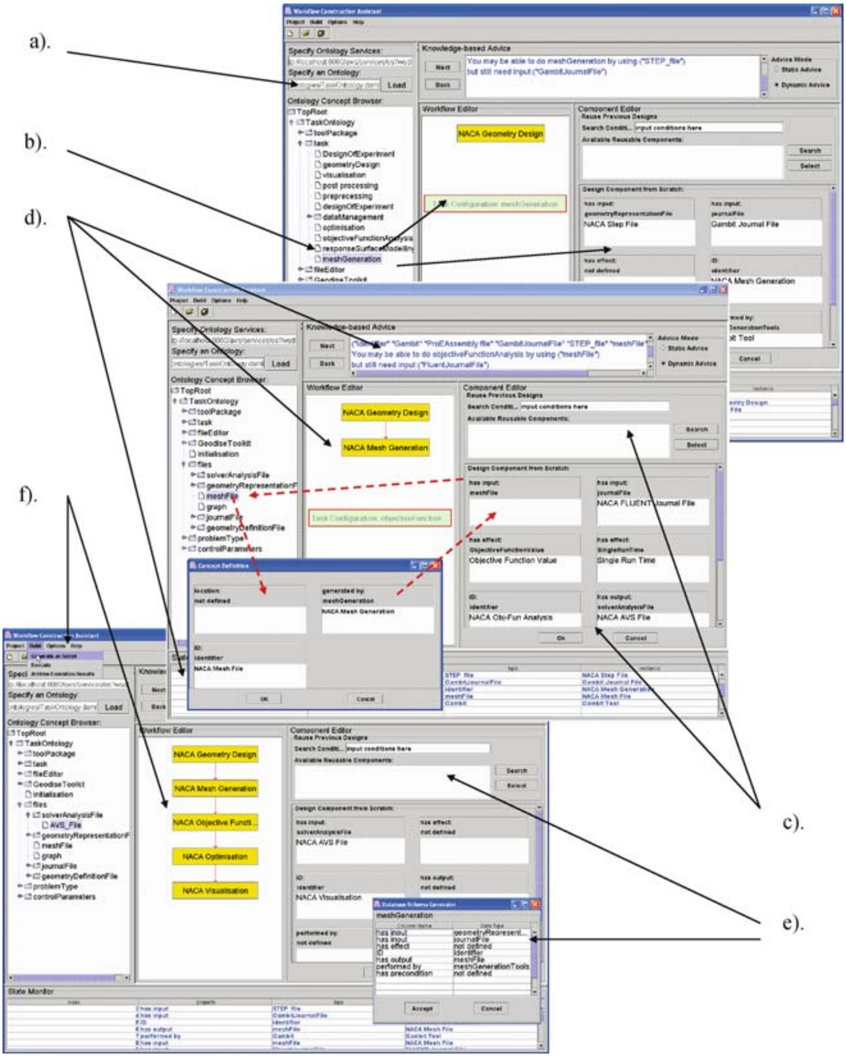

Fig. 7. Screenshots of workflow construction using recommender system

(b) Select a suitable task by navigating the task hierarchy utilizing the initial advice, and drag and drop it into the Workflow Editor. A description form will appear in the Component Editor, which is used to describe the properties of the resource required for the task.
(c) Fill in the property values of the resource description form to frame semantic matchmaking expressions. Users can follow the ontological concept links from the semantic task description to define each property. For example, to define a mesh file for the objective function analysis task, the semantic link of the property "meshFile" will bring you to the "MeshFile" concept in the task ontology. Dragging and dropping the concept into the

property's input area will in turn open a concept definition dialog box for users to input relevant values. This process is demonstrated by the red dashed arrows in Fig. 7.

Once query expressions are framed, users can use the semantic-based search engine (at the top of the Component Editor) to discover resources that can accomplish the task. Users can also partially specify the properties of a resource using the description form and then perform queries.

(d) Performing semantic matchmaking based resource discovery will return a number of qualified resources, which will be added into the WCE's working memory. Three operations will then follow: Firstly, the underlying knowledge-based Resource Selection System will reason against the rule base using these discovered resources along with the states of the WCE's working memory. The recommendation on which resource is the most appropriate is subsequently displayed in the knowledge advice panel. This advice guides users to select a suitable resource from the list of discovered resources. Secondly, an instance of the selected resource with embedded semantics will be added to the Workflow Editor. It will form a step of the workflow specified for the current problem. This is shown as a yellow box in Fig. 7. Finally, the property information of the selected resource, in particular, the input, effect and output parameters, will be added to the working memory of the WCE. These states are displayed in the State Monitor, and ready for further use by the recommender system.

(e) Each time a selected resource is added into a workflow, it will be configured using its semantic descriptions. The instantiated resource can then be archived in the repository. By collecting all the resources created for different problems a semantically-enriched knowledge base for problems and their corresponding workflows can be built over a period of time. This provides semantic content for a search engine to discover solutions, i.e. a workflow, for a problem based on semantic matchmaking in the future.

(f) After an arbitrary number of loops, i.e. selecting a task, performing semantic resource discovery, recommending the most suitable resource, resource configuration and composition, the user can construct a workflow that solves the specific problem. The generated workflow can be submitted to the underlying enactment engine where various resources will be bound together to form an executable. The executable will run in a domain specific execution environment. In GEODISE, the executable is a Matlab .m script and the execution environment is the Matlab environment [28].

6 Conclusions

This paper has described an intelligent recommender system supporting dynamic, contextual Web resource discovery and selection for Web/Grid-based computing environments. A central feature of the system is the exploitation of semantic descriptions for resource discovery via semantic matchmaking and the intensive use of domain-specific knowledge for resource selection based on best practice knowledge and expertise. We have discussed the lifecycle of semantic resource descriptions and the mechanisms for dynamic resource discovery. We have elaborated an ontology-enabled, service-oriented framework for knowledge-based resource selection operating in the context of the technological infrastructure provided by Grid-computing platforms and the Semantic Web. Our approach to recommending Web resources co-opts traditional rule-based knowledge system engineering with the current state-of-the-art in semantic Web services technologies. The prototype system, developed to provide a concrete demonstration of our approach, exemplifies this close synergy and merger of previously disparate technologies, availing itself of both a knowledge-based decision support facility and exploitation of semantically-enriched resource descriptions in a single unitary environment. Such systems empower problem-solving agents to solve problems quickly and at low cost by exploiting available resources.

The importance of domain knowledge and expertise to problem-solving success is nowhere more apparent than in the field of e-Science. We have demonstrated the importance of the synergy of semantics and domain knowledge with respect to one aspect of expertise, namely the discovery, selection and configuration of resources as part of a workflow specification. The approach and the example prototype have both been developed in a specific application context, namely that of design search and optimization. While the full evaluation of this system awaits further investigation and user feedback, our initial results have been promising. This approach is applicable to other types of Web/Grid applications using the SOA computing metaphor.

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An Intelligent Decision Support System Based on Machine Learning and Dynamic Track of Psychological Evaluation Criterion

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Summary. An Intelligent Decision Support System based on Machine Learning and Dynamic Track of Psychological Evaluation Criterion is presented in this paper. It is shown that a complex decision for global situation can be disassembled into a series of simple local problems, from which the most satisfactory decision for the local can be found out by individual ways respectively. At the lower level of total score, the best decision for the local, according to the mathematical interpretation of weight, can be considered as the decision whose distribution of scores is just consistent with the distribution of the psychological weight (or preference) of a decision maker. At a series of moderate levels, the evaluation criterion is given by human–machine interaction, in which some satisfactory samples are chosen by decision maker from a lot of samples, and the barycentre of criterion and the radius of criterion can be estimated by a learning algorithm. In this way, the most satisfactory decision for the local made by the decision maker at each level can be tracked. If we let the collection of satisfactory decision for global be the union of the local's most satisfactory decision at all levels, then the changing process of psychological criteria which varies with the change of total score can be deduced. Finally, a satisfactory degree function with which the global consistency of the collection of local satisfactory decisions at all levels could be retained is given, and a global ranking approach based on the function as well.

1 Introduction

In case of a nuclear accident, not only the nuclear power plant will be destroyed, but the society, public properties and environment might be also extremely disserved. Therefore the attributes of emergency decisions of nuclear accident include many aspects. To make a decision, we need to do hazardous analysis about different aspects that could be damaged by the nuclear accident, and to do cost–benefit evaluation and calculation of different actions according to their cost to reduce damage. Thereafter, several optimal decisions

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can be chosen from possible options, and decision makers can make their decision based on proposed decisions.

According to the suggestion of International Commission on Radiological Protection (ICRP) [1], the making of nuclear emergency decision currently should use the approach of multi-attribute cost–benefit evaluation to get optimal decision. This decision is usually described as the maximum of the following utility function:

$$\operatorname*{Max}_{i} \; \{u = \sum_{j=1}^{m} w_j \; x_{ij}\} \tag{1}$$

in which, $0 \leq \mathrm{x_{ij}} \leq 100$ is the evaluation value (or score) of the jth decision attribute of the ith candidate decision vector, and $\mathrm{w} = (\mathrm{w_1}, \ldots, \mathrm{w_m})$ is the psychological weight (or preference) of the attribute vector of the decision maker, satisfying the condition of reduction to unity: $\sum_{j=1}^{m} w_j = 1$.

However, there are at least two problems in traditional multi-attribute cost–benefit evaluation. First of all, using the utility function not only means that the best choice of solution of the problem has the maximum value with the score of each of its attribute consisted with the weight of the decision maker, but is also based on an assumption that the utility function linearly varies with the psychological weight $\mathrm{w} = (\mathrm{w_1}, \ldots, \mathrm{w_m})$. However, we know that the choice is non-linear correlated with the weight in some cases.

For example, we can see a case of recruiting four new students (Table 1). Their total scores and scores of each subject are shown. To evaluate the students, some basic criteria are given: the total score should be above 200; the score for each subject should be above 40; math should be above 80, and the psychological weight of the decision maker for each subject is (0.2, 0.4, 0.4). Four out of seven students can be picked out. Student A gets full mark with all subjects, and A will be accepted with no doubt. Comparing the ratio of his score and the psychological weight of the decision maker, they are independent from each other. Student B will not be accepted because of his bad job in math. Student C and D have the same total score, and they are

Table 1. An example of decision not linearly depend on weight

Recruit	Total score	English	Math	Physics	Ratio	Compared with weight
A$\surd$	300	100	100	100	(0.33, 0.33, 0.33)	Independent
B$\times$	250	90	70	90	(0.36, 0.28, 0.36)	Inconsist
C$\surd$	250	70	90	90	(0.28, 0.36, 036)	Almost consist
D$\surd$	250	80	80	90	(0.28, 0.28, 0.36)	Inconsist
E$\times$	200	60	80	60	(0.3, 0.4, 0.3)	Inconsist
F$\surd$	200	40	80	80	(0.2, 0.4, 0.4)	Consist
G$\times$	100	20	40	40	(0.2, 0.4, 0.4)	Consist

both qualified. Comparing the ratio of the score and the weight of the decision maker respectively, C's ratio is almost consistent, while D's ration is inconsistent. However they are both accepted. Now let's see student E and F whose total score are the same and they are both qualified. Since only one of them can be chosen, F is picked. The reason is that the ratio of F$'$ score of each subject is consistent with the weight of the decision maker. Now let's look at G. His ration is consistent with the weight of the decision maker, but his total score is not enough. From this example, we can see that in different level of total score, different criterions are used to make decision and they are not always consistent to the psychological weight of the decision maker. Here non-linear correlation exists and results in the problem of how to describe it.

Secondly, the researches in theory of decision support system have shown recently that the so called optimal decision is only a mathematically ideal situation. When the goals of decision attributes conflict, the optimal decision which has the maximum evaluation scores for all attributes do not exist. On the contrary, under most situations, it is only possible to get the most satisfactory decision. Therefore, right now decision scientists need a non-linear evaluation and decision approach based on analysis of satisfactory degree.

In this paper, we propose a new approach of multi attribute decision making, called the Intelligent Decision Support System Based on Machine Learning and Dynamic Track of Psychological Evaluation Criterion. There are three major steps in this approach. First, a complex decision about a global situation could be disassembled into a series of simple local problems, in which the most satisfactory decision for the local can be found out by individual ways respectively. At the lower level of total score, the most satisfactory decision for the local, according to the mathematical interpretation of weight, can be considered as the decision whose distribution of scores is just consistent with the distribution of the psychological weight of a decision maker. At a series of moderate levels, the evaluation criterion is given by man–machine interaction, in which some satisfactory samples are chosen by decision maker from a lot of samples, and the barycentre of criterion and the radius of criterion can be estimated by a learning algorithm, such that the most satisfactory decision for the local of the decision maker at each level can be tracked. Let the collection of satisfactory decision for global be the union of the most satisfactory decision for the all levels, then the changing process of psychological criteria which varies with the change of total score can be surmised. Finally a satisfactory degree function that the global consistency of the collection of local satisfactory decisions of all levels could be able to retainable is given, and a global ranking approach based on the function as well.

Now let's see it step by step.

2 The Basic Model of Decision Making with Psychological Weight

2.1 The Decision Attributes in Evaluation Sub-System

For simplicity, the model presented here assumes only seven decision attributes in the ESY (Evaluation Sub-sYstem) of the emergency decision system of nuclear accident [2] (in real system, decision attributes are usually more than 100). Those seven attributes are (1) economic cost, (2) public health, (3) individual avoidable dose, (4) mass avoidable dose, (5) maximum individual exposure dose, (6) effects on social psychology, and (7) political effects, and are used as axis, and the scores $(x_k, k = 1, \ldots, 7)$ of these seven decision attributes of different decisions are used as coordinate parameters. Therefore, every decision corresponds to a point $x = (x_1, \ldots, x_7)$ in the seven-dimension coordinate K(X). These seven-dimension attributes coordinate can be studied and discussed both qualitatively and quantitatively for evaluation and decision in nuclear accident emergency.

2.2 The Attribute Coordinate System and Representation of Psychological Weight

It is shown that a new mathematical approach in which the dynamic changing process of the evaluation criteria can be represented is the key tool, because evaluations and decisions depend on the decision maker's criterion that varies with his psychological preference and the total score levels [3]. By using the two functions of attribute coordinate system which includes the Cartesian coordinate and the barycentric coordinate system, we have: (1) the different total score levels can be separated in the Cartesian coordinate; (2) the psychological weight of decision maker can be put in the barycentric coordinate system; An Intelligent Decision Support System Based on Machine Learning and Dynamic Track of Psychological Evaluation Criterion is presented here, and the process is as follow:

(1) The evaluation and decision problems in nuclear accident emergency are disassembled into a series of local problems according to total score (equal total score decisions are grouped). Since only within the same total score level it is possible to get reasonable mathematical expression of weights for decision attributes, the evaluation and decision problems at a global level are first of all turn to the problems of finding the optimal local decisions at each level of a series of different total score level.
(2) If the weight distributions of decision attributes are already known, then in each total score level, the most satisfactory decision for the local corresponding the weight distribution can be solved by analysis of attribute coordinate.

(3) If the weight distributions of decision of attributes are unknown, then the decision maker's psychological weight distribution of each decision attribute can be found out through man–machine interaction. Then, return to (2);
(4) From the sets of all local most satisfactory decisions, the global most satisfactory decision can be solved by using the given global most satisfactory degree function, meaning the problems of evaluation and decision in nuclear accident can be solved.

This method describes the changing situation of decision according to the goals of each attribute. It can also learn and estimate the intelligent activity rules of the decision maker through communication between the decision maker and machine, the process of making decision scientifically and reasonably according to external environment, social effects, response of public psychology, resource and, etc. and thus mimic the decision maker's decision behaviors.

Hereafter is a detail description of the three crucial steps in this approach. These three steps are (1) local most satisfactory decision; (2) determination of the weights for each decision attribute through dialogue between decision maker and machine; and (3) global most satisfactory decision degree function.

2.3 The Psychological Weight of Decision Maker

Decision is always regarded as doing cost and benefits analysis evaluation among all the strategies and to finding the most satisfactory ones. For the soundness of evaluation, it's necessary to make the reduction be unified on all the decision attributes. The decision whose all evaluation values of attributes are the maximum scores, e.g. 100, is the most optimal decision, and is called the ideal decision $x_{ideal} = (100, \ldots, 100)$ (Fig. 1) in tradition.

In mathematics, if let $a = (a_1, \ldots, a_m)$ be the vector of m decision attributes $a_j,\ j = 1, \ldots, m,\ x_i = (x_{i1}, \ldots, x_{im})$ the ith candidate decision vector,

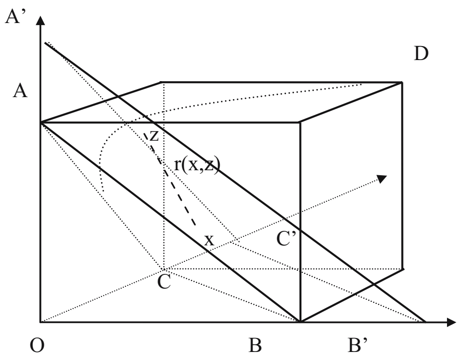


Fig. 1. Learning and criterion line of local most satisfactory decision

x_{ij}, $0 \leq x_{ij} \leq 100$, the evaluation value (or score) of jth decision attribute a_j of the ith decision vector x_i, $T(x_i) = \sum_{j=1}^{m} x_{ij}$ the sum of scores x_{ij} of decision x_i, let $w(z) = (w_1, \ldots, w_m)$, whose components satisfy the condition of reduction to unity: $\sum_{j=1}^{m} w_j = 1$, be the psychological weight vector that the decision maker z assigning to the attribute vector $a = (a_1, \ldots, a_m)$, $u = \sum_{j=1}^{m} w_j x_{ij}$ utility function of the decision x_i, and $U = \{u = \sum_{j=1}^{m} w_j x_{ij}\}$ the utility function space of all decisions, then a decision problem can be described as finding out the maximum of the following utility function (1).

From the mathematical point of view, when a whole decision space is divided into m portions, and w_j is the proportion of jth portion to the whole, then the weight vector $w = (w_1, \ldots, w_m)$ is about the relative strength or relative intensity among m portions of the whole.

If let the w_j of weight vector w for the jth attribute component a_j of vector $a = (a_1, \ldots, a_m)$ be the relative importance of a_j among the set $\{a_j\}$, then the utility function $u = \sum_{j=1}^{m} w_j x_{ij}$ can be interpreted as the synthesis evaluation value of the decision x_i with the weight vector w. If let $T(x_i) = \sum_{j=1}^{m} x_{ij}$ be the total grad or the sum of scores x_{ij} of the vector $x_i = (x_{i1}, \ldots, x_{im})$, because the $w_j = w(x_{ij}) = \frac{x_{ij}}{T(x_i)}$ is naturally of the proportion of x_{ij} to the total grad, the vector $w(x_i) = (w(x_{i1}), \cdots, w(x_{i1})) = (\frac{x_{i1}}{T(x_i)}, \cdots, \frac{x_{im}}{T(x_i)})$ can be take as the weight w for decision x_i.

If let $\beta(z) = (\beta_1(z), \cdots, \beta_m(z))$ be the weight that decision maker z assigns to the attribute vector $a = (a_1, \cdots, a_m)$, $w(x_i^*, \beta(z)) = (w(x_{i1}^*, \beta(z)), \cdots, w(x_{im}^*, \beta(z)))$ the relative importance distribution vector of the decision maker z's with weight $\beta(z)$ assigns to the vector $x_i = (x_{i1}, \cdots, x_{im})$, then a kind of rational interpretation for the psychological evaluation criterion of z with $\beta(z)$ is that

$$\begin{aligned}\beta(z) = (\beta_1(z), \cdots, \beta_m(z)) = w(x_i^*, \beta(z)) = (w(x_{i1}^*, \beta(z)), \cdots, w(x_{im}^*, \beta(z))) \\ = \left(\frac{x_{i1}^*}{T(x_i^*)}, \cdots, \frac{x_{im}^*}{T(x_i^*)}\right)\end{aligned} \tag{1}$$

i.e. about reasonability of the decision distribution of scores component x_{ij} in the vector x_i [4, 5].

Put it in another way, from the decision maker's point of view, it is just the most satisfactory decision whose distribution of scores component x_{ij} in the vector x_i, $w(x_i^*, \beta(z)) = (w(x_{i1}^*, \beta(z)), \cdots, w(x_{im}^*, \beta(z)))$ is just consistent with his the psychology weight $\beta(z) = (\beta_1(z), \ldots, \beta_m(z))$ (Fig. 2).

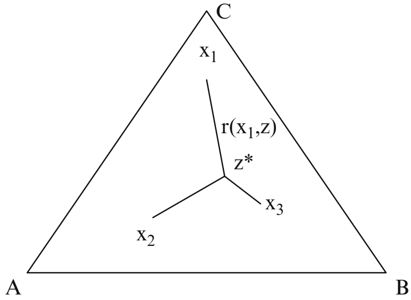


Fig. 2. Local evaluation criterion z^* and distance $r(x, z^*)$

On the other hand, if let the $S_T = \{x_i = (x_{i1}, \ldots, x_{im}) | \sum_{j=1}^{m} x_{ij} = T\}$ be the set of decisions x_i in which sum $T(x_i) = \sum_{j=1}^{m} x_{ij}$ equals to $T(T_0 \leq T \leq T = 100 \times m)$, and called S_T the level of total grad T, $x(S_T, z) = (x_1(S_T, z), \ldots, x_m(S_T, z))$ the evaluation criterion of decision maker z at the level S_T, then $x(S_T, z)$ not only should be the most satisfactory decision in the level S_T, but also could be gotten by the following formula:

$$\begin{aligned} x(S_T, z) &= T \times \beta(z) = T \times (\beta_1(z), \cdots, \beta_m(z)) = T \times w(x_i^*, \beta(z)) \\ &= T \times (w(x_{i1}^*, \beta(z)), \cdots, w(x_{im}^*, \beta(z))) = T \times \left(\frac{x_{i1}^*}{T(x_i^*)}, \cdots, \frac{x_{im}^*}{T(x_i^*)} \right) \\ &= (x_{i1}^*, \cdots, x_{im}^*) = x_i^* \end{aligned} \tag{2}$$

This is to say that, in other words, the decision $x_i^* = (x_{i1}^*, \cdots, x_{im}^*) \in S_T$, whose distribution of scores is just consistent with the distribution of the psychology weight of a decision maker $\beta(z) = (\beta_1(z), \ldots, \beta_m(z))$, could play the part of the evaluation criterion of decision maker z at the level S_T.

Although the above interpretation of evaluation criterion is soundness at the lower level S_T, i.e. T is small, but there are some problems at the high levels S_T (T is big). For example, the most ideal decision x_{ideal} is the decision whose all decision component score $x_{ideal} = (100, \ldots, 100)$ at the top level $S_{T=100\times m}$, but it is not the evaluation criterion of decision maker z at the level $S_{T=100\times m}$, expecting the weight $\beta(z) = (\beta_1(z), \cdots, \beta_m(z)) = (\frac{1}{m}, \cdots, \frac{1}{m})$.

The contravention shows us that the evaluation criterion of decision maker z only varies with the weight $\beta(z)$ at the lower level only, but is not associated with $\beta(z)$ in higher levels.

In order to find the evaluation criterion of decision maker z at a series of moderate levels, an algorithm of machine learning based on the man–machine interaction is given in Sect. 4.

3 Local Most Satisfactory Decision at the Lower Level S_T

Let $X = \{x_i = (x_{i1}, \ldots, x_{im}) | x_{ij} (0 \leq x_{ij} \leq 100)\}$ be the set of all the decisions (or decision space) (under three-dimension, X is the cube in Fig. 1), $S_T = \{x_i = (x_{i1}, \ldots, x_{im}) | \sum_{j=1}^{m} x_{ij} = T\}$ the decisions set in which sum equals to $T(T_0 \leq T \leq 100 \times m)$, and constitutes a contour hyper-surface whose value equals to T, let $S_T \cap X$ be intersection of S_T and X, or a (m-1)-dimensional simplex (in Fig. 1, S_{100} means ΔABC).

Therefore, in simplex $S_T \cap X$ of equal sum, the most reasonable decision distributed by weight $w = (w_1, \ldots, w_m)$ should be $x^* = (x_1^*, \ldots x_m^*) = T \times w = (T \times w_1, \ldots, T \times w_m)$, for $w = (w_1, \ldots, w_m)$ is just the center gravity coordinate of x^* in simplex $S_T \cap X$. namely, $x^* = (w_1, \ldots, w_m)$, $\sum_{j=1}^{m} w_j = 1$. Its physical meaning can be interpreted as: if we put all sub weights $w_j (j = 1, \ldots m)$ on the top point a_j of $S_T \cap X$ respectively, x^* is just the physical center gravity of $S_T \cap X$. Hence, no matter whether from the weight mathematics meaning itself, physics or topology and liner space theory etc. $x^* = (T \times w_1, \ldots, T \times w_m)$ should be the most satisfactory decision in $S_T \cap X$ distributed by weight $w = (w_1, \ldots, w_m)$.

Obviously, if there exists decision $x*$ in simplex $S_T \cap X$, then the local satisfactory decision is determined. On the contrary, if $x*$ doesn't exist, the distance $r(x_i, x*)$ between any decision $x_i = (x_{i1}, \ldots, x_{im})$ of equal sum T and $x*$ can represent the difference of local most satisfactory decision from x_i to decision z.

If let satisfactory degree function of z:

$$sat(x_i, z) = \lambda(x_i, x^* \ (z)) g(r(x_i, x^* \ (z))), \tag{2}$$

here, $\lambda(x_i, x * (z))$ is an undetermined coefficient discussed later, and in order to make it easy to understand, let $\lambda(x_i, x*(z)) = 1$. $g(r(x_i, x*(z)))$ is similarity degree function reflecting the similarity between x_i and $x*$ and satisfies: when $r(x, x * \ (z)) = 0$, then $g(r(x, x * (z))) = 1$; when $r(x, \ x * (z)) = \infty$, $g(r(x_i, x * (z))) = 0$, while the following Qualitative Function given in [4–6] just has these characteristics, so we take $sat(x_i, x * \ (z))$ as:

$$sat\ (x_i,\ x^*\ (z)) = \exp\left(-\frac{\sum_{j=1}^{m} w_j \left|x_{ij} - x_j^*(z)\right|}{\sum_{j=1}^{m} w_j \delta_j}\right) \tag{3}$$

here, $\delta_i = \delta_i(z)$ is deviation on the ith standard z_i by decision-maker z, let weight $w_j = w_j(x_j^*(z), \delta_j)$ be function of $x_j^*(z)$ and $\delta_{i.}$ with practical validation: the z of decision-maker satisfactory degree of all the decisions in $S_T \cap X$ is basically in accordance with the changing law in (3). Hence (3) is called in $S_T \cap X$ as local satisfactory degree function of evaluate decisions to decision-maker.

4 Learning for Psychological Weight of Decision Maker by Machine Learning

Unless the most satisfactory decision $D = (100_1, \dots 100_m)$ or sum grade $T < T_0$ be the most unsatisfactory decision has no business with weight w. When sum T: $T_0 \leq T \leq 100 \times m$, the most satisfactory decision $x* = (x_1^*, \dots x_m^*)|_T$ cannot be easily obtained.

To solve this problem, we have utilized a method using machine's learning to search and gradually approach the local most optimal decision $x* = (x_1^*, \dots x_m^*)|_T$.

Let S_T be the set of all x_i whose the sum of cost x_{ij}, $j = 1, \dots, m$, equals to T, $S_T = \{x_i = (x_{i1}, \dots, x_{im})| \sum_{j=1}^{m} x_{ij} = T\}$, and called T-syherplane, $S' = \{x_k,\ k = 1, \dots, s\} \subseteq S_T \cap X$ subset of sample decision x_i, if decision maker has chosen t sets of decisions $\{x^h,\ h = 1, \dots, t\}$ from $S' = \{x_k\}$ which satisfied him, and marked $v^h(x^h)$, respectively. Because decision space X is a convex set on $v^h(x^h)$, so we can get the center gravity point b $(\{x^h(z)\})$ from $\{x^h(z)\}$ by means of weighing and averaging.

Figure 3 is a choice interface of the experienced criterion of decision maker, in which there are 15 samples of three different kinds, respectively. Decision maker is asked to make a ranking score with his criterion for some samples.

$$b(\{x^h(z)\}) = \left(\frac{\sum_{h=1}^{t} \nu_1^h x_1^h}{\sum_{h=1}^{t} \nu_1^h}, \dots, \frac{\sum_{h=1}^{t} \nu_m^h x_m^h}{\sum_{h=1}^{t} \nu_m^h} \right). \tag{4}$$

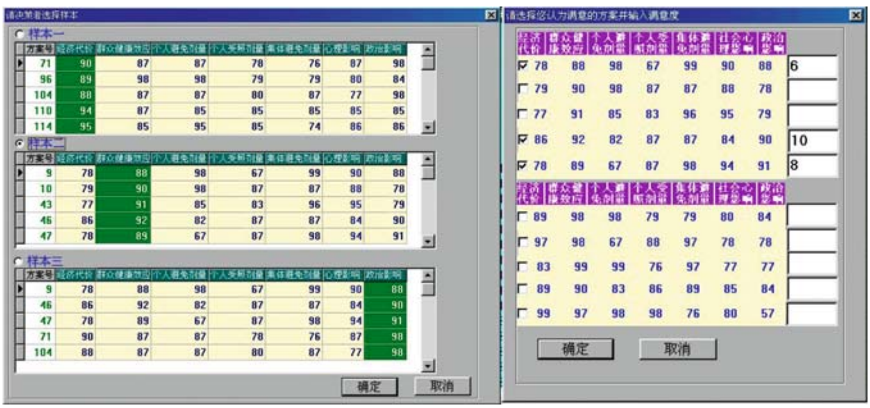


Fig. 3. Learning or choice of an experienced criterion of decision make

Clearly, when training sample set is big enough and has enough training times and enough decision set $\{x^h(z)\}$ chosen by decision maker z, its center gravity point is approaching the local satisfactory optimal decision $x^*|_T$ of $S_T \cap X$ that is: $\lim\limits_{h\to\infty} b(\{x^h(z)\} \to x^*|_T$, here, $b(\{x^h(z)\})$ is the local optimal decision of z in $S_T \cap X$.

It is well worth to point out that we can get a neighborhood $N(b(\{x^h(z)\}), r(\{x^h(z)\}))$ with center $b(\{x^h(z)\})$ and radius $r(\{x^h(z)\})$ each time of learning which makes any decision $x \in N(b(\{x^h(z)\}), r(\{x^h(z)\}))$ be suitable and satisfactory decision for the above study meaning.

When the decision maker z has the most satisfactory decision or mental standard point $b(\{x^h(z)\})|_T$ in $S_T \cap X$, it is not difficult for z to use local optimal satisfactory degree function to evaluate the satisfactory degree among all the decisions in $S_T \cap X$:

$$sat(x_i, z) = \exp\left(-\frac{\sum\limits_{j=1}^{m} w_j \left|x_{ij} - b_{ij}(\{x^h(z))\right|}{\sum\limits_{j=1}^{m} w_j \delta_j}\right). \tag{5}$$

5 Set of Local Most Satisfactory Decisions

We can get the local most satisfactory decision $b(\{x^h(z)\}) \in S_T \cap X$ from the above man–machine interaction, so when T traverses range $[T_0, 100 \times m]$, the set $\{b(\{x^h(z)\})|_{T\in[T0,100\times m]}\}$ can be obtained. Considering that the psychological criterion of decision maker z's continuous change do not leap change on T. $b(\{x^h(z)\})|_{T\in[T0,100\times m]}$ can be regarded as a continuous change, and either set $\{b(\{x^h(z)\})|_{T\in[T0,100\times m]}\}$ will be a smooth curve: noted as $L(b(\{x^h(z)\}))$. That is local most satisfactory decision line or mental criterion line of decision maker z, [6] as shown in Fig. 1.

Let the domain $X = \{x_i = (x_{i1}, \ldots, x_{im})\}$ be a closed and compact topological space. Because there is a finite covering for the space X, the subsets of X and local most satisfactory decision line $L(b(\{x^h(z)\}))$ is a finite covering subspace too. $L(b(\{x^h(z)\}))$ can be obtained by interpolation method or curve simulation method.

Let $b_k(\{x^h(z)\}|_{T_k\in(T_0,100\times m)}$, $k = 1, \ldots, n$, be acquired by (4) through training and learning and the most satisfactory decision of decision maker z in $S_{T_k} \cap X$. For $x_0^* = (T_0 \times w_1, \ldots, T_0 \times w_m)$ and $D = (100, \ldots, 100)$ are the local most satisfactory decisions in $S_{T_o} \cap X$ and $S_{100\times m} \cap X$ respectively, adding $b_k(\{x^h(z)\}|_{T_k\in(T_0,100\times m)}$, it totals up to $n + 2$ most satisfactory decisions from different simplex. Hence, if let the following polynomial function be the interpolation formula:

$$G_j(T) = a_{0j} + a_{1j}\, T + a_{2j}\, T^2 + \cdots + a_{(n+1)j}\, T^{n+1} \tag{6}$$

$a_j = (a_{1j}, \ldots, a_{ij})$, $i = 0, 1, \ldots, n+1$; $j = 0, 1, \ldots, m$, then the local most satisfactory decision line $L(b(\{x^h(z)\}))$ would be done. For the sake of simplicity, it introduces the interpolation method only using three interpolation knots for the local most satisfactory lines as follow.

Let m be the number of decision attribute, $x_1, \ldots, x_m$ the attributes value of the decision samples, and let the insert-value multinomial be the following:

$$G\ (T) = G(g_1(T), \ldots \ldots, g_m(T)) \tag{7}$$

$$\text{Here,} \quad \begin{cases} g_1(T) = a_{01} + a_{11}T + a_{21}T^2 & (7-1) \\ \vdots & \\ g_j(T) = a_{0j} + a_{1j}T + a_{2j}T^2 & (7-j) \\ \vdots & \\ g_1(T) = a_{0m} + a_{1m}T + a_{2m}T^2 & (7-m) \end{cases}$$

The above expression will be the three local satisfactory decisions of decision maker z in $S_{T_0} \cap X$, $S_T \cap X$ and $S_{100\times m} \cap X$.

(1) The local most satisfactory decision in $S_{T_0} \cap X$ is $x_0^* = (T_0 \times w_1, \ldots, T_0 \times w_m)$;
(2) The local most satisfactory decision in $S_T \cap X$:

$$x^*|_T = b(\{x^h(z)\}) = \left(\frac{\sum\limits_{h=1}^{t} \nu_1^h x_1^h}{\sum\limits_{h=1}^{t} \nu_1^h}, \cdots, \frac{\sum\limits_{h=1}^{t} \nu_m^h x_m^h}{\sum\limits_{h=1}^{t} \nu_m^h} \right).$$

The most ideal decision: $x^*|_{100\times m} = D = (100, \ldots, 100)$, Taking the above three points into the following Lagrange insert-value formula:

$$g_i(T) = \frac{(T - x_1^*)(T - x_2^*)}{(x_0^* - x_1^*)(x_0^* - x_2^*)} a_{i0} + \frac{(T - x_0^*)(T - x_2^*)}{(x_1^* - x_0^*)(x_1^* - x_2^*)} a_{i1} + \frac{(T - x_0^*)(T - x_1^*)}{(x_2^* - x_0^*)(x_2^* - x_1^*)} a_{i2}. \tag{8}$$

Then we can get the values of $3 \times m$ coefficients (a_{ij}, $i = 1, 2, 3;$) of equation group $(7 - j, j = 1, \ldots, m)$ and the equation of insert value curve(7) where contains the most satisfactory decision (as the continuous curve z-d in Fig. 1). Then through the following equation

$$\begin{cases} \sum\limits_{j=1}^{m} x_{ij} = T \\ G(T) = G(g_1(T), \ldots, g_m(T)) \end{cases} \tag{9}$$

We can get the most satisfactory decision for the local $b(\{x^h(z)\})|_T$ of any simplex $S_T \cap X, T \in [T_0, 100 \times m]$. If $b(\{x^h(z)\})|_T$ happens to be the practical decision, then it will be the local most satisfactory decision of $S_T \cap X$.

Otherwise, with (5), decision maker z can do satisfactory degree evaluation against any decision $\mathrm{x_i} = (\mathrm{x_{i1}}, \ldots, \mathrm{x_{im}}) \in \mathrm{S_T} \cap \mathrm{X}$ and find the decision having the highest level of satisfactory degree, which could be used as the local most satisfactory decision in $\mathrm{S_T} \cap \mathrm{X}$.

6 Local and Global Satisfactory Degree Function

In general, the larger the sum grade $\sum_{j=1}^{m} x_{ij} = T_i$, the more satisfactory is the local satisfactory decision $(\mathrm{b}(\{\mathrm{x^h(z)}\})$ corresponding T in the $\mathrm{L(b(\{x^h(z)\}))}$. Therefore, the global most satisfactory decision can be found out by ranking all the decisions $\mathrm{x_i} \in \mathrm{L(b(\{x^h(z)\}))}$ according to their the sum grade $\mathrm{T_i}$.

However, it is not difficult to find that all the decisions in $\mathrm{L(b(\{x^h(z)\}))}$ are obtained by learning in different simplex $\mathrm{S_T} \cap \mathrm{X}$, in which the local most satisfactory decision is taken by learning as standard and be fixed by (5) on calculation of satisfactory degree, and an new academic problem will be raised as follows:

The expression (5) starts from one standard point $\mathrm{b_i(\{x^h(z)\})|_{Ti\in(T0,100\times m)}}$ to evaluate the similar degree between the other objects with Z_i, and it lacks the ability to show similarity between globe and integrity. When decision maker z takes the different most satisfactory decisions $\mathrm{b_i(\{x^h(z)\})|_{Ti\in(T0,100\times m)}}$ and $\mathrm{b_k(\{x^h(z)\})|_{Tk\in(T0,100\times m)}}$ as standard to evaluate all decisions in $\mathrm{S_{Ti}} \cap \mathrm{X}$ and $\mathrm{S_{Tk}} \cap \mathrm{X}$, we will get the local most satisfactory degrees $\mathrm{sat(x_i\ z_i)}$ and $\mathrm{sat(x_k,\ z_j)}$ as the optimal decisions X_{iu} and X_{kv}. However from the global point of view, the status (if $\mathrm{T_i} > \mathrm{T_k}$, then $\mathrm{sat(x_{iu}, z_i)} < \mathrm{sat(x_{kv}, z_j)}$) may happen. It is unsound to say sat $\mathrm{(x_{iu}, z_i)}$ is better than $\mathrm{sat(x_{kv}, z_j)}$ only depending on $\mathrm{T_i} > \mathrm{T_K}$.

In order to get a global satisfactory decision from $\mathrm{L(b(\{x^h(z)\}))}$, We need to give an evaluation function which evaluate all the decisions $\mathrm{L(b(\{x^h(z)\}))}$ from the global point of view.

After several adjustments, we find that only let$\lambda(\mathrm{x, z})$ in (2) be the following:

$$\lambda(\mathrm{x,\ z}) = \left(\frac{\sum\limits_{i=1}^{m} x_{ij}}{\sum\limits_{j=1}^{m} X_j} \right)^{\left(\frac{\sum_{i=1}^{m} X_j}{2\left(\sum_{j=1}^{m} x_{ij}\right)} \right)} \tag{10}$$

$\sum_{j=1}^{m} X_j$: all the attribute values are the sum of full grade X_i, and when united, they will be 100 m. $\sum_{ij=1}^{m} x_{ij}$ is the sum of all the attribute values $\mathrm{x_{ij}}$ of decision x_i. Taken into (3) will be:

$$sat(x,z)=\left(\frac{\sum_{i=1}^{m} x_{ij}}{\sum_{j=1}^{m} X_j}\right)^{\left(\frac{\sum_{i=1}^{m} X_j}{2\left(\sum_{j=1}^{m} x_{ij}\right)}\right)} {}^{*}\exp\left(\frac{\sum_{j=1}^{m} w_j|x_j-b(x^h(z_j)|}{\sum_{j=1}^{m} w_j\delta_j}\right) \tag{11}$$

(11) is able to keep satisfactory degree $\mathrm{sat}(\mathrm{X}_i,\mathrm{z})$ in the whole decision space consistently. $\lambda(\mathrm{x},\mathrm{z})$ is called the global consistent coefficient.

From (10), we can see the weight of the suffix reflects the sum grade $\sum_{ij=1}^{m} x_{ij}$ of all the decisions in full grade $\sum_{j=1}^{m} X_j\cdot$ while the index is on the contrary to have the control of whole adjustment [6].

The simulation curve created based on (11) as evaluation standard is shown in Table 2. The ranking result of all decisions based on local and global satisfactory degree calculated based on formula (5) and (11) is given in Fig. 4.

From Table 2, it is ease to see that the local satisfactory degree (calculated from formula (3)) truly reflects the similarity between the decision points and the criterion point, and that the ranking of global satisfactory degree (calculated from formula (11)) show the psychological preference of the decision maker. Therefore, the whole ranking result is satisfactory [6].

The reason why decision No. 138 (total score 629) ranks higher than decision No. 201 (total score 634) and decision No. 136 (total score 635) is that the critical attributes, i.e. public health, political effect and mass avoidable dose, in decision No. 138 have higher scores than those in the later two decisions.

Figure 5 shows that the decision maker regards mass health and political effects as the most important attribute, followed by mass avoidable dose, and the rest attributes should have acceptable scores.

In the above learning and evaluation of the most satisfactory decisions, we repeatedly use the liner coordinate system which consists of decision space X and the barycentric coordinate system which consists of simplex $\mathrm{S_T}\cap\mathrm{X}$, so we also call the above approach as The Evaluation and Decision Approach Based on Analysis and Learning of Attribute Coordinate (EDABALAC), for short is Evaluation and Decision Approach of Attribute Coordinate (EDAAC).

The computational simulation experiments show that this analysis approach based on attribute coordinate can not only learn, infer and simulate the changing process of psychological evaluation criteria of decision makers, but also give the satisfactory degree at both local (or certain level) and global scale, and further justify them qualitatively and quantitatively in mathematics. Therefore, it is an approach worth further research and can be considered as a candidate approach in nuclear accident emergency evaluation and decision.

Table 2. Local and global satisfactory degree calculated based on formula (5) and (13)

Decision no.	Economic cost	Public health	Individual avoidable dose	Individual exposure dose	Mass avoidable dose	Effects on social psychology	Political effects	Local satisfactory degree	Global satisfactory degree	Total score
139	83	99	99	76	97	77	77	0.7605	0.5759	608
46	86	92	82	87	87	84	90	0.9193	0.6961	608
9	78	88	98	67	99	90	88	0.749	0.5672	608
182	90	80	75	90	90	89	93	0.8606	0.6492	607
10	79	90	98	87	87	88	78	0.8295	0.6258	607
96	89	98	98	79	79	80	84	0.8082	0.6097	607
147	89	90	83	86	89	85	84	0.9188	0.6906	606
110	94	87	85	85	85	85	85	0.8757	0.6582	606
114	95	85	95	85	74	86	86	0.7959	0.5982	606
43	77	91	85	83	96	95	79	0.8094	0.6084	606
112	86	87	87	68	85	94	98	0.8111	0.6073	605
161	99	97	98	98	76	80	57	0.6768	0.5067	605

Note: the evaluation criterion point is (85.425, 93.896,81.013, 86.866, 87.619, 83.750, 91.898)

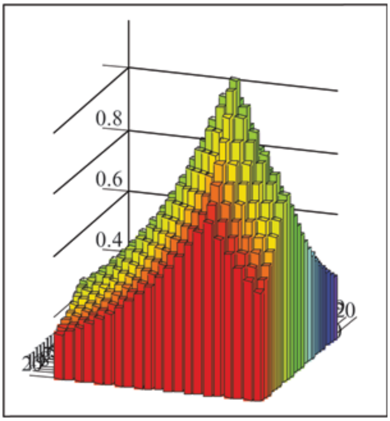
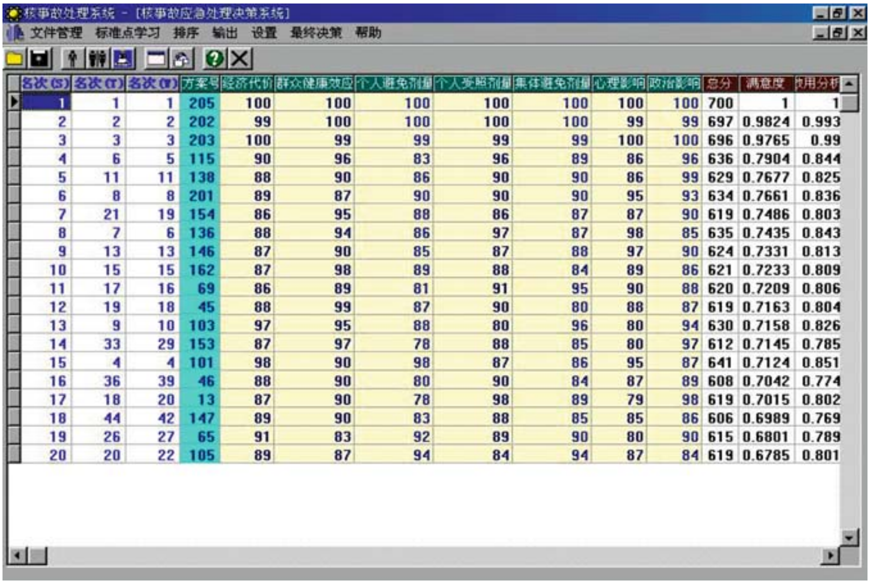


Fig. 4. The global satisfied degree function



名次(S)	名次(T)	名次(Y)	方案号	经济代价	群众健康效应	个人避免剂量	个人受照剂量	集体避免剂量	心理影响	政治影响	总分	满意度	用分析
1	1	1	205	100	100	100	100	100	100	100	700	1	1
2	2	2	202	99	100	100	100	100	99	99	697	0.9824	0.993
3	3	3	203	100	99	99	99	99	100	100	696	0.9765	0.99
4	6	5	115	90	96	83	96	89	86	96	636	0.7904	0.844
5	11	11	138	88	90	86	90	90	86	99	629	0.7677	0.825
6	8	8	201	89	87	90	90	90	95	93	634	0.7661	0.836
7	21	19	154	86	95	88	86	87	87	90	619	0.7486	0.803
8	7	6	136	88	94	86	97	87	98	85	635	0.7435	0.843
9	13	13	146	87	90	85	87	88	97	90	624	0.7331	0.813
10	15	15	162	87	98	89	88	84	89	86	621	0.7233	0.809
11	17	16	69	86	89	81	91	95	90	88	620	0.7209	0.806
12	19	18	45	88	99	87	90	80	88	87	619	0.7163	0.804
13	9	10	103	97	95	88	80	96	80	94	630	0.7158	0.826
14	33	29	153	87	97	78	88	85	80	97	612	0.7145	0.785
15	4	4	101	98	90	98	87	86	95	87	641	0.7124	0.851
16	36	39	46	88	90	80	90	84	87	89	608	0.7042	0.774
17	18	20	13	87	90	78	98	89	79	98	619	0.7015	0.802
18	44	42	147	89	90	83	88	85	85	86	606	0.6989	0.769
19	26	27	65	91	83	92	89	90	80	90	615	0.6801	0.789
20	20	22	105	89	87	94	84	94	87	84	619	0.6785	0.801

Fig. 5. Figure 5 gives the first 20 satisfactory decisions (with global satisfactory degree), and we can see the decision with total score 700 rank first

7 Arithmetic Process of the Intelligent Decision Support System Based on Man–Machine Interaction and Dynamic Track of Psychological Evaluation Criterion

The arithmetic process of the evaluation and decision approach based on analysis and learning of attribute coordinate is following:

(1) Make sure of all the factors (attribute of object) having utility on decision, and evaluate and qualitative all the practical decisions;
(2) Use qualitative mapping function (exp. 3) to unite the attribute utility values;
(3) Let $\mathrm{T_0}$ be critical sum grade, and choose several points equably in terms of cur simulation:
$\mathrm{T_1, T_2, \ldots, T_{n-1}}$ choose several sample decisions on the point with full grade $\mathrm{T_i (i = 1, 2, 3, \ldots, n-1)}$ to learn; then find the center gravity coordinate with full grade $\mathrm{T_i (i = 1, 2, 3, \ldots, n-1)}$ according to (4), and this is the local satisfactory decision;
(4) Use insert value formula (6) to do curve simulation to find mental standard line (local most satisfactory decision line) $\mathrm{L(b(\{x^h(z)\}))}$;
(5) Calculate the global satisfactory degrees on all decisions according to (11) and sort on them to get the best one.

To sum up, in evaluation and decision method based on attribute coordinate, the local satisfactory degrees truly reflect the similarity degree between decision coordinate and standard point (barycentric coordinate) and the global satisfactory degrees show the decision maker's psychological weight, and therefore it can get much more satisfactory result.

8 Conclusions

Using the model and approach in this paper, a new model of Evaluation SubsYstem(ESY) of The Decision Support Subsystem of Emergency of Nuclear Accident is presented, a college in China has adopted it as recruiting students system of test to enrolling examination for years and the result shows that it not only takes the student's sum grade into account but also reflect the needs of different majors on different courses.

The computer simulation and calculation shows that the model in this paper can learn, predict and simulate the changing procedure of the decision maker's mental evaluation standard curve as well as providing the local and global evaluation satisfactory degree and it can also give the mathematical interpretation on the rationality with qualitative and quantitative approach. So this method can well represent the changing procedure of experiential data and can also reflect the thinking procedure of people's judgment and decision depending on experience and sense, which is a rather effective approach of evaluation and decision.

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Handling Uncertain and Qualitative Information in Impact Assessment – Applications of IDS in Policy Making Support

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Summary. Impact assessment (IA) in policy making processes has received increasing attention in recent years. One of the major challenges in IA is how to rationally handle and make maximum use of information in uncertain and qualitative data so that the best course of action can be reliably identified. It is discussed in this chapter how the Evidential Reasoning (ER) approach for multiple criteria decision analysis (MCDA) can be used to take the challenge. The ER approach and its software implementation, called the Intelligent Decision System (IDS), are developed with a focus on rationally handling a large amount of information of both a qualitative and quantitative nature and possibly with different degrees of uncertainties in assessment problems. It applies belief decision matrices for problem modelling so that different formats of available data and uncertain knowledge can be incorporated into assessment processes. It uses an evidential reasoning process on the data to generate assessment outcomes that are informative, rational and reliable. Several examples are examined to demonstrate how IDS can be used to support activities in different stages of an IA process, namely (a) problem structuring, (b) assessment model building, including value elicitation, (c) data collection, management, and aggregation, and (d) data presentation and sensitivity analysis. This investigation shows that IDS is not only a versatile assessment supporting tool, but also a knowledge management tool which helps to organise assessment knowledge and data systematically for better traceability, consistency and efficiency in assessment.

1 Introduction

Policies and regulations affect many people or businesses in many ways. To enable better policy making, impact assessment (IA), a process of identifying the future consequences of a current or proposed action, has received increasing attention in recent years among OECD countries (Organisation for Economic Co-operation and Development) [10, 17].

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Initially IA was focused on whether regulations would impose an unnecessary burden on the private, public or third sectors. It was essentially an economic cost benefit analysis tool. Realising that an assessment may not be complete without properly taking into account all factors in question, over recent years, a number of countries have begun to establish new forms of integrated IA that include the assessment of unintended, long-term or non-market effects and inter linkages between different issues of concern. For example in the UK, IA has been expanded to include the consideration of social, environmental and economic impacts [4, 10] and is becoming more complicated.

To further add to the complication, various types of uncertainty may exist in data collected for IA, such as probability due to random events and factors, imprecise estimates for long term effects, vagueness in subjective judgements, and incomplete data sets due to unknown or missing parts of facts. How to rationally incorporate qualitative criteria and uncertain knowledge in an assessment poses a major challenge to both IA practitioners and researchers in the field of multiple criteria decision analysis (MCDA).

To cater for the needs of handling the increasing complexity and difficulty in IA, MCDA approaches have been introduced and applied in IA as reported in numerous literatures. [16, 25, 47]. In this chapter, it is illustrated by examples how the recently developed approach, the Evidential Reasoning approach in MCDA, and its software implementation, Intelligent Decision System (IDS) [40,43,44] can be applied to support IA and what are its advantages and limitations.

Generally, there are four stages in an IA process. The first two stages are concerned with the modelling process of an assessment problem, which are relatively independent of individual policy options to be assessed. The other two stages are mainly specific to individual policies. In practice, it may be necessary to go through some of the stages a number of times in order to refine the assessment model and clarify some of the uncertainties in the assessments of alternative options. The four stages are summarised as follows.

The first stage is to define and construct an assessment problem. At this stage, the following questions need to be addressed. What are the scopes of the assessment? What are the alternative options? In what areas or on which criteria the performances of the options need to be assessed?

The second stage is to establish an assessment framework or model by asking the following questions. How should the performance of each option in each area be measured? Are better performances in some areas more important than in others? If so, how to elicit the relative importance of each area or criterion? How uncertainties in assessments can be clarified and recorded for further analysis?

The third stage is data collection and handling. At this stage data from different sources are collected in order to rate the performances of each option in the concerned areas. The data may be of heterogeneous nature, and their quality may vary. Hence potential problems in this stage are how to manage data from different sources and extract quality information from the data, how to handle uncertainties in the data, and how to aggregate the data to arrive at reliable and rational assessment outcomes.

The fourth stage is the interpretation of the assessment outcomes and the following questions may be asked. Are the outcomes convincing? Have they included all aspects and taken into account all opinions of different stakeholders? Are the outcomes explainable and can they be traced back to their sources? What are the effects of any uncertainty in data and subjective judgements? How can the outcomes, the effects of any uncertainties, and their traceability be clearly presented to stakeholders?

In this chapter, it is described how IDS can support IA in each of the four stages. It is arranged as follows. In the next section, the ER approach and the IDS software are briefly outlined. The processes of using IDS to support IA in its four stages are then illustrated using examples. The features and advantages of the ER approach are discussed in the concluding remarks.

A few points should be noted while reading this chapter.

- In MCDA, attribute and criterion are often used interchangeably. It is also the case in this chapter.
- The following section on the ER approach may be skipped for readers who are not interested in the technical details of the approach. To apply the approach, the IDS software provides friendly interfaces for users to construct assessment models, record assessment data and carry out necessary calculations.

2 The ER Approach and IDS

MCDA is a branch of operational research concerned with making assessments and choices when there are several alternatives, and when each alternative has merits as well as drawbacks. Over its short history of over 30 years, along with the advancement of computer technology, many approaches have been developed to support systematic analysis of complex MCDA problems [2]. One of the major challenges in the MCDA is how to rationally handle uncertain knowledge including qualitative factors [5,31,38,39]. Without properly taking all relevant attributes or criteria into account, an assessment is incomplete and the outcome may be biased [12, 21, 22, 29, 42].

Over the past two decades, considerable research has been conducted on integrating techniques from artificial intelligence and operational research for handling uncertain information [1,3,6,45]. Along this line of research, the ER approach and IDS software are developed in response to the growing needs to develop scientific methods and tools for dealing with MCDA problems under uncertainty in a way that is rational, reliable, repeatable, and transparent. The ER approach uses concepts from several disciplines, including decision sciences in particular utility theory [14], artificial intelligence in particular the theory of evidence [26] statistical analysis and computer technology [41,

Table 1. Decision matrix

	Attribute 1	...	Attribute l	...	Attribute L
Alternative 1	$S(A_1(O_1)) = H_3$		$S(A_l(O_1))$		$S(A_L(O_1))$
...					
Alternative m	$S(A_1(O_m))$		$S(A_l(O_m))$		$S(A_m(O_L))$
...					
Alternative M	$S(A_1(O_M))$		$S(A_l(O_M))$		$S(A_M(O_L))$

Table 2. Belief decision matrix

	Attribute 1	...	Attribute l	...	Attribute L
Alternative 1	$S(A_1(O_1))$ $=\{(H_1, \beta_{l,1}), \ldots$ $(H_N, \beta_{l,N})\}$		$S(A_l(O_1))$		$S(A_L(O_1))$
...					
Alternative m	$S(A_1(O_m))$		$S(A_l(O_m))$		$S(A_m(O_L))$
...					
Alternative M	$S(A_1(O_M))$		$S(A_l(O_M))$		$S(A_M(O_L))$

42, 46]. Compared with conventional MCDA methods, in the ER approach a MCDA problem is modelled using a belief decision matrix [11, 43], of which the conventional decision matrix [9], as indicatively shown in Table 1, is a special case.

2.1 MCDA Problem Modelling Using Belief Decision Matrix

In a belief decision matrix, the performance of an assessed option on a criterion is represented by a distribution instead of a single value, as indicated in Table 2. For example, some business people believe that if UK joins the Euro, there will be less uncertainty in their business planning because the uncertainty associated with the fluctuation of exchange rates between pound sterling and the Euro is no longer an issue. However, for businesses whose customers and suppliers are either in the UK or other countries outside Euro zone, there will be no differences. If people are asked to rate the impact of UK Euro membership on "Stability for business planning", it is unlikely to get a unanimous answer. Suppose we use the following five grades to rate the impact

- H_1: Very negative
- H_2: Negative
- H_3: Neutral
- H_4: Positive
- H_5: Very positive

and 70% of the responses are Positive and 30% Neutral, then the assessment (or a piece of performance evidence) should be expressed as

$$\begin{aligned} S(A_1(O_1)) &= \{(\beta_{1,1}, H_1), (\beta_{2,1}, H_2), (\beta_{3,1}, H_3), (\beta_{4,1}, H_4), (\beta_{5,1}, H_5)\} \\ &= \{(0, H_1), (0, H_2), (0.7, H_3), (0.3, H_4), (0, H_5)\} \end{aligned} \tag{1}$$

Equation (1) is referred to as a distributed assessment or simply a distribution where O_1 denotes option 1 (UK to join the Euro), A_1 criterion 1 (Stability for business planning), and $S(A_1(O_1))$ the performance of O_1 on A_1. $0 \leq \beta_{n,1} \leq 1$ $(n = 1, \ldots, 5)$ denotes the degree of belief that the alternative O_1 is assessed on A_1 to the grade H_n. $S(A_1(O_1))$ reads that O_1 is assessed to the grade H_n to a degree of $\beta_{n,1}$ on the criterion A_1 $(n = 1, \ldots, 5)$, or the option "Joining the Euro" is assessed to be Positive on "Stability for business planning" to degree of 30% and neutral 70%.

Using decision matrix, the performance information shown in (1) needs to be approximated by a single value, such as "Positive", while in belief decision matrix, each element can be a distribution and it accepts the distributed performance information as it is without approximation.

Further more, if there is missing information in data, it can be represented by a distribution without either adding new or taking away existing information from the data. For example, suppose the responses in the above example are 25% Positive, 60% Neutral and 15% no answers given. Normally either the missing answers need to be replaced by some estimates or the responses with missing answers are discarded, including the answers to other questions. Either way, information in data may have been distorted. Using a distribution, the information in data can be maintained by expressing the assessment as

$$\begin{aligned} S(A_1(O_1)) &= \{(\beta_{1,1}, H_1), (\beta_{2,1}, H_2), (\beta_{3,1}, H_3), (\beta_{4,1}, H_4), (\beta_{5,1}, H_5)\} \\ &= \{(0, H_1), (0, H_2), (0.6, H_3), (0.25, H_4), (0, H_5)\} \end{aligned}$$

Note that in the above equation, $\sum_{n=1}^{5} \beta_{n,1} = 0.85 \leq 1$. Generally, there must be $\sum_{n=1}^{5} \beta_{n,1} \leq 1$ and if $\sum_{n=1}^{5} \beta_{n,1} < 1$, then the assessment $S(A_1(O_1))$ is considered to be incomplete. Obviously, if $\sum_{n=1}^{5} \beta_{n,1} = 1$ then the assessment is complete. In the ER framework, both complete and incomplete assessments can be accommodated [40].

More generally, if an assessment problem has L attributes A_i $(i = 1, \ldots, L)$, M options O_j $(j = 1, \ldots, M)$ and using N evaluation grades H_n $(n = 1, \ldots, N)$ to assess the options on each attribute, then a matrix can be constructed with $S(A_i(O_j))$ as its element in the ith row and jth column where $S(A_i(O_j))$ is given as follows:

$$\begin{aligned} S(A_i(O_j)) = \{(H_n, \beta_{n,i}(O_j)), \quad n = 1, \ldots, N\} \\ i = 1, \ldots, L, \quad j = 1, \ldots, M \end{aligned} \tag{2}$$

This matrix is called belief decision matrix (Table 2), in contrast to the normal decision matrix (Table 1). It should be noted that a performance on a criterion can be measured using numerical values or a set of evaluation grades. It should also be noted that different grade sets, possibly with different number of grades in them, may be used for assessing different attributes [40].

It is commonly known that different attributes may play different roles in an assessment and their importance is represented by attribute weights. Suppose ω_i is the weight of attribute A_i $(i = 1, \ldots, L)$. Because weights represent the relative importance of attributes, they can be scaled (or normalised). In the ER approach, the normalisation is such that $0 \leq \omega_i \leq 1$ and $\sum_{i=1}^{L} \omega_i = 1$.

2.2 ER Approach for Information Aggregation

Instead of aggregating average scores, the ER approach employs an evidential reasoning algorithm [40–42] developed on the basis of the evidence combination rule of the Dempster–Shafer theory [26] to aggregate belief degrees in performance distributions. The outcome of the aggregation is also a distribution, not a single score.

Without loss of generality and for illustration purpose, the ER algorithm is presented below by assuming that the performance of an alternative option is decided by its performances on two criteria A_1 and A_2. Detailed descriptions and the properties of the aggregation process can be found in [43, 44].

Suppose the performance on criterion A_1 is given by (1) and on A_2 by

$$\begin{aligned} S(A_2(O_1)) &= \{(\beta_{1,2}, H_1), (\beta_{2,2}, H_2), (\beta_{3,2}, H_3), (\beta_{4,2}, H_4), (\beta_{5,2}, H_5)\} \\ &= \{(0, H_1), (0.5, H_2), (0.5, H_3), (0, H_4), (0, H_5)\} \end{aligned} \tag{3}$$

Further suppose the normalised weights of A_1 and A_2 are $\omega_1 = 0.4$ and $\omega_2 = 0.6$ respectively. The problem is to aggregate the two assessments $S(A_1(O_1))$ and $S(A_2(O_1))$ to generate a combined assessment $S(A_1(O_1)) \oplus S(A_2(O_1))$. In the example $S(A_1(O_1))$ and $S(A_2(O_1))$ are both complete. If not, the rational handling of the unknown portion of its performances is to assume that the missing portion of the performance can be rated to any grade from H_1 to H_5. The details of the ER algorithm for the example is given below and its more generic format capable of aggregating both complete and incomplete assessments is described in [41] and [40]. Let

$$p_n = \omega_1 \beta_{n,1} \ (n = 1, \ldots, 5) \text{ and } p_H = 1 - \omega_1 \sum_{n=1}^{5} \beta_{n,1} = 1 - \omega_1 = 0.6 \tag{4}$$

$$q_n = \omega_2 \beta_{n,2} \ (n = 1, \ldots, 5) \text{ and } q_H = 1 - \omega_2 \sum_{n=1}^{5} \beta_{n,2} = 1 - \omega_2 = 0.4 \tag{5}$$

where each p_n or q_n $(n = 1, \ldots, 5)$ is referred to as basic probability mass, and p_H and q_H are the remaining probability mass unassigned to any of the grade H_n $(n = 1,\ 2,\ 3,\ 4,\ 5)$. Their values are given in the 1$^{\text{st}}$ row and 1$^{\text{st}}$ column of Table 3.

The ER algorithm is used to aggregate the basic probability masses to generate combined probability masses, denoted by r_n $(n = 1, \ldots, 5)$ and r_H using the following equations:

Table 3. Probability masses

		$S(A_1(O_1))$					
	$S(A_1(O_1))\oplus$ $S(A_2(O_1))$	$p_1 = 0$ $\{H_1\}$	$p_2 = 0$ $\{H_2\}$	$p_3 = 0.28$ $\{H_3\}$	$p_4 = 0.12$ $\{H_4\}$	$p_5 = 0$ $\{H_5\}$	$p_H = 0.6$ $\{H\}$
$S(A_2(O_1))$	$q_1 = 0$ $\{H_1\}$	$p_1q_1 = 0$ $\{H_1\}$	$p_2m_1 = 0$ $\{\Phi\}$	$p_3q_1 = 0$ $\{\Phi\}$	$p_4q_1 = 0$ $\{\Phi\}$	$p_5q_1 = 0$ $\{\Phi\}$	$p_Hq_1 = 0$ $\{H_1\}$
	$q_2 = 0.3$ $\{H_2\}$	$p_1q_2 = 0$ $\{\Phi\}$	$p_2q_2 = 0$ $\{H_2\}$	$p_3q_2 = 0.084$ $\{\Phi\}$	$p_4q_2 = 0.036$ $\{\Phi\}$	$p_5q_2 = 0$ $\{\Phi\}$	$p_Hq_2 = 0.18$ $\{H_2\}$
	$q_3 = 0.3$ $\{H_3\}$	$p_1q_3 = 0$ $\{\Phi\}$	$p_2q_3 = 0$ $\{\Phi\}$	$p_3q_3 = 0.084$ $\{H_3\}$	$p_4q_3 = 0.036$ $\{\Phi\}$	$p_5q_3 = 0$ $\{\Phi\}$	$p_Hq_3 = 0.18$ $\{H_3\}$
	$q_4 = 0$ $\{H_4\}$	$p_1q_4 = 0$ $\{\Phi\}$	$p_2q_4 = 0$ $\{\Phi\}$	$p_3q_4 = 0$ $\{\Phi\}$	$p_4q_4 = 0$ $\{H_4\}$	$p_5q_4 = 0$ $\{\Phi\}$	$p_Hq_4 = 0$ $\{H_4\}$
	$q_5 = 0$ $\{H_5\}$	$p_1q_5 = 0$ $\{\Phi\}$	$p_2q_5 = 0$ $\{\Phi\}$	$p_3q_5 = 0$ $\{\Phi\}$	$p_4q_5 = 0$ $\{\Phi\}$	$p_5q_5 = 0$ $\{H_5\}$	$p_Hq_5 = 0$ $\{H_5\}$
	$q_H = 0.4$ $\{H\}$	$p_1q_{\mathrm{H}} = 0$ $\{H_1\}$	$p_2q_{\mathrm{H}} = 0$ $\{H_2\}$	$p_3q_{\mathrm{H}} = 0.112$ $\{H_3\}$	$p_4q_{\mathrm{H}} = 0.048$ $\{H_4\}$	$p_5q_{\mathrm{H}} = 0$ $\{H_5\}$	$p_Hq_{\mathrm{H}} = 0.24$ $\{H\}$

$$r_n = k(p_nq_n + p_Hq_n + p_nq_H),\ (n = 1, \ldots, 5) \tag{6}$$

$$r_H = k(p_Hq_H) \tag{7}$$

where

$$k = \left(1 - \sum_{t=1}^{5} \sum_{\substack{n=1 \\ n \neq t}}^{5} p_tq_n\right)^{-1} \tag{8}$$

From Table 3, we have

$$k = (1 - (0.084 + 0.036 + 0.036))^{-1} = 0.844^{-1} = 1.185,$$
$$r_1 = 0,\ r_2 = k \times p_Hq_2 = 1.185 \times 0.18 = 0.213,$$
$$r_3 = k \times (p_3q_3 + p_Hq_3 + p_3q_H) = 1.185 \times (0.084 + 0.18 + 0.112) = 0.446$$
$$r_4 = k(p_4q_H) = 1.185 \times 0.048 = 0.057,\ r_H = k(p_Hq_H) = 1.185 \times 0.24 = 0.284$$

If there are more than two criteria, the combined probability masses can then be aggregated with the third assessment in the same way. The process is repeated until all assessments are aggregated. The combined probability masses are independent of the order in which individual assessments are aggregated. If there are several levels of criteria in a hierarchy, the aggregation process is carried out from the bottom level criteria one branch at a time until the top of the hierarchy is reached. The belief degrees in the aggregated performance distribution are calculated from the combined probability masses. Suppose the final combined assessment for the option O_1 is represented as follows:

$$S(O_1) = \{(H_1, \beta_1), (H_2, \beta_2), (H_3, \beta_3), (H_4, \beta_4), (H_5, \beta_5)\} \tag{9}$$

where β_n $(n = 1, \ldots, 5)$ are the combined belief degrees generated by:

$$\beta_n = \frac{r_n}{1 - r_H}(n = 1, \ldots, 5) \tag{10}$$

For the example, we have $\beta_1 = 0$, $\beta_2 = \frac{r_2}{1-r_H} = \frac{0.213}{1-0.284} = 0.297$, $\beta_3 = 0.623$, $\beta_4 = 0.080$, and $\beta_5 = 0$.

2.3 Expected Utility Scores

If necessary a score can be calculated from the distribution. Before the calculation, a utility value needs to be assigned to each grade to represent the preference of policy makers towards the grade [14]. For example, suppose the utilities for the five grades in (1) are as follows:

$$u(H_1) = 0,\ u(H_2) = 0.25,\ u(H_3) = 0.5,\ u(H_4) = 0.75,\ \text{and}\ u(H_5) = 1$$

An expected utility score for O_1, denoted by $u(O_1)$, can be calculated as follows with the belief degrees as weights,

$$u(O_1) = \sum_{i=1}^{5} u(H_i)\beta_i = 0.45 \tag{11}$$

It should be noted that the ER aggregation is in essence a statistical and non-linear approach, which reinforces harmonic judgements and weaken conflict ones [44].

2.4 Applying the ER Approach through IDS

As we can see from the example, ER approach involves handling data in a structured way and without computer support it is difficult to be applied manually. To facilitate its easy application, IDS[1] is developed to transform the model building and result analysis processes into an easy window-based click and design activity. It aims to provide not only technical supports in data processing including data collection, storing, retrieving and presentation, but also cognitive supports in problem structuring and assessment process. The rest of the chapter is devoted to demonstrating the application of IDS in each of the four stages of an IA process.

3 IDS and Its Applications in Impact Assessment Support

IDS is a Windows based software tool based on the ER approach. During the past few years, it has been applied to support assessment activities in different areas. Example of such applications include supplier assessment in

[1] A free demo version of IDS can be obtained from Prof J B Yang via email: jian-bo.yang@mbs.ac.uk or www.e-ids.co.uk

procurement [28,37], market performance assessment and consumer preference identification in new product design [7], business performance assessment and organisational self-assessment in total quality management [8, 19, 27, 35], customer satisfaction survey [37] in customer relationship management, impact assessment in policy making [33, 34], and risk assessment in engineering design [15]. The results show that the ER approach, supported by IDS, has significantly helped to improve consistency, transparency and objectivity in the assessments.

In the following discussion, the impact assessment of UK Euro membership is used as an example to illustrate the application of the IDS in each of the four stages of an IA as outlined in Sect. 1, namely problem structuring, establishing an assessment model, data collection and handling, and interpretation of outcomes.

3.1 Problem Structuring

In the problem structuring phase, stakeholders, an initial set of alternatives, key issues, constraints, and uncertainties need to be identified.

There are many qualitative frameworks for problem structuring. Many soft operational research techniques can be used. The value focused thinking [13] is also an excellent and well accepted approach for generating new alternatives creatively. Post-It is often used for capturing and organising ideas. Belton and Stewart [2] provide a comprehensive summary on approaches for problem structuring. The CAUSE framework is one of them. The acronym CAUSE stands for

- C – identifying Criteria. Criteria should be measurable and understandable, cover all aspects of concern to decision makers, and should not have redundancy
- A – identifying Alternatives
- U – identifying Uncertainties
- S – identifying Stakeholders
- E – identifying Environmental factors and constraints

In the UK Euro membership problem, there are two natural alternatives: either join or not join. It is important that opinions from both pro- and anti-Euro sides are taken into account so that a balanced assessment can be made. A quick search of the Internet can lead to many sites discussing the gains and losses of UK joining the Euro in various aspects. Those aspects form the basic sets of assessment criteria for the problem.

Generally, in an assessment problem, alternative options are assessed by many criteria and sub criteria. If the sub criteria are still too general and abstract to be measured, they should be broken down further until they are measurable. The process leads to the formation of a criterion hierarchy. IDS provides user friendly interfaces to document the alternatives and construct the criterion hierarchy.

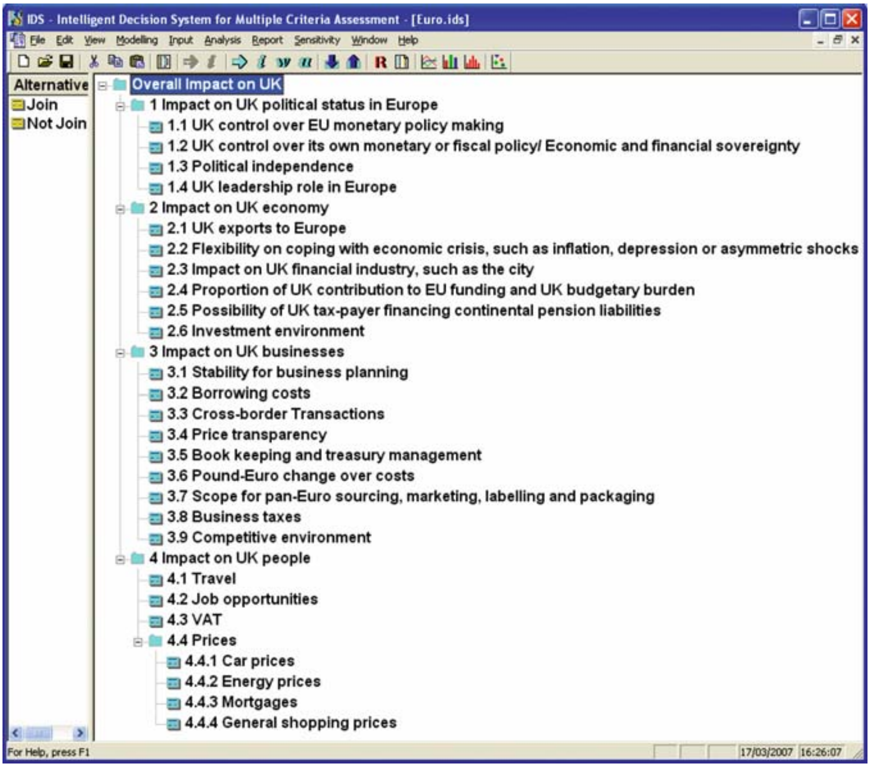

Fig. 1. Support of problem structuring: assessing UK Euro membership

In its main window (Fig. 1), there are two panes, the left is for listing the alternative options (or simply alternatives), and the right for listing a criterion hierarchy. New alternatives can be added by clicking on the left pane once and then the yellow arrow button  on the Toolbar of the main window. The alternatives can be renamed, and described with more details if necessary by right clicking on it once. New criteria can be added at any position by clicking at the desired position and then the blue arrow button  (Fig. 1). The newly added criteria can also be renamed and defined with more details. For example, from searching the Internet, the impacts of UK Euro membership are mainly on the following four areas: Political, Economy, Business and People. Under each category, there are more detailed sub areas which are treated as sub criteria and the criterion hierarchy can be built using the IDS as shown in Fig. 1. IDS also provides the facility to delete, copy and paste criteria and alternatives if necessary.

3.2 Assessment Model Building

Having identified the options and the assessment criteria, and implemented the criterion hierarchy in IDS, in the second phase, we need to address the following three issues and build the assessment model accordingly; (a) how the performance of each option can be measured on each criterion, (b) what weights should be assigned to each criterion so that its relative importance can be represented and (c), what is the preference or risk attitude of policy makers towards each assessment grade or value in the measurement scale of each criterion. Those three elements together with the criterion hierarchy built earlier constitute an assessment model which is used for assessing all the policy options in an IA problem. The three issues are discussed in turn in the following sub-sections.

Assessment Criterion Definition

Issue (i) is concerned with how performances can be measured on each criterion. The simplest cases are when the performance of each option can be measured numerically on a criterion without uncertainty, such as the pound and euro changeover costs if it can be estimated more or less accurately. It is more complicated for other cases. If qualitative judgements are unavoidable, there is an issue of how to reduce subjectivity and increase consistency in the assessment. If the performances are associated with certain random factors, the issue is then how to clarify and represent the uncertainty in the model so that the risks associated with the uncertainty can be revealed and examined.

On qualitative criteria, the performance of each option is commonly assessed by grades. For example, the impact of UK Euro membership in many areas can only be measured qualitatively and a frequently used set of measurement grades are:

- Very negative
- Negative
- Neutral
- Positive
- Very positive

One problem with qualitative grades is that the meaning of a grade may mean different standards for different people. To reduce subjectivity, it is also a common practice to clearly define the standards of all grades.

For a quantitative criterion with probability uncertainty, traditionally the expected or mean value is used to represent the performance of an option on the criterion. This, however, introduces information losses. Ideally the probability distribution of a performance should be preserved and the associated risks be explicitly explored in an assessment process.

The IDS software is designed with a focus on supporting the model building process of IA problems with both qualitative and quantitative criteria

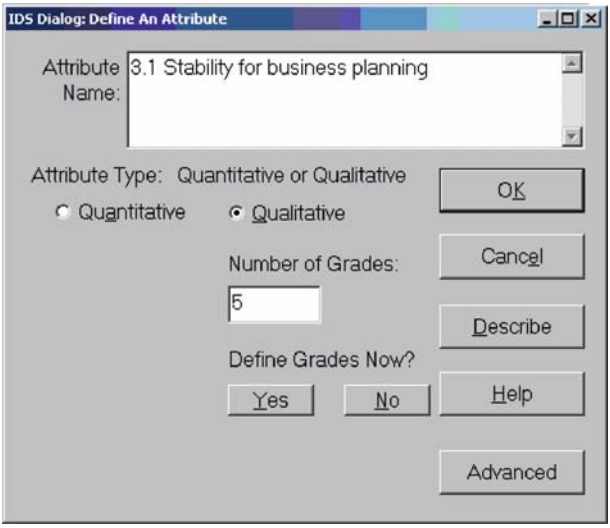

Fig. 2. Define qualitative criteria

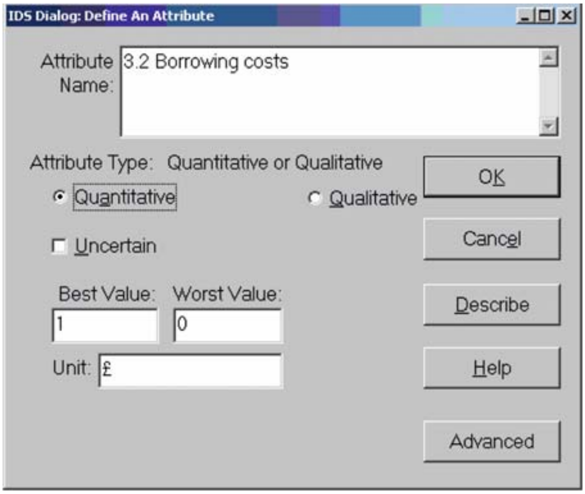

Fig. 3. Define quantitative criteria

under various types of uncertainties. It starts by prompting users to classify a criterion into one of the three logical categories: qualitative, quantitative (without uncertainty) and quantitative with uncertainty (Figs. 2 and 3).

For a qualitative criterion, further interfaces are provided for users to define assessment grades, their corresponding standards and utilities (Figs. 4, 5 and 8). Late on, at the data collection and handling stage, when the performance of an alternative on this very criterion is assessed and rated, the

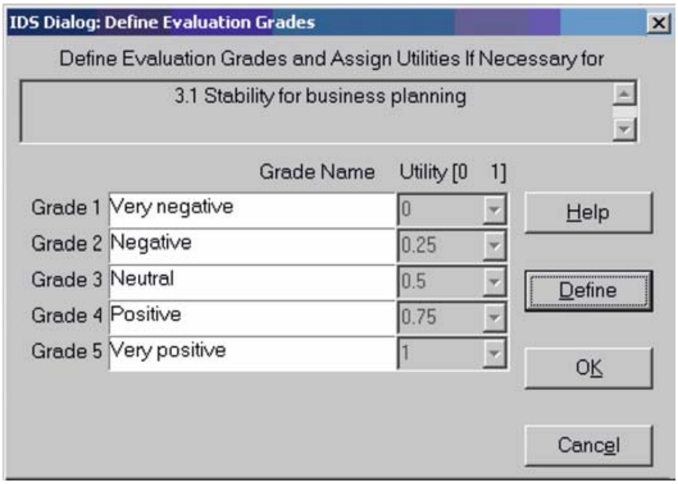

Fig. 4. Define assessment grades

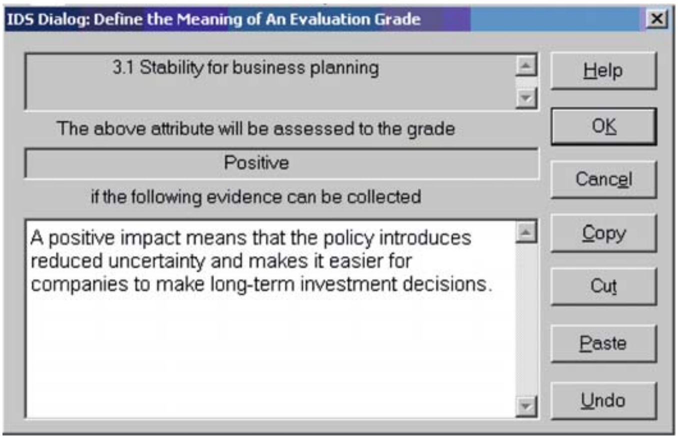

Fig. 5. Define assessment grade standards

grading standards defined here will be conveniently accessible so that users can make a reference to it to ensure the consistency of the assessment.

For a quantitative criterion without uncertainty, IDS prompts users to identify the performance variation range of alternative options on it (Fig. 3), and the preferences of policy makers towards the different performances. If the performance of any alternative on the criterion is anticipated to be a probability distribution, then the "Uncertain" box (Fig. 3) should be checked and later in the data collection stage users will have the flexibility to record the performance of an alternative on the criterion using a distribution.

Relative Importance of Criteria and Weight Elicitation

Issue (ii) is concerned with the role each criterion can play in an assessment or its weight assignment. The assignment process involves significant subjective judgements and need to be supported in order to get a satisfactory set of weights.

In IDS, there are a couple of interfaces dedicated to support criterion weight elicitation. The first one is the visual assignment window (Fig. 6). From this window, a number of methods can be used for eliciting and recording the weights through an interactive graph. One is the direct assignment method [20] and is used when policy makers have more or less decided what weight to give to each criterion. The second one is the SMART (Simple Multi-Attribute Rating Technique) [30] method, which assigns 10 points to the least important criterion and more than 10 to the second least important criterion and so on. The third one is the SWING method [30], which is somehow opposite to SMART. It gives 100 points to the most important criterion and less than 100 points to other criteria. To apply any of the three methods in IDS, users need only to drag and drop each bar in the interactive graph to an appropriate height.

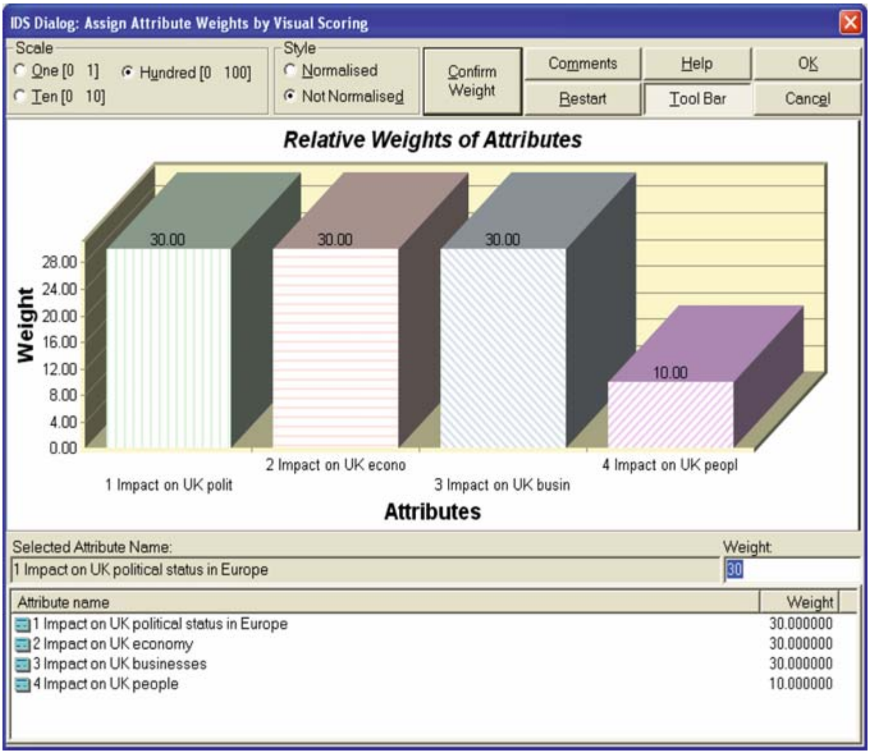

Fig. 6. Weight assignment by interactive graph

The second interface is for supporting weight assignments using paired comparison. It considers only two criteria at a time. This is a frequently used method due to the simplicity of the idea, even though the derived process is quite tedious. From the interface, the comparisons can be carried out between either all possible pair combinations, or one criterion and each of the others ($n-1$ pairs if the number of criteria in consideration is n) [22, 24]. Once the comparisons are finished, the set of weights best fit the comparisons is then calculated and any inconsistency noted by IDS.

When there are multiple stakeholders, and a consensus set of weights can not be achieved, average weights or weight intervals given by members may be used. The intervals of weights can then be used to guide the sensitivity analyses in the next phase for weight fine-tuning (Fig. 7).

Elicitation of Preference of Policy Makers

Issue (iii) is concerned with the preference or risk attitude measurement of policy makers towards the performances of an alternative on each criterion. The measurement is accomplished by using a common scale, normally between 0 and 1 with 0 corresponding to the least and 1 the most preferred levels of a performance respectively. Such a common scale is referred to as utility function in decision theory [14]. For example, the impact of UK's Euro membership on

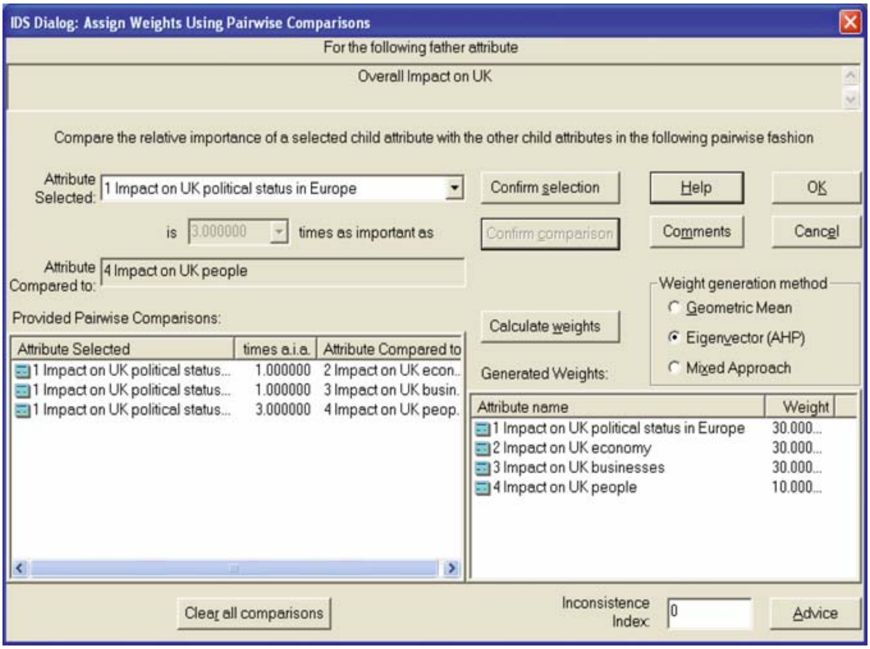

Fig. 7. Weight assignment by pairwise comparison

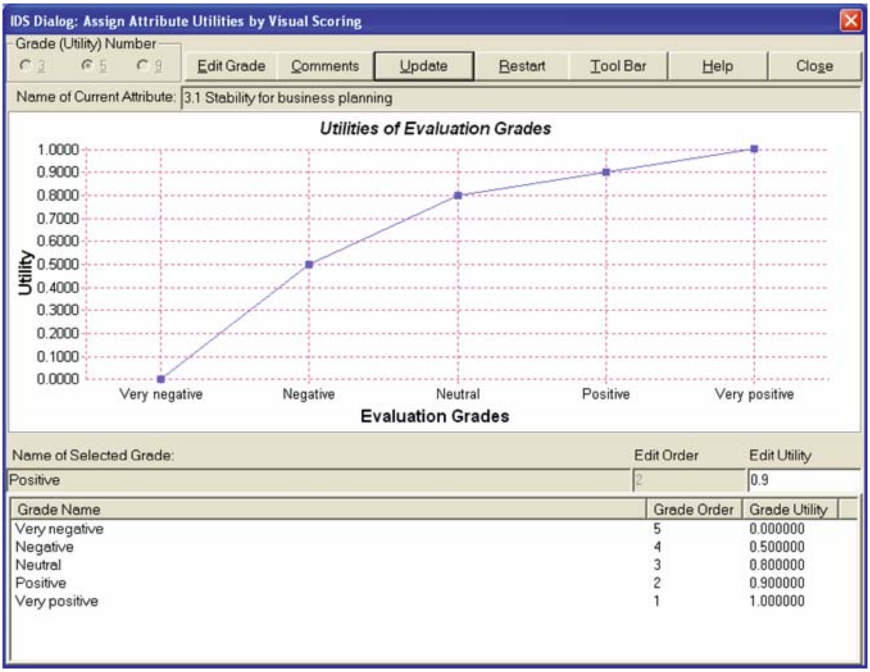

Fig. 8. Interfaces for defining utility functions

Stability for Business Planning is measured by the following 5 grades: Very Negative, Negative, Neutral, Positive and Very Positive. If the policy makers assign utility of 0, 0.5, 0.8, 0.9 and 1 to each of the five grades respectively, the utility function for this criterion may look like the curve shown in Fig. 8. If the policy makers wish to assign different utilities to the grades, it is supported in the IDS by an interactive interface (Fig. 8) where users can drag and drop the points on the curve to a desired position.

As indicated by (11), from utility functions and the performance distributions of alternative options, scores can be calculated and ranking can be generated based on the scores. Therefore one of the purposes of utility functions is to facilitate the comparability of alternatives on each criterion at any level of the hierarchy. Through the use of utility functions, alternative options can be assessed on each criterion using its own most appropriate scale first and then the assessments are transformed to the common scale. IDS has such information transformation procedures [40] built-in to ensure that, although different assessment grades are used, policy makers' preferences are equivalently preserved in the transformation processes and properly presented in the aggregated outcomes.

3.3 Data Collection and Data Handling

Having established and implemented an assessment model using the IDS software, our attention can now turn to assessing individual policies. To assess the impact of a policy in each area (or on each criterion), data need to be collected from different sources, including looking at historical data and seeking expert opinions on the potential costs and benefits, tangible or intangible, of implementing and enforcing a policy. There are inevitably uncertainties in the estimates and judgements. IDS provides a number of interfaces to support data collection and input processes. The aim of the supports are to help improve consistency in judgements, clarify and reduce uncertainties in assessments, and manage the data colleted.

There are three different interfaces for data input in IDS, each for one of the three types of criteria as discussed in Sect. 3.2: quantitative (without uncertainty), quantitative with uncertainty, and qualitative.

Entering assessment data on quantitative type of criteria is straightforward therefore it is not discussed further. If there is uncertainty in quantitative assessments, they can normally be represented as probability distributions. For example, suppose the "Pound-Euro changeover costs" if UK adopts the Euro are estimated to be 3, 3.5 and 4 billion pounds sterling with probability of 30, 50 and 20% respectively. IDS then provides both interfaces to accept the information as it is and an algorithm to properly aggregate the information in the data so that the effects associated with the uncertainties can be revealed in the outcomes.

For qualitative type of criteria, the support to reduce subjectivity in assessments is from two fronts. One is the provision of an evidence mapping interface (Fig. 9). It displays the assessment standards, as defined earlier in the assessment framework (Fig. 5), and the related evidence and judgements, collected and entered by users at the current stage, side by side so that the comparison of a performance against the standards are made easier. In this way the assessments made by different assessors are geared to follow the same standards and improved consistency can be achieved. On the second front, if a performance matches a mixed grade standards, users have the flexibility to assign portions of the performance to a number of grades using belief degrees as discussed in Sect. 2.1 (Fig. 10). In this way, the assessment can be made more objective and accurate.

The supports from IDS also include the structured recording of the assessment knowledge and performance evidences for traceability and future references. From the data and the recorded knowledge, an assessment report for each policy option can be generated automatically. This can further save time, and improve accuracy and efficiency in report preparation.

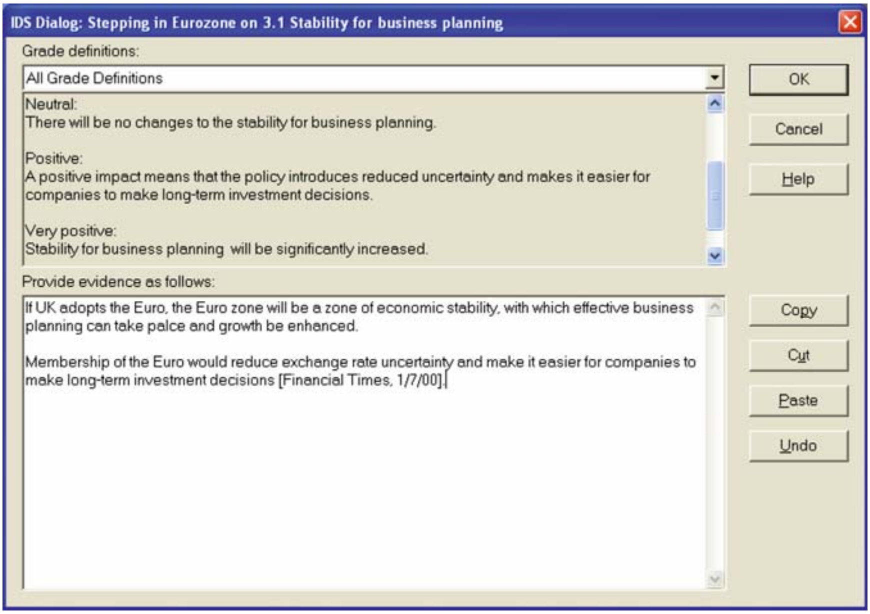

Fig. 9. Making qualitative assessment through evidence mapping

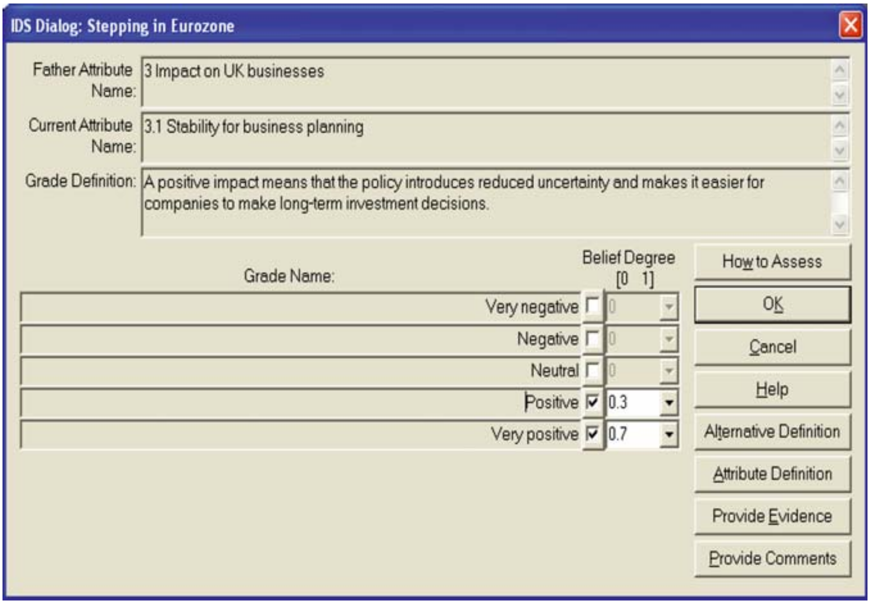

Fig. 10. Making qualitative assessment using belief degrees

3.4 Outcome Interpretation and Sensitivity Analysis

Outcomes and Interpretations

IDS generates different assessment results in both numerical and textual formats. To help the interpretation and the communication of the results, numerical ones are normally presented using graphs, including overall assessment scores of policy options, the potential performance variation ranges when there is missing information in an assessment (Fig. 11), and performance distributions (Fig. 12). Those graphs enable the comparisons among alternative policy options and are available on any selected areas at different levels of the assessment criteria hierarchy.

Ranking is based on overall assessment scores, a weighted sum of utilities of the grades in the aggregated performance distribution of each option, with belief degrees as weights as calculated by (11). The dark grey area in the ranking score graph (Fig. 11) indicates that there is some missing information in the assessment of the option "Not Join" and its performance score can be as high or low as the value marked by the top or bottom of the dark grey area respectively. The height of the dark grey area indicates the combined effect of the missing information. In the example shown in Fig. 11, the effect is small and will not affect the ranking no matter whether the missing information turns out to be in favour of the option or not.

Figure 12 shows the distributed overall performance of the two options regarding the UK Euro membership, based on the information collected in a

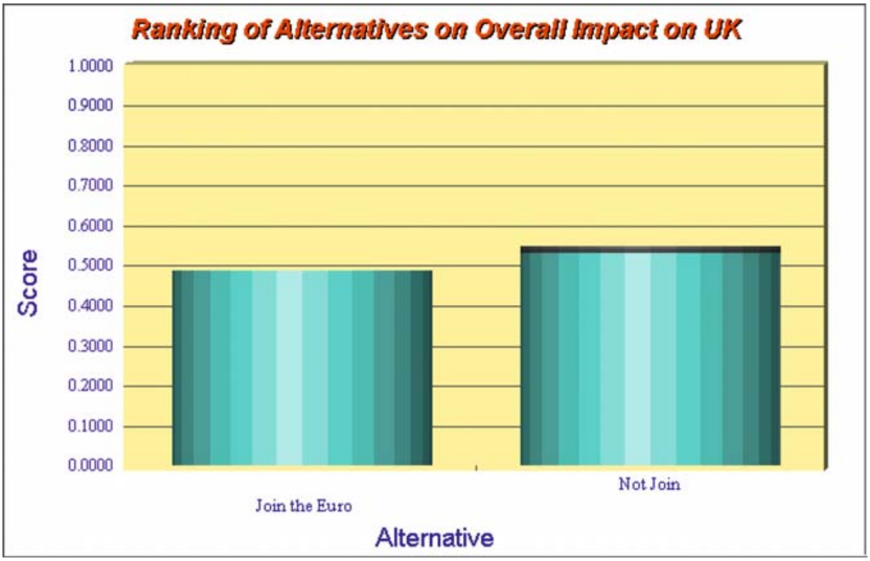

Fig. 11. Ranking of alternatives and performance variations due to uncertainty

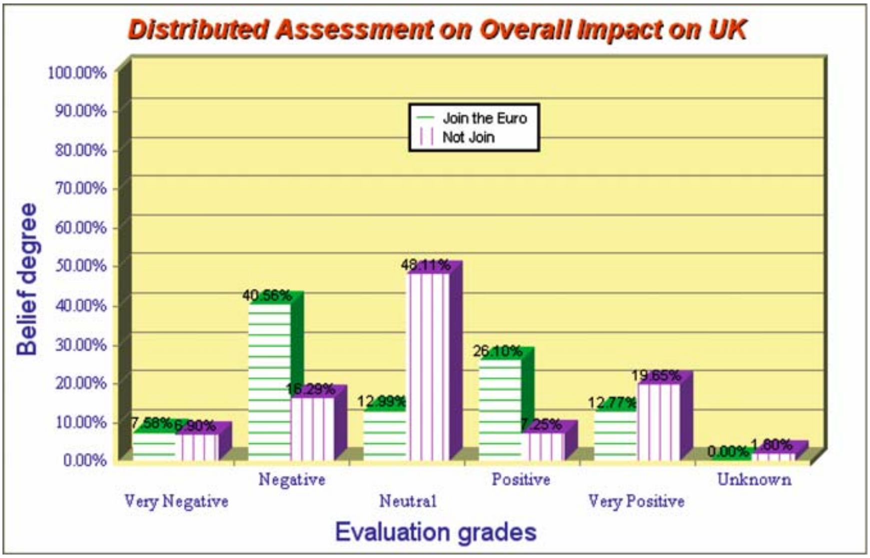

Fig. 12. Performance distributions

study. It reveals the performance composition in different categories (grades), and sheds light on why one option may be better than the other. Note that the portion of missing information is also revealed as a percentage in the Unknown category. The distribution shows that there are both negative and positive impacts if UK joins the Euro, and mostly neutral impacts if not. Such information allows policy makers to make an informed selection. If it is desirable to find the best or worst performing areas for an option, IDS provides a searching function for the purpose so that policy makers knows where exactly the risks are if going for the option.

To improve transparency in policy making processes, those graphical outcomes are available at not only the overall level represented by the top criterion, but also any level in the criteria hierarchy. Performances of all or selected options can also be compare on a selected set of criteria across different levels of the hierarchy.

To save time in assessment report preparation, IDS generates a tailor made assessment report for each option based on the evidence recorded and the assessment model, highlighting key areas to consider for each option. The assessment model, including assessment criteria, assessment grades and grading standards, and assessment results on every attribute, can all be saved in text files. The text files provide a basis with accurate and essential information for generating a detailed report. Together with a range of graphical display of outcomes, the report should help to communicate the assessment outcomes effectively.

Sensitivity Analysis

Sensitivity analysis is regarded as one of the very important step in any decision analysis process. It examines the effects of changes in some of the assumptions and judgements made during assessment processes, including parameters such as attribute weights, shapes of utility curves, and belief degrees assigned to the grades in an assessment. As those judgements and assumptions are somehow subjective in nature and difficult to be precise, sensitivity analysis will help to reveal how robust the outcomes, such as rankings of alternative options, are and therefore help decision makers to understand any risks involved in taking a particular course of action.

There are a range of sensitivity analysis functions supported by IDS which allow most parameters to be changed and the effects displayed. Three typical graphical sensitivity analysis interfaces are briefly described below.

The first type is interactive charts displaying the effects of changes in criterion weights and belief degrees assigned to a performance. For example Fig. 13 is a graph for examining the ranking changes of the 2 policy options in the Euro problem (join or not join the Euro) when the weight for the criterion "Impact on UK Business" changes. The current weight is 30 and the option "Not Join" is ranked higher than "Join". However, the graph shows that the ranking order will change if the weight becomes 40 or larger. If any weight is around a sensitive zone, the graph helps to draw the attention of policy

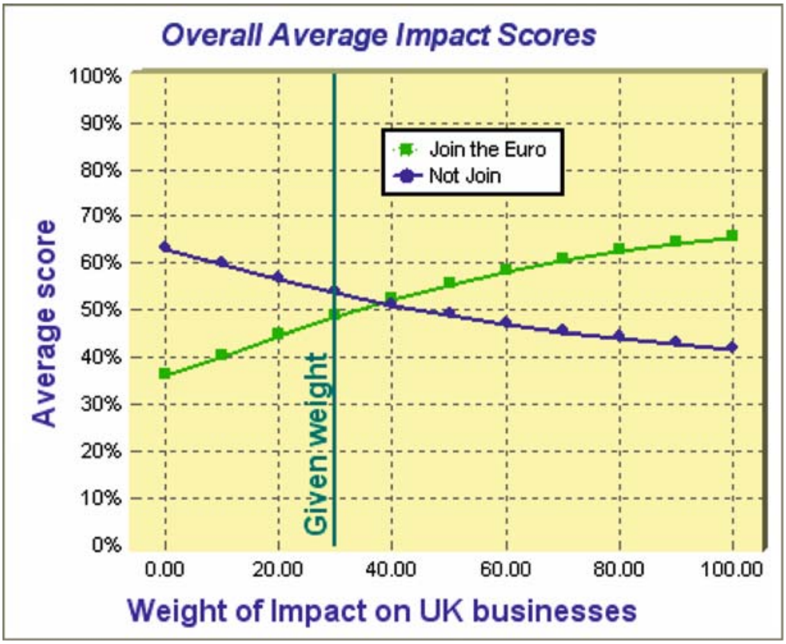

Fig. 13. Performance distributions

makers to the weight which may need to be re-examined and elicited using a number of approaches.

The second type of graphs shows the combined effects of different parameter changes on outcomes. This type of sensitivity analysis is normally referred to as global sensitivity analysis in literature [23, 36]. For example, Fig. 11 is one of such graphs displaying the combined effect of missing information in the assessments of "Not Join" on a number of criteria. Capable of providing global sensitivity information is a unique feature of IDS while most tools allow only one parameter to be changed at a time during sensitivity analyses.

The third type is the so called cost benefit or trade-off analysis graphs. It displays the scores of all alternative options on only two criteria at a time. For example, if the two criteria are "Costs" and "Benefits", as shown in Fig. 14, the two policy options in the Euro problem can then be positioned in the graph according to their performances on the two criteria. This type of graph allows users to exam whether the potential benefits of joining the Euro are worth the costs.

Model Fine Tuning

Impact assessment problems are complicated and it is unlikely to establish satisfactory models for the problems straight away. It is expected that the modelling phases need to be revisited from a number of times to make some adjustments on parameters such as weights after sensitivity analysis. It may also be necessary to check if there are any missing factors that need to be taken into account, or redundant attributes that need to be deleted. At the same time, the policy makers may need to challenge their own intuitions and rethink the problem and their preferences. Therefore the four phases of the

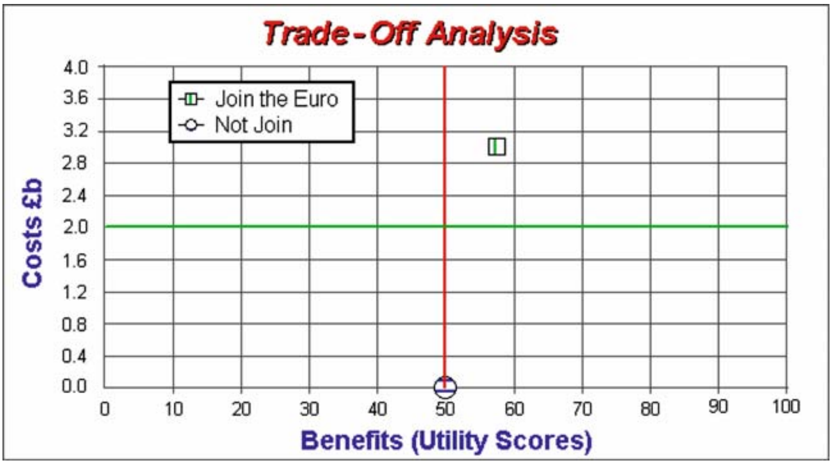

Fig. 14. Cost benefits analysis

MCDA process may need to be repeated until the policy makers are relatively satisfied with the model. The resulted model is termed as requisite, instead of optimal by [18]. This process is incisively summarised by French [9, p. 110].

"The decision makers begin the analysis ill at ease, discomforted by some half-perceived choice before them. As the analysis proceeds, their perceptions, beliefs and preferences evolve, guided by the consistency inherent in the underlying theory. Initially, the models used are very simple. But, gradually as intuitions emerge, the models are refined. A cyclic process is followed in which models are built, the output reflected upon and examined for sensitivity, intuitions emerge leading to revision of the models, and so on. This process is stopped when no further intuitions emerge."

4 Concluding Remarks

Policy making is a complicated process involving dealing with heterogeneous types of data with uncertain and missing information. As such, it needs to be supported with appropriate methodologies and tools. The ER approach and its software implementation, the IDS tool, are purposefully developed for dealing with such complication in IA assessment problems. Through a wide range of applications in supporting many complicated assessment activities, it is demonstrated that IDS is a flexible tool capable of handling data with uncertainties and providing more transparent, informative and reliable outcomes.

The capabilities of the ER approach are achieved through the use of a belief decision matrix to model an assessment problem. The use of belief decision matrix provides the following four advantages.

1. It helps maintain the originality of information in data. Using a conventional decision matrix, the distributed performance information, such as the one shown in (1) has to be approximated by a single value or grade which inevitably introduces information losses or distortion. Therefore the assessment of an option can be more reliably and realistically represented by a belief decision matrix than by a conventional decision matrix.
2. It provides policy makers with flexibility to collect and document assessment information in formats that are appropriate to certain circumstances, such as in single numerical values, probability distribution or subjective judgements with belief degrees. Consequently, it helps strengthen both the confidence and commitment levels of policy stakeholders in their chosen courses of action.
3. It allows all available information embedded in different data formats, including qualitative and incomplete data, to be maximally incorporated in the assessment processes, which again leads to more reliable outcomes.
4. It allows the assessment outcomes to be presented more informatively, which helps the effective communication of the outcomes.

The IDS software is developed to facilitate the application of the ER approach and realise its potential. It provides not only the technical support to apply the ER approach through friendly interfaces, but also cognitive support in the assessment process, and knowledge management, report generation and data presentation facilities. Encouraged and requested by users of IDS, a web based version of the tool has also been developed [33] and the UK Euro membership assessment example is made available online, which is accessible from the web site www.e-ids.co.uk.

The main limitation of the ER approach may be that people who are used to using conventional decision matrices for modelling MCDA problems may find that using belief decision matrices may look complicated, in particular for modelling purely quantitative MCDA problems. With the support of the IDS software and the power of modern computers, the complication associated with data processing is less a concern. To conclude this chapter, it may be noted that modelling an assessment problem using a conventional decision matrix is the same as using a belief decision matrix if all belief degrees in the latter are either 0 or 1.

Acknowledgement

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Fuzzy Decision Trees as Intelligent Decision Support Systems for Fault Diagnosis

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Summary. In the present work, an intelligent decision support system is proposed to assist the operators in fault diagnosis tasks. The underlying approach relies on a systematic procedure to manipulate measured data of the monitored variables for constructing transparent fuzzy if-then rules associating different patterns of evolution to different faults and anomalies. The resulting fuzzy classification model can then be represented in the form of a Fuzzy Decision Tree. A case study regarding the classification of simulated faults in the feedwater system of a Boiling Water Reactor is presented.

1 Introduction

A fundamental task of fault diagnosis consists in the identification of the occurred fault on the basis of monitored signals representative of the system behavior. Control Room operators are alerted by any meaningful departure of the monitored signals from their steady state and then required to identify the associated fault causes, based on the different patterns of evolution thereby developing. Assisting the operators in this complex diagnostic task has the potential to significantly increase the availability, reliability and safety of the systems and plants, by avoidance of errors that lead to trips or that endanger safety. This is of paramount importance in major hazard plants, such as the nuclear power plants, where the large number of process parameters and the complexity of the system interactions pose great difficulties to the human operators of the control room, especially during abnormal operation and emergency when stress and emotional states come into play [1].

In recent years, many efforts have been devoted to the development of automatic diagnostic techniques for the support of the control room operators in the diagnostic tasks. In particular, techniques based on statistical or geometric methods, neural networks, expert systems, fuzzy and neuro-fuzzy approaches have proven very effective, although often remain "black boxes" as to the interpretation of the physical relationships underpinning the fault classification [2–5].

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In this work, a systematic approach to fault classification is propounded. To obtain the classification model, available pre-classified, labeled data are first fuzzy-clustered using the algorithm proposed in [6]; then, the procedure presented by the authors in [7] is applied to the fuzzy clusters found in order to derive the Fuzzy Sets (FSs) and the Fuzzy Rule Base (FRB) underpinning the classification model.

Once the classification model has been built and its fuzzy rules explicited, every FS in the Universes of Discourse (UODs) of the monitored signals is associated to a symptom of the fault and the FRB of the model is translated into a Symptom Table in which the relationships between faults and symptoms are explicitly laid out [8]. During operation, when some symptoms are detected it is usually difficult to attribute them to a given fault type, given that one fault may cause several symptoms and thus a symptom may describe more than one possible fault. To solve this problem, the relationships between faults and symptoms contained in the FRB are systematically represented in a Fuzzy Decision Tree (FDT). The occurrence of a symptom is measured by the degree of Membership Function (MF) of the associated FS: the degrees of activation of the symptoms are propagated through the FDT to obtain the fuzzy classification of the transient patterns in the different fault classes [8].

The design of the FDT entails the successive consideration of the symptoms. These can be considered in different orders, leading to different structures of the FDT and thus different classification performances. Hence, a combinatorial optimization problem arises with regards to the FDT design: a single-objective genetic algorithm search is devised to find the sequence of symptoms leading to the optimal configuration of the FDT, i.e. that which achieves the maximum classification performance.

The main advantages of the proposed approach are the transparency of the resulting classification model and its visualization to the operator in the form of a Decision Tree (DT).

The Chapter is organized as follows. In Sect. 2, the basic concepts underpinning the fuzzy reasoning are introduced for completeness. Section 3 sketches the steps of the procedure for obtaining a transparent FRB. In Sect. 4, the methodology for constructing the FDT is presented. Section 5 presents a genetic algorithm-based method for optimizing the FDT design. Section 6 reports the case study regarding the classification of faults in a section of the feedwater system of a nuclear Boiling Water Reactor (BWR) [9].

2 Fuzzy Rules for Classification

The classifier proposed in this work is based on a set of fuzzy if-then rules inferred from available data. In this Section, a short description of fuzzy reasoning is provided [10,11]: the content is limited to the general basic concepts, terminologies and notation necessary for completeness and self-consistency of the paper.

The two key elements of fuzzy reasoning are the FRB and the fuzzy inference engine. The former consists of a set of R if-then rules. The generic jth fuzzy rule, $j = 1, \ldots, R$, is made up of a number of *antecedent* and *consequent* linguistic statements, suitably related by fuzzy *connections*:

$$R_j:\ if\ \ (x_1\ is\ X_{1j})\ and \ldots\ and\ \ (x_n\ is\ X_{nj}) \\ then\ \ (y_1\ is\ Y_{1j})\ and \ldots\ and\ \ (y_m\ is\ Y_{mj}) \tag{1}$$

The linguistic variables $x_p,\ p = 1, \ldots, n$, are the antecedents, represented in terms of the FSs X_{pj} of the UOD U_{x_p}, with MFs $\mu_{X_{pj}}(x_p)$. The linguistic variables $y_q,\ q = 1, \ldots, m$, are the consequents, represented by the FSs Y_{qj} of the UOD U_{y_q}, with MFs $\mu_{Y_{qj}}(y_q)$. The connective operator *and* links two fuzzy concepts and it is generally implemented by means of a *t-norm*, typically the minimum operator or the algebraic product. The rules of the FRB are joined by the connective *else* and are generally implemented by means of an *s-norm*, typically the maximum operator [10].

The fuzzy inference engine receives the (linguistic) variables which constitute the Fact, viz.,

$$Fact : x_1\ is\ X'_1\ and\ \ldots\ and\ x_n\ is\ X'_n \tag{2}$$

where X'_p is a FS on the UOD U_{x_p} of the pth linguistic input variable x_p, and compares it with the antecedents of the rules in the FRB to arrive at the Conclusion, viz.,

$$Conclusion:\ \ y_1\ is\ Y'_1\ and\ \ldots\ and\ y_m\ is\ Y'_m \tag{3}$$

where Y'_q is a FS on the UOD U_{y_q} of the qth output variable y_q.

In the case of fault classification, the antecedents are the monitored variables. A discrete output variable $y_q,\ q = 1, \ldots, c$, is assigned to each fault class to be distinguished [12, 13]. Each output variable is described by two linguistic labels $\{YES, NO\}$, with corresponding singletons FSs Y_q^{NO} and Y_q^{YES} (Fig. 1). In the consequent part of a fuzzy rule representing the jth class, all the output variables $y_q,\ q \neq j$, appear labeled with the FS Y_q^{NO}, except the jth output variable y_j, representing the jth class, which is labeled with Y_q^{YES}:

$$if\ \ (x_1\ is\ X_{1j})\ and\ \ldots\ and\ (x_n\ is\ X_{nj})\ then \\ \left(y_1\ is\ Y_1^{NO}\right)\ and\ \ldots\ \left(y_j\ is\ Y_j^{YES}\right)\ \ldots\ and\ \left(y_c\ is\ Y_c^{NO}\right) \tag{4}$$

This form of the consequents has been chosen because it allows an easier handling of multiple faults [12].

The assignment of an incoming pattern of signals to a class is realized as follows: the fuzzy inference engine (1) receives as Fact the n values of the monitored variables, possibly fuzzyfied to account for measurement imprecision, (2) computes the 'strength' with which each of the R rules in the FRB

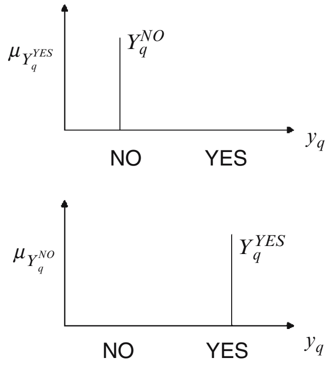


Fig. 1. The two singletons FSs Y_q^{NO} and Y_q^{YES} associated to the qth output variable

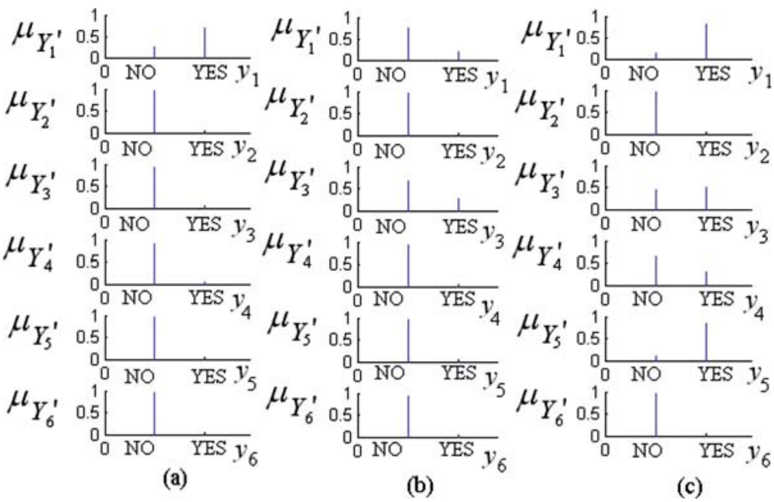


Fig. 2. Example of a classification of a pattern to class 1 (**a**), as atypical (**b**), as ambiguous (**c**)

is activated by the incoming input Fact and (3) properly combines the consequents of the rules, weighed by their respective strengths, to determine the output memberships to the different fault classes [10, 11].

The final assignment of an incoming pattern of signals to a class is conservatively realized as follows: the pattern is assigned to all the classes whose corresponding output y_q, $q = 1, \ldots, c$, has the FS Y_q' with membership value to the linguistic label $\{YES\}$ larger than a threshold γ (chosen equal to 0.6 in the applications which follow). If none of the membership grades to the label $\{YES\}$ is larger than γ, then the pattern is labeled 'atypical'. If more than one membership grade is larger than γ, then the pattern is labeled 'ambiguous'.

Figure 2 shows an example of classification of a pattern to class 1 (a), as atypical (b), and as ambiguous (c).

3 Building a Transparent Fuzzy Rule Base for the Classifier

For ease of presentation, let us consider the four-dimensional artificial classification problem of Fig. 3. The relative data comprise six classes of patterns obtained by random sampling from six different Gaussian distributions and can be assumed to represent the system response signals resulting from six different types of faults to be classified.

For the development of the classification model, a set of N, n-dimensional patterns $\vec{x}_k,\ k = 1,\ldots,N$, pre-classified to c a priori known classes, is assumed available. This information is used to find c geometric clusters as close as possible to the a priori known physical classes, accordingly to the fuzzy clustering algorithm detailed in [13]. The c identified clusters are FSs in the n-dimensional space of the monitored variables, each FS being associated to a different class.

Then, a transparent FRB is constructed from these multidimensional FSs according to the following 3 steps:

1. P*rojection of the n-dimensional fuzzy clusters into n mono-dimensional FSs.* According to the clustering classification algorithm presented in [14], the n-dimensional training patterns $\vec{x}_k,\ k = 1,\ldots,N$ are classified into the c classes with given memberships $\mu_i(\vec{x}_k),\ i = 1,\ldots,c$. This produces c clusters represented by an equal number of n-dimensional FSs, each of which can be projected onto the input variables as follows [15]:

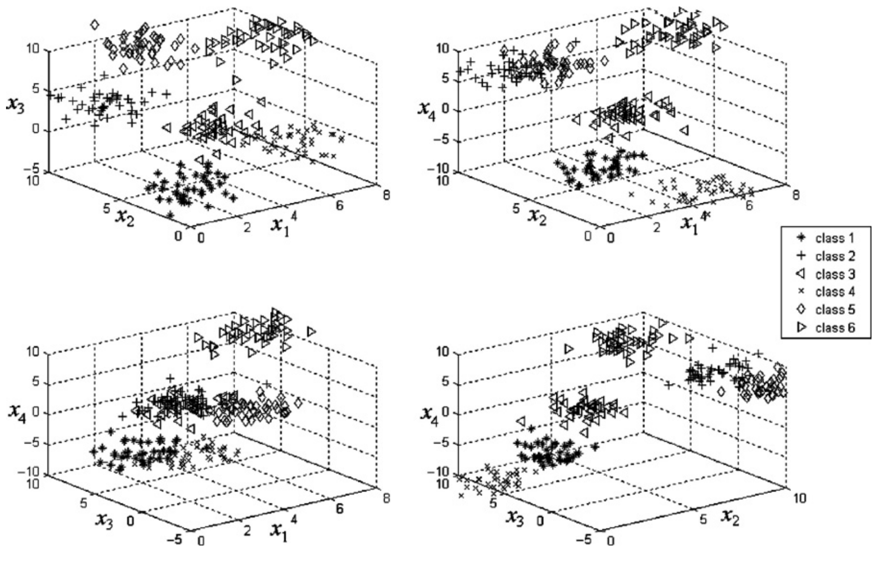


Fig. 3. Four dimensional data set comprised of six classes (for visual clarity, only 240 data out of the 2,400 available have been plotted)

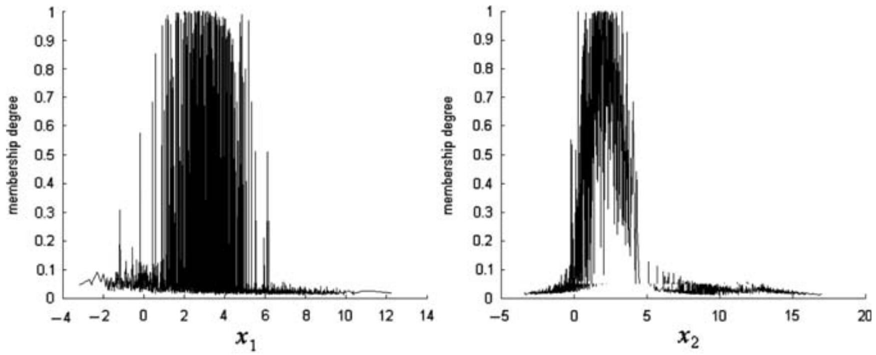


Fig. 4. Projections of the cluster corresponding to class 3 of Fig. 3, onto the UODs of the antecedents x_1 and x_2 (abscissa: antecedent value; ordinate: membership value of the generic kth pattern $\vec{x}_k$ to the cluster projection, $k = 1, \ldots, N$)

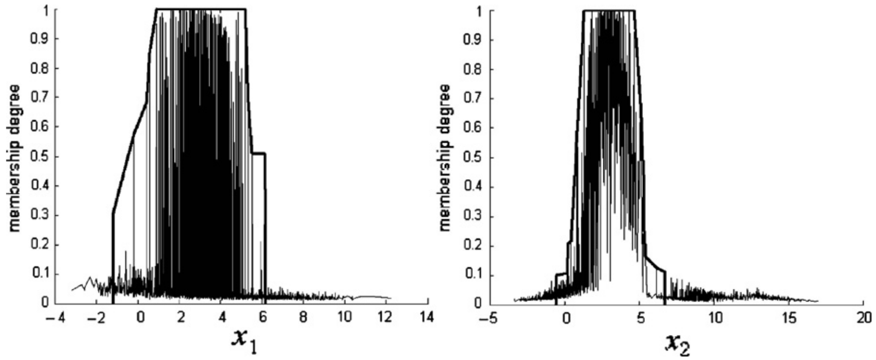


Fig. 5. Approximation of the cluster projections of Fig. 4 into convex FSs

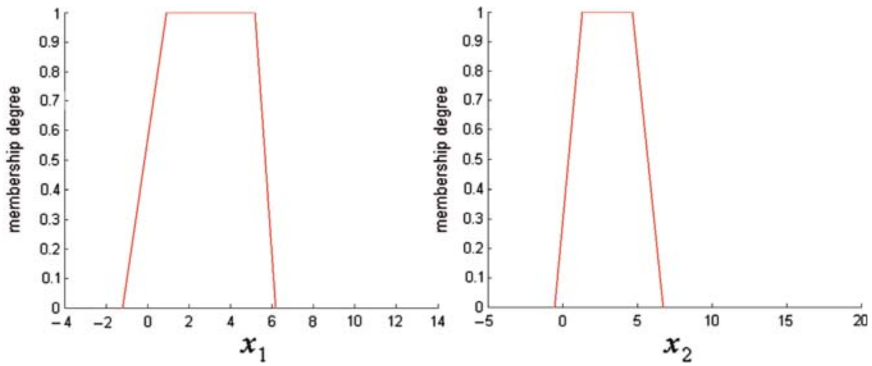


Fig. 6. The trapezoidal FSs corresponding to the cluster projections of Fig. 4

(a) The mono-dimensional MFs of the antecedents FSs are generated by pointwise projection of the membership value $\mu_i(\vec{x}_k)$ onto the antecedent variables UODs [1, 12, 15, 16] (Fig. 4).

(b) The resulting non-convex MFs are transformed into convex MFs (Fig. 5). To do this, starting from the smallest value of the antecedent x_n, only the membership of those values that have a higher membership than the previous one are kept, until the maximum membership value is reached [17]. Then, the same procedure is applied starting from the highest value of the antecedent, until the maximum MF is reached.

(c) The convex FSs are approximated by linear interpolation to MFs of trapezoidal shape (Fig. 6). Before performing the linear interpolation, all membership values under a threshold (chosen to be 0.1 in the present work) are rounded off to 0 and analogously all membership values above an upper threshold (chosen to be 0.9 in the present work) are rounded off to 1.

By so doing, the n-dimensional FS X_i representing the ith cluster is transformed into a fuzzy proposition of the kind:

$$if \ (x_1 \ is \ X_{1i}) \ and \ \ldots \ and \ (x_n \ is \ X_{ni}) \tag{5}$$

where X_{pi} is the projection of cluster i onto the pth input variable, $i = 1, \ldots, c$, $p = 1, \ldots, n$. Obviously, the method is approximate and some information on the cluster is inevitably lost in the projection, due to the decomposition error arising from projecting the multi-dimensional FS into its mono-dimensional constituents [15]. On the other hand, it enables expressing the FRB in a form with a clear and interpretable semantic meaning.

2. *Enforcement of appropriate semantic constraints on the obtained FSs.* To achieve the physical interpretability of the model, semantic constraints are imposed to the FSs obtained in the previous step in an attempt to obtain an "optimal" interface [18]. This is sought through the procedure described below in which each of the FSs modifications required is actually carried out only if the classification performance on the training data is not significantly decreased.

(a) *Pruning of FSs covering a large portion of the UOD.* Some FSs projections can turn out to be covering great portions of the variables UODs, adding little specific information to the model and over-shadowing more focused FSs. An hypothetical example of FS pruning is shown in Fig. 7. Such sets can be removed from the antecedents of the rules [19]. The criterion for elimination of the FSs widely covering the UOD U_{x_p} is [20]:

$$\beta_o l_{X_{pi}} \geq U_{x_p}; p = 1, \ldots, n; \ i = 1, \ldots, c \tag{6}$$

where $l_{X_{pi}}$ is the width at half-height of the ith FS X_{pi} of variable x_p and $\beta_o \geq 1$ is the so-called overlap parameter. The larger is the value of β_o, the more severe is the pruning criterion.

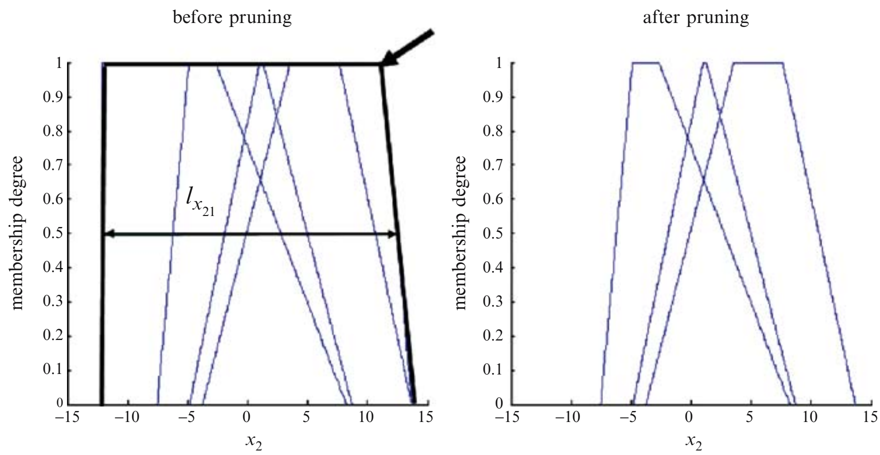


Fig. 7. Overlapping MFs obtained from the clusters projection. The thick solid line in the left Figure denotes the FS to be pruned

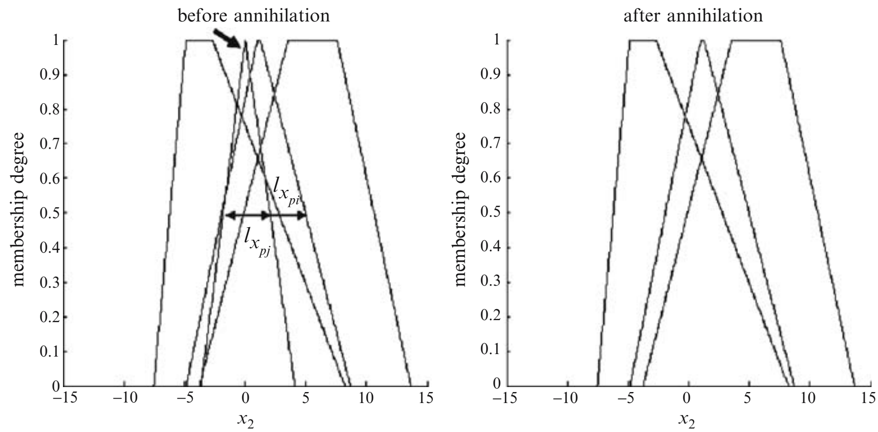


Fig. 8. Annihilation of a narrow FS (*arrow*)

The pruning of a FS modifies only the rules in which the FS appears as antecedent. The modification amounts to canceling from the antecedents the one corresponding to the eliminated FS.

(b) *Addition of FS "nearly zero"*. If the training data do not contain realizations from the class of no faults (stationary state), there is no cluster representing such situation and correspondingly no antecedents FSs and no rules. In this case, a new triangular FS called "nearly zero" is forced in the partition of the UOD U_{x_p} of each variable x_p. The new FS is centered in 0 and the zero-membership vertices are arbitrarily chosen equal to ± 0.1 of the minimum and maximum of the

UOD U_{x_p} of the antecedent variable x_p, respectively. A rule tailored to stationary conditions can then be added to the FRB.

(c) *Annihilation of narrow FSs.* In order to avoid the overlapping among pairs of linguistic terms and the possible consequent semantic inconsistencies, it is necessary to have sufficiently distinct FSs. If a FS X_{pj} were too narrow, for example as in Fig. 8, its contribution is too specific and model transparency is somehow lost. Annihilation of FS X_{pj} is performed if there is a FS X_{pi} for which the following criterion is satisfied [19]:

$$l_{X_{pi}} \mu_{X_{pi}} \left(\frac{z_1 + z_2 + z_3 + z_4}{4} \right) \geq \beta_a l_{X_{pj}};$$
$$i = 1, \ldots, c; j = 1, \ldots, c; i \neq j \tag{7}$$

where $l_{X_{pi}}$ and $l_{X_{pj}}$ are the half-height widths of the FSs X_{pi} and X_{pj} of the same input variable x_p, $\beta_a \geq 1$ is the annihilation parameter and z_s, $s = 1, 2, 3, 4$, stands for the input variable values corresponding to the four vertices of a trapezoidal MF [21–23]. The larger is the value of β_a, the more severe is the annihilation criterion [20, 21].

The FRB is appropriately modified by replacing the canceled FS X_{pj} with the FS X_{pi}.

(d) *Fusion of similar FSs.* If two FSs describing the same variable are sufficiently overlapped, then they should be fused into a single FS because similar [20, 21]. Appropriate measures can be used in order to asses the pairwise similarity of the FSs in the FRB.

The similarity measure Ω of the two FSs X_{pi} and X_{pj} here adopted is given by the ratio between the intersection and the union of their two areas [24]:

$$\Omega(X_{pi}, X_{pj}) = \frac{|X_{pi} \cap X_{pj}|}{|X_{pi} \cup X_{pj}|} = \frac{|X_{pi} \cap X_{pj}|}{|X_{pi}| + |X_{pj}| - |X_{pi} \cap X_{pj}|} \tag{8}$$

If the value of Ω is higher than a pre-established threshold, the two FSs are deemed similar and they are fused (Fig. 9). The four parameters of the new, fused trapezoidal MF will be:

$$z_{fus,s} = \frac{z_i l_{X_{pi}} + z_j l_{X_{pj}}}{l_{X_{pi}} + l_{X_{pj}}}; s = 1, 2, 3, 4 \tag{9}$$

where $z_{fus,s}$ stands for the input variable values corresponding to the four vertices of the trapezoidal MF [20–23] resulting from the fusion and $l_{X_{pi}}$, $l_{X_{pj}}$ are the half-height widths of the FSs X_{pi} and X_{pj}, respectively.

3. *Generation of the fuzzy rules.* The implementation of the previous steps 1 and 2 leads to the generation of a FRB formed by c rules, one for each physical class, of the kind (4).

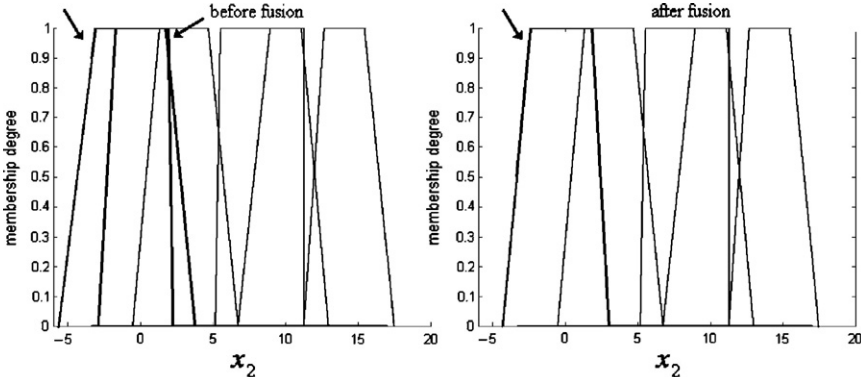


Fig. 9. Fusion of two similar FSs (arrows) corresponding to the projection of class 1 and 2, represented in Fig. 3 with * and +, respectively, onto the second signal UOD

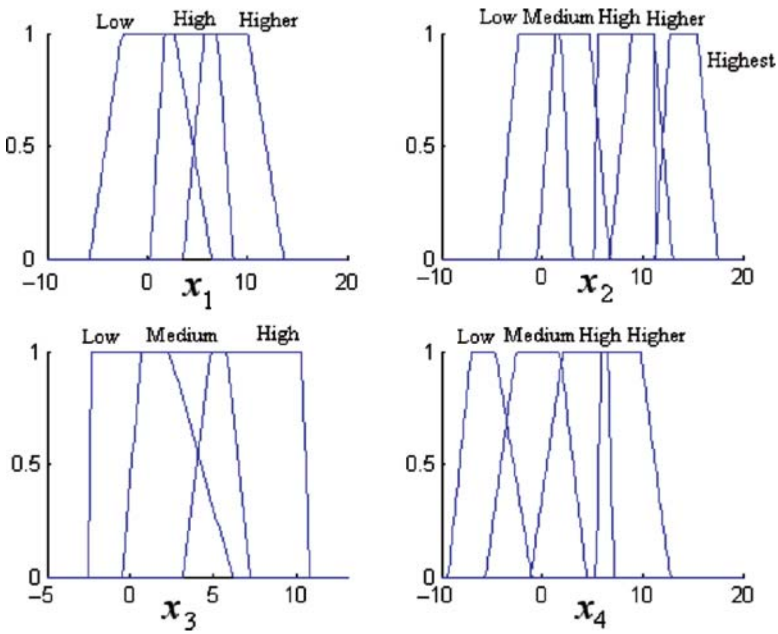


Fig. 10. Final FSs obtained after the projection of the clusters corresponding to the artificial case study

3.1 Application to the Artificial Case Study

Six fuzzy clusters have been identified by applying the algorithm described in [13] to the 2,400 data of Fig. 3.

The application of the procedure just illustrated in Sect. 3 leads to the projection of the six clusters into the FSs of Fig. 10 and to the generation of a corresponding FRB composed of six rules, one for each class (Table 1).

Table 1. The rules of the FRB

Rule		x_1	x_2	x_3	x_4		y_1	y_2	y_3	y_4	y_5	y_6
1	IF	Low S_1	Low S_4	Low S_9	Medium S_{12}	THEN	Yes	No	No	No	No	No
2		High S_2	Medium S_5	Medium S_{10}	Medium S_{13}		No	Yes	No	No	No	No
3		High S_2	High S_6	Medium S_{10}	High S_{13}		No	No	Yes	No	No	No
4		High S_2	Low S_4	Medium S_{10}	Low S_{14}		No	No	No	Yes	No	No
5		High S_2	Higher S_7	Medium S_{10}	Medium S_{12}		No	No	No	No	Yes	No
6		Higher S_3	Highest S_8	High S_{11}	Higher S_{15}		No	No	No	No	No	Yes

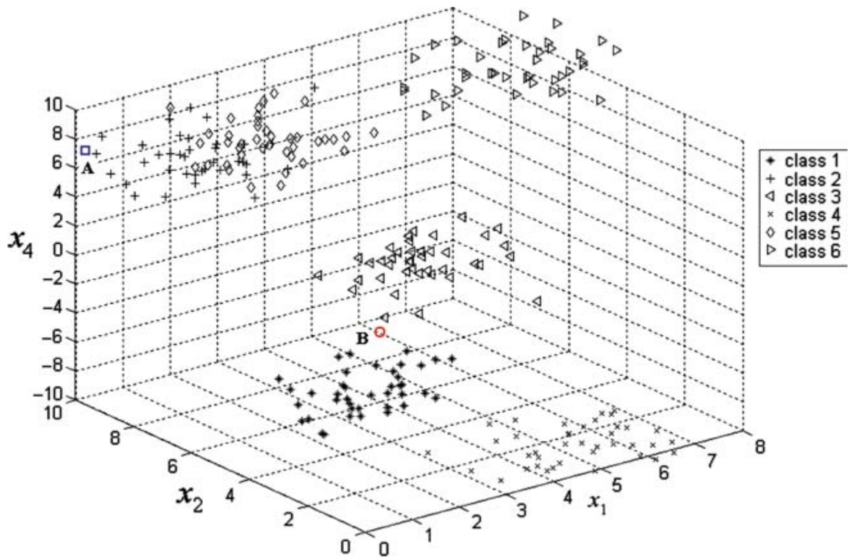


Fig. 11. Example of atypical (A, *square*) and ambiguous (B, *circle*) patterns

Adopting a class membership threshold $\gamma = 0.6$, the classification results for 600 data newly sampled from the underlying six Gaussian distributions are: 85.33% patterns correctly assigned, 7% atypical, 7.67% ambiguous and no pattern assigned to a wrong class.

To picture atypical and ambiguous patterns, consider the patterns A and B represented in Fig. 11 (square and circle, respectively) in the subspace of signals x_1, x_2, x_4. Pattern A belongs to class 2 but is located somewhat far away from the cluster of the other patterns of class 2; for this reason, it is weakly assigned to all six classes with membership values lower than the pre-established classification threshold of 0.6 (Fig. 12a) and, thus, classified as atypical. Pattern B belongs to class 1 but is located at the boundary between classes 1 and 3; for this reason, it is assigned to both classes with membership values above 0.6 (Fig. 12b) and, thus, classified as ambiguous.

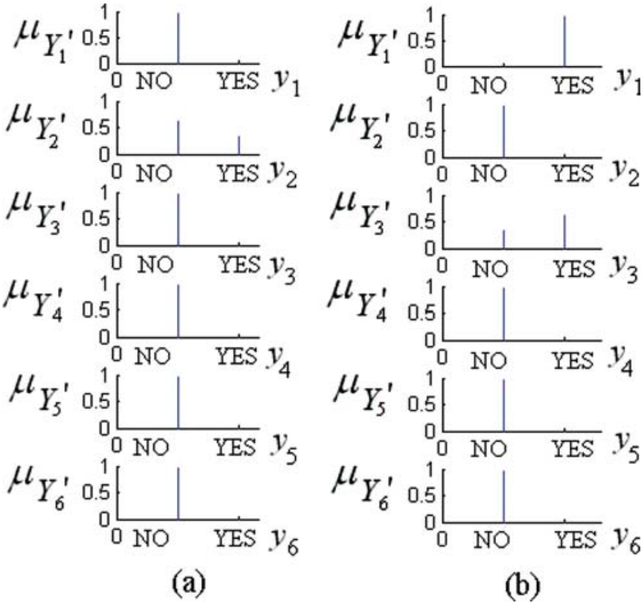


Fig. 12. Classification of an (**a**) atypical pattern and (**b**) ambiguous pattern

4 The Fuzzy Decision Tree

In this Section, the procedure for constructing a FDT starting from the fuzzy rule-based model presented in the previous Section is proposed. In general, DTs are a standard tool used by control room operators for fault classification. Thus, the fact of translating the classifier into a DT bears the great advantage of rendering the diagnostic tool easily received and accepted by the operators.

When a generic fault of class Γ_j, $j = 1, \ldots, c$, occurs, corresponding representative symptoms should be observable by the monitoring system. A symptom associated to the fault of class Γ_j is a deviation, caused by the occurrence of fault Γ_j, of a monitored signal from its reference value. In this work, each one of the FSs obtained in the previous Section represents a deviation and thus a symptom, except those FSs representing steady state conditions of the signals, i.e. the introduced "Nearly Zero" FSs. Correspondingly, the generic FS X_{pj} associated to the pth antecedent in rule j, $p = 1, \ldots, n, j = 1, \ldots, c$, represents a symptom for the class of faults Γ_j.

Notice that the relations between faults and symptoms (signals deviations) are not univocal: one fault may cause several symptoms and in turn one symptom may represent several possible faults. However, if the monitoring system is adequately designed it should be possible to associate to each fault a unique set of symptoms (signals deviations). In our fuzzy classification scheme, these are the FSs representing the signals deviations in the antecedent part

Table 2. Symptom Table: Reference relations between faults and symptoms [25]

Fault class	Symptom type				
	S_1	...	S_r	...	S_s
Γ_1	I_{11}	...	I_{1r}	...	I_{1s}
...	...	...	...	...	...
Γ_j	I_{j1}	...	I_{jr}	...	I_{js}
...	...	...	...	...	...
Γ_c	I_{c1}	...	I_{cr}	...	I_{cs}

(5) of the corresponding rule. This leads to a Symptom Table such as the one reported in Table 2, where $S_r,\ r = 1, \ldots, s$, denotes the generic symptom.

The binary vector $\boldsymbol{\sigma}_\mathrm{j} = [I_{j1},\ I_{j2}, \ldots, I_{js}]$ represents the reference symptoms vector for fault class $\Gamma_j,\ j = 1, \ldots, c$. Each I_{jr} is a binary value that corresponds to the presence or absence of symptom r when fault Γ_j is present, $r = 1, \ldots, s,\ j = 1, \ldots, c$. For example, $\boldsymbol{\sigma}_1 = (1, 0, 0, 1, 0, 1)$ implies that the occurrence of fault type Γ_1 causes S_1, S_4, and S_6 to appear, among the $s = 6$ possible symptoms.

During operation, an observation vector $\sigma' = (I'_1, I'_2, \ldots, I'_s)$ carries the information on the presence or absence of the symptoms, obtained from the measurements of the plant signals. As explained earlier, a symptom is present in the system if its representative measured signal has deviated from its nominal value. For example, a patient has the symptom "fever" if his or her monitored temperature rises to a "high" value, i.e. above 37 °C. However, often in practice the presence or absence of a symptom is affected by uncertainty and ambiguity due to the complexity of the nonlinear signal behaviors associated to the various faults, to the measurement errors of the monitoring sensors and to the imprecise and ambiguous definition of the signal deviation ranges and the associated linguistic labels. In practice then, to a pattern of deviations of the monitored signals measured in correspondence of a given fault, a fuzzy observation vector $\sigma'_f = (\mu'_1, \mu'_2, \ldots, \mu'_s)$ can be associated, where $\mu'_r,\ r = 1, \ldots,\ s$, is the value of the membership of the FS corresponding to the symptom and gives the degree of presence of symptom S_r in the monitored situation being examined.

Once the fuzzy observation vector σ'_f has been obtained, the problem is to identify which fault type is occurring in the plant. To tackle this problem a systematic procedure for constructing a DT is proposed.

4.1 Decision Tree

The architecture of the tree is obtained by means of a procedure, derived from [25], which applies a hierarchy of Boolean tests to split the sample space into disjoint sections.

Taking into consideration all possible combinations of symptoms, the DT would have 2^s branches given that each of the s symptoms can be either present or absent. On the other hand, only one combination of symptoms corresponds to a given fault: thus, only c of the 2^s tree branches correspond to a class while the remaining $2^s - c$ combinations of symptoms cannot be associated to a class.

For building a smaller, more transparent and easier to interpret DT, two main hypotheses are assumed [25]: (1) if a symptom is indicated as present in the measured observation vector σ', it is certainly present in the system; (2) the presence of a single symptom characteristic of a fault suffices to conclude that the measured pattern of signals belongs to that fault class.

In this context, an "unwanted" symptom is defined as a symptom that, although not present in the system, somehow is present by mistake in the observation vector and a "missing" symptom as a symptom that is not observed although it is present in the system [25]: the first hypothesis can then be called of "impossibility of unwanted symptoms" and the second of "possibility of missing symptoms".

The procedure for building the DT proceeds as follows:

1. A root node is placed at the top of the tree. This node refers to all possible fault classes identified for the system under analysis.
2. A symptom from the Symptom Table is associated to this node.
3. The root node is split into two branches: the left corresponding to the presence of the symptom, the right to the absence of the symptom.
4. The fault classes for which the symptom is present are associated to a node under the left branch. If only one fault class is found to contain the symptom, then the associated node is a terminal leaf of the branch and its identification is guaranteed by the fact that it has been assumed that a symptom that is absent in the system cannot be indicated as present (impossibility of unwanted symptoms hypothesis). The fault class associated to the identified leaf may be also associated to other leaves, at the end of other branches in the tree. This accounts for the possibility that a symptom is not indicated as present by the monitoring system although it actually is (possibility of missing symptoms hypothesis). If more than one fault class are associated to the node characterized by the identified symptom, a new symptom is searched in the Symptom Table and associated to the node in order to differentiate between the identified fault classes. To select the new differentiating symptom, the previous procedure is applied, starting from step 2.
5. The right branch from the root node is further developed by first adding a node associated to all possible fault classes. This node is then treated as a local root node to which the branching procedure is applied starting from step 2.
6. The tree development terminates when all symptoms have been considered and their associated branches developed down to the distinguishing leaves of the individual fault classes.

7. A path through the branches of the tree, from the root node to a leaf, identifies a crisp observation vector σ' of symptoms representative of the fault class associated to the leaf. As pointed out above, different paths may lead to different leaves associated to the same fault class, due to the possibility of missing symptoms.

In operation, the DT gives the correct diagnosis when the measured symptom vector matches completely with the reference symptom vector of a fault class; on the contrary, the diagnosis is conservative in case of a missing symptom, i.e. it is not necessary to have all the symptoms to diagnose the fault.

Finally, in case of unwanted symptoms, the classification is driven by the structure of the tree and the classification will be wrong if the first symptom considered is an unwanted symptom.

From the above it appears that the DT design must be optimized with respect to the order with which the successive symptoms are considered, for optimal classification performance.

4.2 Classification by the FDT

In the realistic case of ambiguity in the presence or absence of a symptom, in correspondence of a given pattern of signal deviations the degree of activation of each symptom S_r, $r = 1, \ldots, s$, is computed from the MF of the corresponding FS. The DT then becomes a FDT and the classification of a given pattern of measured signal deviations is performed by proceeding through all the branches of the tree and computing the MFs to each fault class, at the tree leaves.

The symptoms degrees of activation are then propagated through the FDT according to the rules of FS theory. In particular, the logic operator of negation of a symptom S_r is implemented by $(1 - \mu_{S_r})$ in the right branch corresponding to the absence of the symptom whereas its complement μ_{S_r} is propagated along the left branch associated to its presence (Fig. 13). The

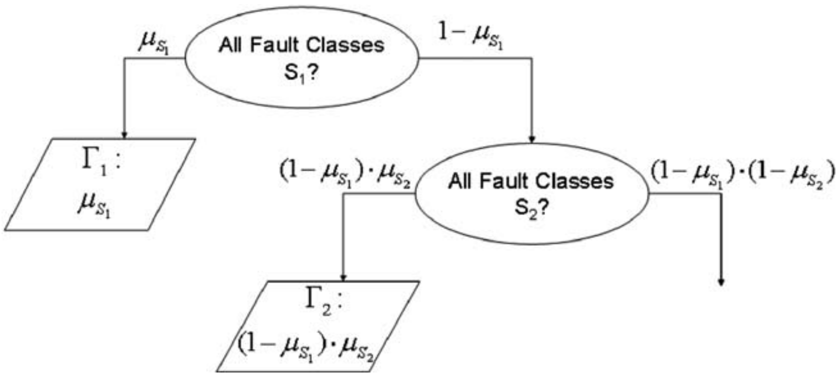


Fig. 13. Propagation of fuzzy information to the DT

connection between two nodes of the tree represents a logic operator of intersection (*and*), here implemented by means of the algebraic product of the membership values.

Finally, since more than one terminal leaf can indicate the same class, the final membership to a given class is computed through the logic operation of union (*or*) of all the leaves associated to that class. The logic operator *or* is here implemented as the MFs sum limited to 1, accordingly to the rules of FS arithmetic.

Differently from the case of crisp symptoms which activate only one terminal leaf, the fuzzy propagation of ambiguous symptoms in the FDT leads to a more realistic classification into different faults with different membership degrees of an ambiguous pattern of deviations, rather than to one definite fault, possibly wrong.

4.3 Application to the Artificial Data

To build the FDT, first each antecedent FS of Fig. 10 is associated to a symptom, resulting in 15 possible symptoms, indicated as S_i, $i = 1, \ldots, 15$, in Table 1. This allows the translation of the FRB in the Symptom Table 3.

By applying the steps 1–6 of the procedure for building the DT (Sect. 4.1) on the sequence of symptoms $\Sigma_0 = [S_1; S_2; \ldots; S_{15}]$, one obtains the DT reported in Fig. 14.

The quantification of the degree of membership to the different classes is performed as previously described, by propagating through the branches of the tree the degree of activation of each symptom.

The test on the same set of 600 data considered in Sect. 3.1, with membership threshold $\gamma = 0.6$, results in only 40.67% correct classifications to the six fault classes, while 10.5% of the data are considered as atypical, 2.33% as ambiguous and 46.5% are assigned to the wrong class.

The obtained performance is obviously unacceptable and motivates the search for an optimal or near-optimal sequence of symptoms upon which to build the FDT. The objective of the optimization algorithm is to find the sequence of symptoms that leads to the FDT with the best classification performance in terms of percentage of correct classifications. The number of

Table 3. Symptom Table

Class	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
Γ_1	1	0	0	1	0	0	0	0	1	0	0	1	0	0	0
Γ_2	0	1	0	0	1	0	0	0	0	1	0	0	1	0	0
Γ_3	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0
Γ_4	0	1	0	1	0	0	0	0	0	1	0	0	0	1	0
Γ_5	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0
Γ_6	0	0	1	0	0	0	0	1	0	0	1	0	0	0	1

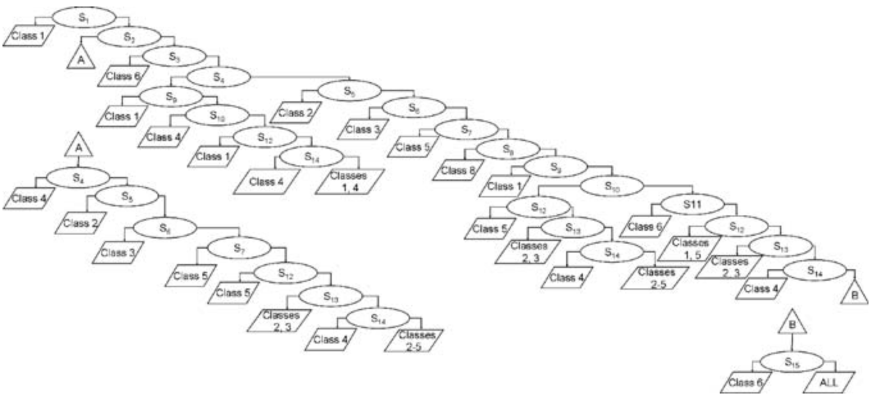


Fig. 14. DT for classification of the artificial data of Sect. 3.1, built with the ordered sequence of symptoms Σ_0

possible sequences of symptoms is 15! ($\sim 10^{11}$). A procedure based on a single-objective genetic algorithm is adopted to solve this combinatorial optimization problem.

5 FDT Optimization by a Genetic Algorithm

In this Section, a procedure based on a single-objective genetic algorithm is carried out for determining the sequence of symptoms to which corresponds the FDT with the maximum classification performance. The genetic algorithm can be seen as performing a wrapper search [26] around the classification algorithm (Fig. 15) in which the symptoms sequence selected during the search is evaluated using as criterion (fitness) the percentage of correct classified data achieved by the FDT itself.

The data and rules of the genetic algorithm search are given in Table 4. These parameters have been established through a systematic procedure of experimentation. The objective (fitness) function to be maximized is the percentage of correct data classifications; the decision variable is the symptoms sequence.

With reference to the artificial case study, each chromosome is made up by 15 genes, one gene for each symptom. The single gene can assume any integer value in $[15, 15]$ that encodes the "swap" position of the symptom along the sequence. An example of a chromosome coding a particular sequence is given in Fig. 16. To decode the chromosome in its corresponding symptom sequence, a 15–steps procedure is performed, one for each gene. At the generic step $i = 1, \ldots, 15$, the ordered sequence Σ_{i-1} and the value k contained in the ith gene are considered: the symptom in the ith position of Σ_{i-1} is then swapped with the symptom in the kth position of the sequence. For example in the first

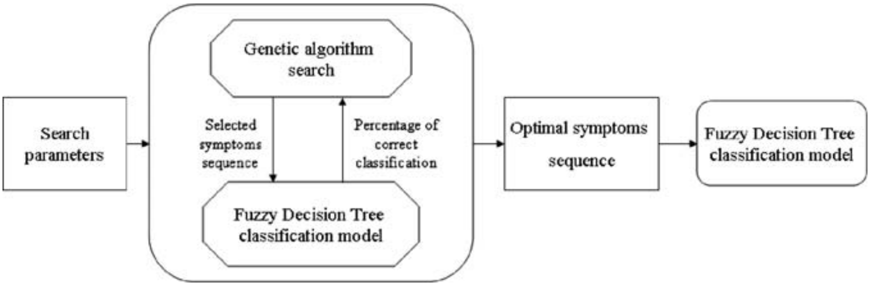
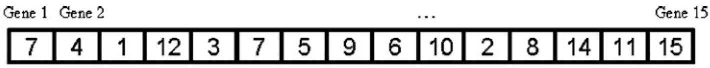


Fig. 15. Single-objective genetic algorithm "wrapper" search

Table 4. GA run parameters

Number of chromosomes in the population	100
Number of generations (termination criterion)	50
Selection	Standard Roulette
Replacement	Children – Parents
Mutation probability	0.01
Crossover probability (one-site)	1



$$\Sigma_0 = [S_1; S_2; S_3; S_4; S_5; S_6; S_7; S_8; S_9; S_{10}; S_{11}; S_{12}; S_{13}; S_{14}; S_{15}]$$

Step 1 → Gene 1 = 7

$$\Sigma_1 = [S_7; S_2; S_3; S_4; S_5; S_6; S_1; S_8; S_9; S_{10}; S_{11}; S_{12}; S_{13}; S_{14}; S_{15}]$$

Step 2 → Gene 2 = 4

$$\Sigma_2 = [S_7; S_4; S_3; S_2; S_5; S_6; S_1; S_8; S_9; S_{10}; S_{11}; S_{12}; S_{13}; S_{14}; S_{15}]$$

...

$$\Sigma_{13} = [S_3; S_{11}; S_5; S_{12}; S_6; S_8; S_7; S_2; S_1; S_{10}; S_4; S_9; S_{14}; S_{13}; S_{15}]$$

Step 14 → Gene 14 = 11

$$\Sigma_{14} = [S_3; S_{11}; S_5; S_{12}; S_6; S_8; S_7; S_2; S_1; S_{10}; S_{13}; S_9; S_{14}; S_4; S_{15}]$$

Step 15 → Gene 15 = 15

$$\Sigma_{15} = [S_3; S_{11}; S_5; S_{12}; S_6; S_8; S_7; S_2; S_1; S_{10}; S_{13}; S_9; S_{14}; S_4; S_{15}]$$

Fig. 16. Example of a chromosome and the corresponding sequence

step of Fig. 16, the value 7 in gene 1 means that the symptom S_1 is placed in position 7 of the sequence and simultaneously the symptom that occupied position 7 is swapped to position 1. This operation is carried out until the 15th gene of the chromosome is worked out, leading to the final sequence:

$$\Sigma_{15} = [S_3; S_{11}; S_5; S_{12}; S_6; S_8; S_7; S_2; S_1; S_{10}; S_{13}; S_9; S_{14}; S_4; S_{15}]$$

Note that this original random design of the chromosome leads to a coherent symptom sequence, i.e. without repetition of symptoms, thus avoiding computationally burdensome chromosome coherence checking a posteriori of its creation.

The optimal sequence found at convergence of the genetic algorithm is:

$$\Sigma_1 = [S_4; S_6; S_7; S_3; S_{12}; S_{10}; S_{13}; S_{15}; S_5; S_1; S_{14}; S_{11}; S_8; S_9; S_2]$$

The FDT built following this sequence increases the fraction of patterns correctly classified from 85.33%, obtained with the FRB classifier, to 91.34%. The percentage of patterns considered atypical is reduced to 5.33% with respect to the previously obtained 7%. Furthermore, the percentage of ambiguous patterns is reduced to 0.33% from the previously obtained 7.6% whereas the percentage of patterns assigned to the wrong class increases from 0 to 3%.

In particular the atypical and ambiguous, patterns A and B of Fig. 11 are now correctly classified. Pattern A is assigned to class 2 with a membership value of 1 due to the symptom S_5 that is characteristic only of this class and that has an activation degree equal to 1 for this pattern. Pattern B is correctly assigned to class 1 due to the degree of activation equal to 1 of the symptom S_9 that is characteristic only for class 1. Thus, the resolution of previously ambiguous and atypical classifications by the FRB is achieved by the FDT thanks to the fact that in the cases considered the activation with high degree of membership of just one characteristic symptom is sufficient for assigning the pattern to the corresponding class. On the other hand, in general the percentage of errors may increase due to the fact that for a given pattern an unwanted symptom activated with a high membership by such pattern, may be placed in the FDT before the representative symptoms for the real class of the pattern.

6 Fault Classification in a Boiling Water Reactor

6.1 Problem Statement

The problem under consideration concerns the identification of a predefined set of faults in a BWR. A set of transients of the monitored signals under different fault conditions have been simulated by the HAMBO simulator of the Forsmark 3 BWR plant in Sweden [9]. Figure 17 shows a sketch of the system [9].

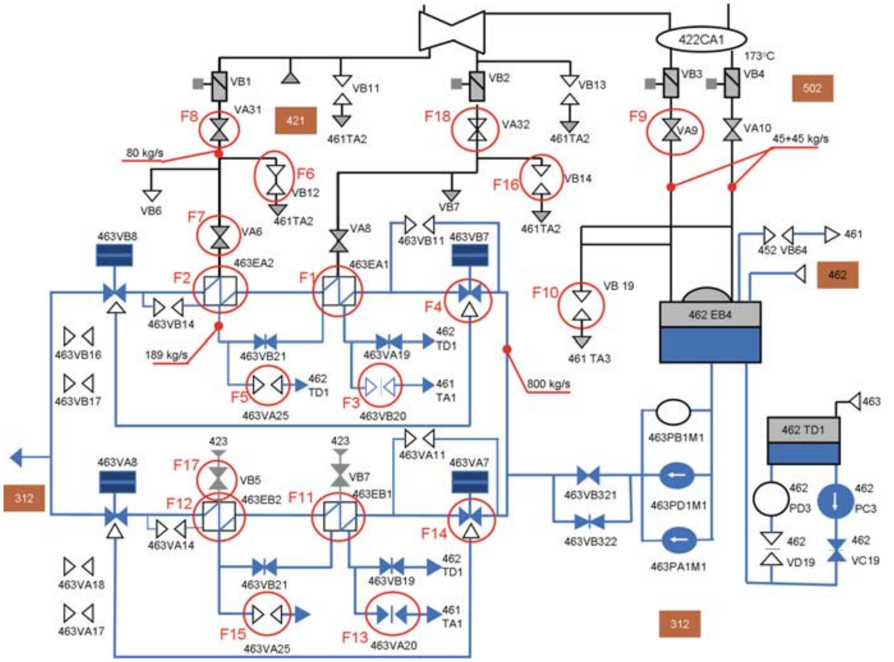


Fig. 17. Sketch of the feedwater system [9]

The considered faults occur in the section of the feedwater system of a BWR where the feedwater is preheated from 169 °C to 214 °C in two parallel lines of high-pressure preheaters while going from the feedwater tank to the reactor. Process experts have identified a set of 18 faults that are generally hard to detect for an operator and that produce efficiency losses if undetected [27]. The $c = 6$ faults regarding line 1 are here considered as the classes to be distinguished by the classification. These are numbered F1–F5 and F7, coherently with the original numbering [9].

For each type of fault, the patterns to be used for building the classification model have been constructed by simulating transients with the plant at 80% of full power, taking values every 6 s from $t_{in} = 80\,s$ to $t_{fin} = 200\,s$.

Among the 363 monitored signals, only $n = 5$ signals have been chosen for the transient classification using the feature selection algorithm proposed in [28]: position level of control valve for preheater EA1 (PLV), temperature of drain 4 before valve VB3 (T1), water level of tank TD1 (WL), feedwater temperature after preheater EA2 (T2) and feedwater temperature after preheater EB2 (T3).

6.2 Application and Results

To test the methodology proposed in this work, the available set of preclassified patterns is subdivided as follows: 80% have been used for building

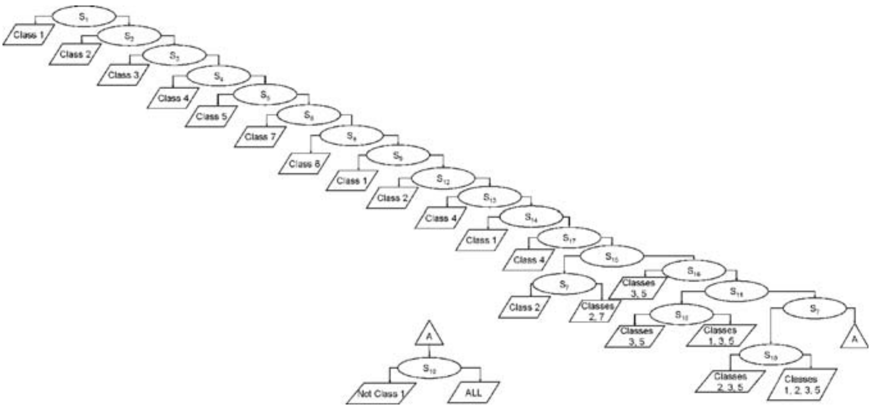


Fig. 18. DT for the classification of BWR feedwater system faults

the diagnostic fuzzy rules and the associated FDT and the remaining 20% have been used for testing the method accuracy.

The application of the fuzzy clustering method presented in this Chapter leads to six clusters, each one corresponding to a different type of fault. Projecting the multi-dimensional clusters onto the UODs of the five input signals and applying the transparency constraints of Sect. 3 for obtaining an optimal partition of the UODs a FRB composed of six rules characterized by five antecedents in the form of (5) is obtained.

As a result, 96% of the test patterns are correctly classified using this more transparent FRB. In particular, all the test patterns are correctly classified except one pattern, which turns out to be characterized by the first input variable x_1 having a value out of the range of the training patterns. This pattern is correctly labelled as atypical by the FRB of the classification model.

As explained in Sect. 4 to build the DT, first each antecedent of the FRB is associated to a symptom. This gives rise to the translation of the FRB in the form of a Symptom Table. On the basis of the Symptom Table the DT is developed (Fig. 18) following the guidelines illustrated in Sect. 4.

Propagating the symptoms fuzzy membership information along the DT of Fig. 18, the test pattern classified as atypical using the fuzzy rule-based classifier turns out now to be correctly assigned to fault class F_1. Notice that, in this case S_1 is a missing symptom but the pattern is still correctly classified, thanks to the hypothesis of possibility of missing symptoms underlying the DT construction procedure.

7 Conclusions

Fault classification is often based on ambiguous information which can be effectively handled within a fuzzy logic framework.

In this context, this Chapter has illustrated a fuzzy-logic based intelligent decision support system to assist the operators in the fault diagnosis tasks. Each step of the proposed methodology is presented with respect to a case study regarding the classification of a set of artificial data randomly sampled from six different Gaussian distributions.

The method is based on a FRB made of one fuzzy classification rule for each fault class. The antecedent FSs in each rule represent the characteristic symptoms (signals deviations) for the corresponding fault class.

A DT is then built to logically structure the uncertain information available. Such DT is quantitatively processed by propagating the degrees of presence of the various possible symptoms.

The classification performance by the resulting FDT is dependent on the order in which the symptoms are considered in the building procedure of the DT. This leads to a combinatorial optimization problem with respect to the construction of the tree. As shown in this work, this problem can be effectively tackled by a genetic algorithm search.

The proposed intelligent decision support system has been tested on a case study regarding the classification of simulated faults in a section of the feedwater system of a BWR. The results obtained are very satisfactory in both classification performance and transparency.

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Linguistic Assessment Approach for Hierarchical Safety Analysis and Synthesis

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Summary. Engineering systems in industry are most often concerned with safety issues. Many of these systems are intended to work properly even in contexts where information is missing, incomplete or unreliable. This chapter introduces a safety model based on the concept of approximate reasoning for safety analysis. Parameters of the safety level, including failure rate, failure consequence severity and failure consequence probability, are all described by fuzzy linguistic variables. A fuzzy rule-base is used to capture the uncertainty and the non-linear relationships among these parameters. A safety estimate for possible causes of a technical failure can be obtained by the approximate reasoning approach. A safety synthesis is then applied to integrate all possible causes for a specific technical failure, or applied at the safety estimate made by a panel of experts. The synthesis is based on an ordinal fuzzy linguistic approach by means of a direct computation on linguistic values instead of the approximation approach by their associated membership functions. The use of the ordinal fuzzy linguistic approach makes the safety analysis more effective. Subsequently, the ranking and interpretation of the final safety synthesis of a concerned system are also described. Application of this proposed approach is demonstrated by a real-world case study in the offshore engineering.

1 Introduction

The growing technical complexity of large engineering systems such as offshore platforms and offshore support vessels, together with the intense public concern over their safety, has stimulated the research and development of novel safety analysis methods and safety assessment procedures.

Many typical safety assessment approaches (such as probabilistic risk assessment approach) may be difficult to use in situations with a lack of information and past experiences, or ill-defined situation for risk analysis [10, 16],

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e.g., at the initial design stages. In certain circumstances, probability theory can be a powerful tool. However, the type of uncertainty encountered in engineering projects (e.g., offshore) does not always adhere to the axiomatic basis of probability theory, simply because uncertainty in these projects is usually caused by the inherent fuzziness of the estimates of the parameters rather than randomness.

In addition, the safety of a system is affected by various factors, such as design, manufacturing, installation, commissioning, operations and maintenance [14]. The safety of a structure is often determined by all the associated failure events of each individual component that makes up the structure. Problems may then arise such as how to synthesize uncertain evaluations of the safety analysis for all the failure events of a component in a rational way, as well as how to attain an evaluation of this component safety. The problem may be ultimately generalized to estimate the safety of a hierarchy system.

This work aims to establish a framework that provides a basis and hence a tool for safety analysis and synthesis in engineering systems. In particular this framework deals with information that may be unquantifiable due to its nature and that may be imprecise, ill-defined, and incomplete. It will further provide a subjective safety modelling for safety analysis using an approximate reasoning approach to capture uncertainty and non-linear casual relationships in safety assessments.

Fuzzy logic approach [20] provides a systematic way to represent linguistic variables. It can be used as a powerful tool complementary to traditional methods to deal with imprecise information, especially linguistic information. Actually, linguistic variables are commonly used to represent risk factors in risk analysis [1,2,9,10,13–15]. It does not require an expert to provide a precise point of a potential risk. Approximate reasoning [19–21] based on fuzzy IF-THEN rules can model the safety of the system without employing precise quantitative analyses [5].

Moreover, the use of linguistic variables implies “Computing with Words” processes. In the literature there are two main linguistic computational approaches:

(1) The linguistic computational approach based on the Extension Principle [20, 21], that operates over the associated membership functions of the linguistic variables.
(2) The linguistic computational symbolic approach (or the ordinal fuzzy linguistic approach) which acts by a direct computation on labels [4,6,17,18]. An extended ordinal fuzzy linguistic approach, called the 2-tuple linguistic representation model has been presented in [7,8] to improve the accuracy of the computing with words processes.

Our proposed framework will use for the safety synthesis the 2-tuple linguistic representation approach in order to facilitate the computing with words processes and the comprehension of the safety estimate.

This paper is organized as follows. Section 2 introduces a framework for modelling system safety by an approximate reasoning approach and for safety synthesis by the 2-tuple linguistic representation approach. A case study based on the collision risk of a floating production storage offloading (FPSO)-shuttle tanker during a tandem offloading operation is presented in Sect. 3 to demonstrate this proposed approach. A conclusion of the approach presented in the paper is provided in Sect. 4.

2 A Safety Model – A Framework for Safety Analysis and Synthesis

A generic framework for modelling system safety by an approximate reasoning approach and for safety synthesis by the ordinal fuzzy linguistic approach is depicted in Figs. 1 and 2, respectively.

The proposed framework consists of six major phases:

(i) Identify all the anticipated causes/factors to the technical failure of an engineering system;
(ii) Identify and name the linguistic variables for the antecedent parameters that define the safety level, i.e., *failure rate, consequence severity* and *failure consequence* probability as well as the linguistic variables for the

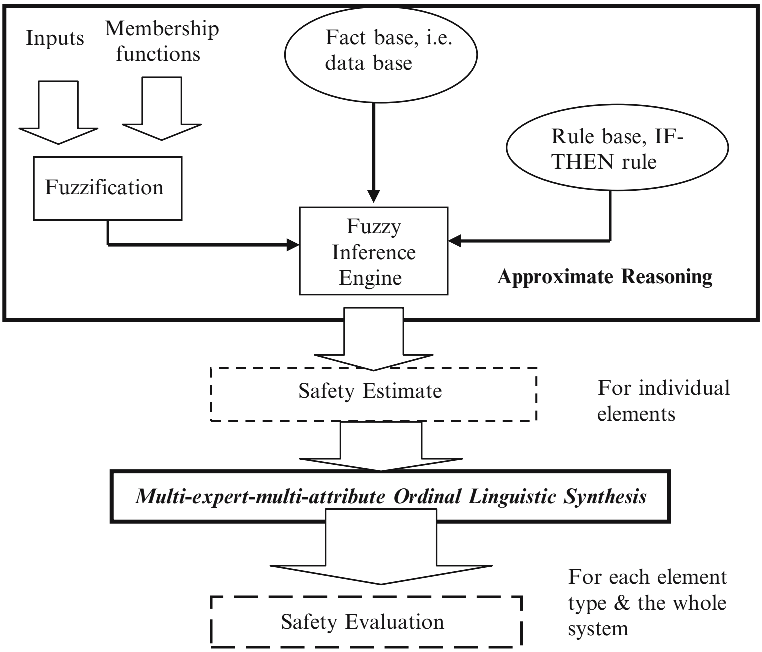

Fig. 1. A generic qualitative safety assessment framework

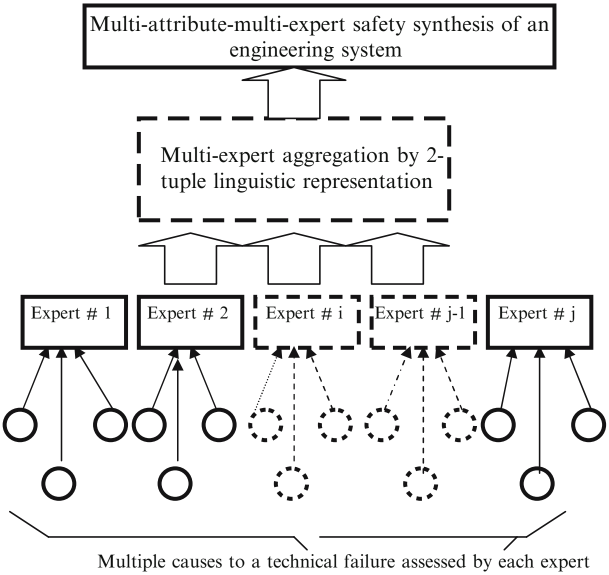

Fig. 2. Multi-attribute-multi-expert safety synthesis

consequent, i.e., *safety estimate* and create fuzzy membership functions for all related linguistic variables for the antecedent parameters;

(iii) Construct the fuzzy rule bases;

(iv) Create resultant safety estimate for a particular cause to a technical failure using a fuzzy inference method;

(v) Safety synthesis using the ordinal fuzzy linguistic approach;

(vi) Ranking and interpretation of the final safety synthesis of a system.

Each phase of the framework is described in detail as follows.

Phase #1: Identification of causes/factors

In this phase, all anticipated causes/factors to the technical failure of an engineering system are identified. This needs the judgment from a panel of experts $E = \{e_1, \ldots, e_p\}$ during a brainstorming session at the early stages of the system.

Phase #2: Identify and name the linguistic variables for the antecedent and the consequent attributes and create fuzzy membership functions for all related linguistic variables for the antecedent parameters

The three fundamental parameters used to assess the safety level of an engineering system on a subjective basis are the *failure rate* (**FR**), the *consequence severity* (**CS**) and the *failure consequence probability* (**FCP**). Subjective assessments (using linguistic variables instead of ultimate numbers in probabilistic terms) are more appropriate for their analysis because these three parameters are always associated with great uncertainty [9, 10, 13–15].

The granularity of the linguistic term sets used for describing each fundamental parameter is decided according to the situation of the case of interest. The recent literature survey indicates that linguistic term sets with a granularity from four to seven labels are commonly used to represent risk factors in risk analysis [1, 2, 9, 10, 13–15].

A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The simplest membership functions are the triangular membership function and trapezoidal membership function. Both of these memberships are commonly used to describe risks in safety assessment [15].

It is possible to have some flexibility in the definition of membership functions to suit different situations. The application of categorical judgments has been quite positive in several practical situations [12]. It is also common and convenient for safety analysts to use categories to articulate safety information. The fuzzy membership functions are generated utilizing linguistic categories identified in knowledge acquisition and consisting of a set of overlapping curves. The typical linguistic variables used to describe **FR, CS** and **FCP** are defined and characterized as follows [13].

FR describes failure frequencies in a certain period, which directly represents the number of failures anticipated during the design life span of a particular system or an item, as illustrated in Fig. 3. Table 1 describes the range of the frequencies of failure occurrence and defines the fuzzy set of **FR**. To estimate the **FR**, one may choose to use such linguistic values as "*very low*," "*low*," "*reasonably low*," "*average*," "*reasonably frequent*," "*frequent*," and "*highly frequent*."

CS describes the magnitude of possible consequences, which is ranked according to the severity of failure effects. To estimate the **CS**, one may choose to use such linguistic values as "*negligible*," "*marginal*," "*moderate*," "c*ritical*" and "*catastrophic*." The fuzzy **CS** set definition is shown in Fig. 4. Table 2 shows the criteria used to rank the **CS** of failure effects.

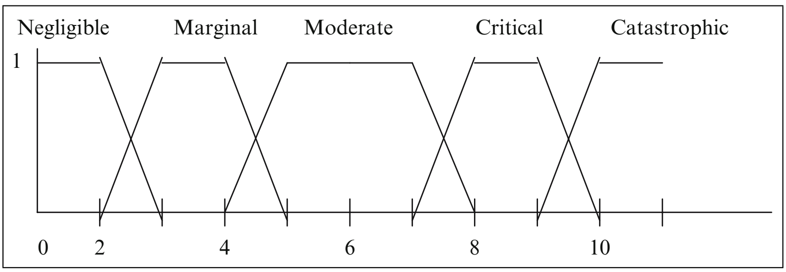

Fig. 3. Fuzzy failure rate set definition

Table 1. Failure rate (**FR**)

Rank	**FR**	Meaning (general interpretation)	Failure rate (1/year)
1,2,3	Very low	Failure is unlikely but possible during lifetime	$<10^{-6}$
4	Low (Lo)	Likely to happen once during lifetime	0.25×10^{-5}
5	Reasonably low (RLo)	Between low and average	0.25×10^{-4}
6	Average (A)	Occasional failure	10^{-3}
7	Reasonably Frequent (RF)	Likely to occur from time to time	0.25×10^{-2}
8, 9	Frequent (F)	Repeated failure	0.125×10^{-1}
9,10	Highly frequent (HF)	Failure is almost inevitable or likely to exist repeatedly	$>0.25 \times 10^{-1}$

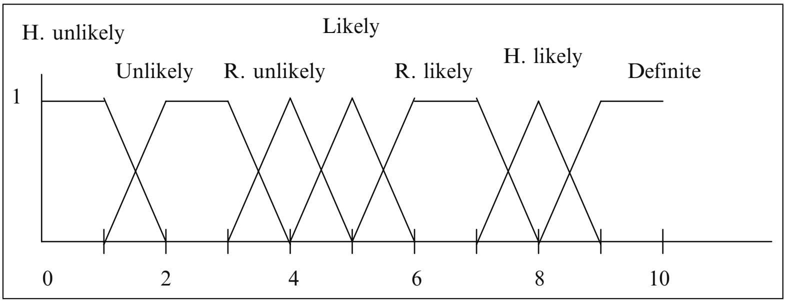

Fig. 4. Fuzzy consequence severity set definition

FCP defines the probability of the possible consequences given the occurrence of the event. To estimate the **FCP**, one may choose to use such linguistic values as "*highly unlikely*," "*unlikely*," "*reasonably unlikely*," "*likely*," "*reasonably likely*," and "*definite*." Table 3 and Fig. 5 describe the **FCP**.

The descriptions of these linguistic variables have been detailed in [13] and the fuzzy membership functions for these linguistic variables are generated utilizing linguistic categories identified in knowledge acquisition [13].

Safety estimate is the output attribute used in this study to produce a safety assessment for a particular cause to a technical failure. This variable is described and determined by the above three parameters and also assessed linguistically, in a linguistic term set noted as, S_{T}, in this paper:

$$S_{\mathrm{T}} = \{\text{"}Poor\text{"}, \text{"}Low\text{"}, \text{"}Average\text{"}, \text{"}High\text{"}, \text{"}Good\text{"}\}$$

Table 2. Consequence Severity (**CS**)

Rank	**CS**	Meaning (generic offshore structure/system interpretation)
1	Negligible (N)	At most a single minor injury or unscheduled maintenance required (service and operations can continue)
2, 3	Marginal (Ma)	Possible single or multiple minor injuries or/and minor system damage. Operations interrupted slightly, and resumed to its normal operational mode within a short period of time (say less than 2 h)
4, 5, 6	Moderate (Mo)	Possible multiple minor injuries or a single severe injury, moderate system damage. Operations and production interrupted marginally, and resumed to its normal operational mode within, say no more than 4 h
7, 8	Critical (Cr)	Possible single death, probable multiple severe injuries or major system damage. Operations stopped, platform closed, shuttle tanker's failure to function. High degree of operational interruption due to the nature of the failure such as an inoperable platform (e.g. drilling engine fails to start) or an inoperable convenience subsystem (e.g. DP, PRS)
9, 10	Catastrophic (Ca)	Possible multiple deaths, probable single death or total system loss. Very high severity ranking when a potential failure mode (e.g. fire and explosion) affects safe platform operation and/or involves non-compliance with government regulations

Any linguistic term, s_i, of the above linguistic term sets has the following characteristics:

(1) The set is ordered: $s_i \leq s_j$ if $i \leq j$.
(2) There is the negation operator: $\mathrm{Neg}(s_i) = s_j$ such that $j = T - 1 - i$.
(3) There is the maximization operator: $\mathrm{Max}(s_i,\ s_j) = s_i$ if $s_j \leq s_i$.
(4) There is the minimization operator: $\mathrm{Min}(s_i,\ s_j) = s_i$ if $s_i \leq s_j$.

Phase #3: Construct a fuzzy rule-base

Fuzzy logic systems are knowledge-based or rule-based ones in the form of fuzzy IF–THEN rules [21]. The starting point of constructing a fuzzy logic system is to obtain a collection of fuzzy IF–THEN rules from human experts or based on domain knowledge.

In our case, we assume that the three antecedent parameters, **FR, CS** and **FCP** can be described by J_i linguistic terms $\{A_{ij},\ j = 1, \ldots, J_i\},\ i = 1,\ 2,\ 3$, respectively. One consequent variable ***safety estimate*** is described by a linguistic term set $S_T = \{D_0,\ D_2, \ldots, D_{T-1}\}$ with T linguistic terms. Let $A_i^k \in \{A_{ij},\ j = 1, \ldots, J_i\}$ be a linguistic term corresponding to the *ith*

Table 3. Failure consequence probability (**FCP**)

Rank	**FCP**	Meaning
1	Highly unlikely (HU)	The occurrence likelihood of possible consequence is highly unlikely given the occurrence of the failure event (extremely unlikely to exist on the system or during operations)
2,3	Unlikely (U)	The occurrence likelihood of possible consequences is unlikely but possible given that the failure event happens (improbable to exist even on rare occasions on the system or during operations)
4	Reasonably unlikely (RU)	The occurrence likelihood of possible consequences is reasonably unlikely given the occurrence of the failure event (likely to exist on rare occasions on the system)
5	Likely (Li)	It is likely that consequences happen given that the failure event occurs (a programme is not likely to detect a potential design or operations procedural weakness)
6,7	Reasonably likely (RLi)	It is reasonably likely that consequences occur given the occurrence of the failure event (i.e. exist from time to time on the system or during operations, possibly caused by a potential design or operations procedural weakness)
8	Highly likely (HL)	It is highly likely that consequences occur given the occurrence of the failure event
9,10	Definite (D)	Possible consequences happen given the occurrence of a failure event (i.e. likely to exist repeatedly during operations due to a anticipated potential design and operations procedural drawback)

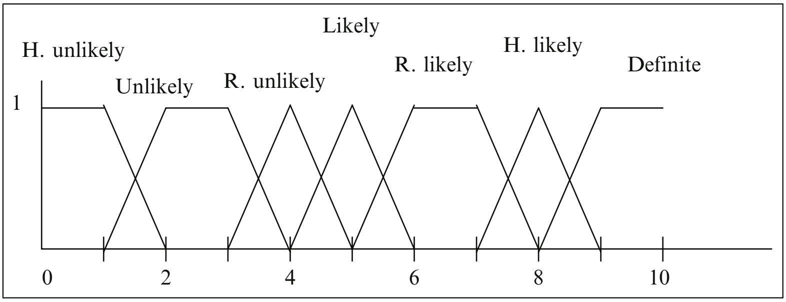

Fig. 5. Fuzzy failure consequence probability set definition

attribute of the kth rule, with $i = 1, 2, 3;\ k \in \{1, \dots, N\}$. Thus the kth rule in a rule base can be written as:

$$R_k : \text{IF } \mathbf{FR} \text{ is } A_1^k \text{ AND } \mathbf{CS} \text{ is } A_2^k \text{ AND } \mathbf{FCP} \text{ is } A_3^k \text{ THEN } \boldsymbol{safety\ estimate} \text{ is } D_k \quad (1)$$

Here $\{A_1^k,\ A_2^k,\ A_3^k\}$ is called the *packet of antecedents* and for convenience, denoted as A^k (i.e., the packet of antecedents in the kth rule, $k \in \{1, \dots, N\}$).

For the case study in Sect. 3, we suppose that a linguistic term set with seven labels is used for **FR** (i.e., $J_1 = 7$); one with five labels for **CS** (i.e., $J_2 = 7$), and a seven labels term set for **FCP** (i.e., $J_3 = 7$). They have been described in Phase #2, respectively. In addition, we also suppose that $T = 5$, and $D_t \in S_T = \{s_0 = \text{‘}Poor\text{'},\ s_1 = \text{‘}Low\text{'},\ s_2 = \text{‘}Average\text{'},\ s_3 = \text{‘}High\text{'},\ s_4 = \text{‘}Good\text{'}\}$ $(t = 0, \ldots, 4)$.

A sample of 245 rules of a rule-base will be used in the case study in Sect. 3 for safety estimate [13]:

- Rule # 1: IF **FR** is *very low* AND **CS** *is negligible* AND **FCP** is *highly unlikely* THEN ***safety estimate*** is *good*
- Rule # 2: IF **FR** is *very low* AND **CS** is *negligible* AND **FCP** is *unlikely* THEN ***safety estimate*** is *good*
- ...
- Rule # 244: IF **FR** is *highly frequent* AND **CS** is *catastrophic* AND **FCP** is *highly likely* THEN ***safety estimate*** is *poor*
- Rule # 245: IF **FR** is *highly frequent* AND **CS** is *catastrophic* AND **FCP** is *definite* THEN ***safety estimate*** is *poor*

Phase #4: Fuzzy inference scheme

The inference procedure is basically composed of three steps, summarized as follows:

Step 4.1: *Discretization of an input into the distributed representation of the linguistic values in antecedents*

This step determines the degrees of membership of an input to each linguistic value in the antecedent, i.e., the matching degree between the input and the antecedents.

An input may be uncertain and can be obtained from history data or expert's experiences. This framework offers the following numerical forms to suit conditions under study:

- A single deterministic value with 100 % certainty;
- A closed interval defined by an equally likely range;
- A triangular distribution defined by a most likely value, with lower and upper least likely values;
- A trapezoidal distribution defined by a most likely range, with lower and upper least likely values.

The input is transformed into a distributed representation of linguistic values in antecedents. In general, we may consider a linguistic term in the antecedent as an evaluation grade, the input for an antecedent attribute, A_i, can be assessed to a distribution representation of the linguistic term sets using matching degrees:

$$f(A_i^*) = \{(A_{ij};\ \alpha_{ij}),\ j = 1, \ldots, J_i\},\ i = 1, 2, 3, \tag{2}$$

f is the distribution representation of a linguistic term, A_i^* $(i = 1, 2, 3)$ that is the input for **FR, CS, FCP** respectively, and α_{ij}, represents the matching degree to which A_i^* belongs to the jth defined linguistic term A_{ij} of the ith antecedent parameter, that is computed by means of a matching function.

A simple matching function, τ, to compute α_{ij} is given as follows [21]:

$$\alpha_{ij} = \tau(A_i^*,\ A_{ij}) = \max_x[\min(\mu_{A_i^*}(x), \mu_{A_{ij}}(x))],$$
$$\alpha_{ij} \in [0, 1]\ (i = 1,\ 2,\ 3 \text{ and } j = 1,\ 2, \ldots, J_i) \tag{3}$$

where x covers the domain of the input A_i^*. In fact, this is *the highest point of intersection* of the input A_i^* and the fuzzy linguistic term A_{ij}.

Finally, an input to the rule-base can be expressed as follows:

$$\textbf{FR} \text{ is } f(A_1^*) \text{ AND } \textbf{CS} \text{ is } f(A_2^*) \text{ AND } \textbf{FCP} \text{ is } f(A_3^*) \tag{4}$$

where f is given by (2) and (3).

Comparing (4) with each rule given in (1), an input can be decomposed into the following form:

$$\textbf{FR} \text{ is } (A_1^k; \alpha_1^k) \text{ AND } \textbf{CS} \text{ is } (A_2^k; \alpha_2^k) \text{ AND } \textbf{FCP} \text{ is } (A_3^k; \alpha_3^k) \tag{5}$$

Here $A_i^k \in \{A_{ij},\ j = 1, \ldots, J_i\}$, $i = 1, 2, 3$; $\alpha_i^k \in \{\alpha_{ij};\ i = 1, 2, 3$ and $j = 1,\ 2, \ldots, J_i\}$. The final objective in this phase is to infer the conclusion using the rule-base (1) for the given input (4).

If the numerical values for the antecedent parameters (e.g., **CS**) are not available at all, then, the assessment of the antecedent parameters can also be carried out based only on experts' subjective judgements, i.e., they can be directly assessed to a distribution representation of each corresponding linguistic value with the degree of credibility. The corresponding f is a kind of subjective assignment. For example, **CS** could be assessed by a subjective distribution vector as follows:

$$\textbf{CS}: \{(\textit{marginal},\ 0.7),\ (\textit{moderate},\ 0.2),\ (\textit{critical},\ 0.1)\}.$$

This input assessment means that we are only 70% sure that **CS** is *marginal*, 20% sure that **CS** is *moderate*, and 10% sure that **CS** is *critical*.

Step 4.2: *Selection of "AND" connectives to reflect the dependencies of the antecedent parameters of a rule.*

Since the IF-part of a given rule has more than one antecedent parameter, the fuzzy operator AND is applied to obtain one global matching degree for that rule.

It should be noted that the *minimum* operator considers only one of several antecedent parameters and does not allow for any compensation among them. Due to this fact, in the safety estimate, we consider "AND" as that the consequent of a rule is not believed to be true unless all the antecedent parameters of the rule are activated. Therefore, in such cases we propose the use of the *product* operator as the AND connective to reflect the dependencies of the three parameters **FR, CS**, and **FCP**, i.e., the global matching degree α_k that the input $A^*{}_i (i = 1, 2, 3)$ belongs to the packet of antecedents A^k in the kth rule can be calculated as follows:

$$\alpha_k = \prod_{i=1}^{3} \alpha_i^k. \tag{6}$$

If the relative importance of the antecedent parameters is considered, the following weighted multiplicative aggregation function is used to calculate α_k:

$$\alpha_k = \prod_{i=1}^{3} \left(\alpha_i^k\right)^{\bar{\delta}_i} \tag{6a}$$

where

$$\bar{\delta}_i = \frac{\delta_i}{\max\limits_{i=1,\ldots,3} \{\delta_i\}} \text{ so } 0 \leq \bar{\delta}_i \leq 1. \tag{6b}$$

δ_i is the weight of the ith parameter ($i = 1,\ 2,\ 3$). Note that $0 \leq \alpha_k \leq 1$, $\alpha_k = 1$ if $\alpha_i^k = 1$ for all $i = 1, 2, 3$, and $\alpha_k = 0$ if $\alpha_i^k = 0$ for any $i = 1, 2, 3$. Also, the contribution of an antecedent parameter towards α_k is positively related to the weight of the attribute. In other words, the more important attribute the greater role in determining α_k.

Step 4.3: *Rule combination using an aggregation operator to create a resultant safety estimate*

To reach a final conclusion, all rules must be combined since the conclusion is based on the testing of all the rules in a fuzzy inference system. The input of the aggregation process is the list of global matching degrees for the antecedents in each rule. The classical fuzzy inference method infers the output with the greatest matching degree. Hence, the Arithmetic Mean aggregation function is suggested to use in this study. The assessment done by the *ith* expert e_i on the *lth* potential cause a_l to a technical failure by the aggregation of the consequent across the rules, i.e., the *safety estimate* $S(e_i(a_l))$, is expressed as follows:

$$S\left(e_i\left(a_l\right)\right) = \left\{\left(Poor; \vartheta_{0i}^l\right); \left(Fair; \vartheta_{1i}^l\right), \left(Average; \vartheta_{2i,}^l\right); \left(Low; \vartheta_{3i,}^l\right); \left(Good; \vartheta_{4i}^l\right)\right\}, \tag{7}$$

where $\vartheta_{ti}^l = \frac{\sum\limits_{r \in K_t} \alpha_r}{|K_t|}$ $(t = 0, \ldots, T = 4)$, $\alpha_r = \prod\limits_{i=1}^{3} \alpha_i^r$, e_i represents the *ith* expert ($i = 1, \ldots, p$) and a_l represents the *lth* ($l = 1, \ldots, q$) potential cause to a technical failure. Let R be the number of all the rules fired in the evaluation, K_t represents the set of all the fired rules in which D_t ($t = 0, \ldots, 4$) is the output term, here $D_t \in S_T \cdot |K_t|$ is the cardinality of the set K_t, hence $R = \sum\limits_{t=0}^{4} |K_t|$. Note that $S(e_i(a_l))$ actually can be viewed as a fuzzy set on S_T, $\vartheta_{ti}^l \in [0, 1]$ represents the membership degree of which the *safety estimate* belongs to D_t.

Phase #5: Safety synthesis

To achieve a logical and effective evaluation process, it is necessary to break down the complex systems into the simpler sub-systems in a hierarchical manner. The hierarchical framework of attributes or experts is used to guide the overall evaluation of multi-attributes or multi-experts or a combination of multi-attributes-multi-experts decision problems as shown in Figs. 1 and 2.

The first four phases of the framework mainly focus on the safety assessment of a single cause to a technical failure done by an expert. This phase is concerned with the safety synthesis of a system at various levels, such as:

- A synthesis of the safety estimates of various causes to a technical failure done by an expert; or
- A synthesis of the safety estimates of a specific cause to a technical failure done by a panel of experts; or
- A combination of the above two forms, i.e., a multi-attribute-multi-expert safety synthesis (see Fig. 2).

Considering that the safety level is expressed as a linguistic variable in qualitative nature, it is difficult to establish their membership functions. The ordinal fuzzy linguistic approach is considered here to use the direct computation on linguistic values instead of using their membership functions. In this framework, particularly a 2-tuple linguistic representation model [7,8] is used to perform the safety synthesis of an engineering system with a structure that is capable of being decomposed into a hierarchy of levels. The number of levels required in safety synthesis is determined by the degree of complexity of a system under scrutiny or the number of experts taking part in the assessment.

The safety synthesis procedure can be summarised as the following five steps:

Step 5.1: *Transforming the safety estimate into the linguistic 2-tuple.*

Advantages of the 2-tuple linguistic representation to manage linguistic information over classical models were shown in [8], some concepts and properties are referred to [7,8].

In this phase we transform the fuzzy set $S(e_i(a_l))$ obtained in (7) on the S_T into a linguistic 2-tuple over the S_T. A function χ_i^l is introduced that transforms a fuzzy set in a linguistic term set S_T into a numerical value in the interval of granularity of S_T, $[0, T-1]$, T is the cardinality of S_T; $F(S_T)$ denotes the set of all fuzzy sets on the S_T:

$$\begin{aligned}\chi_i^l : F(S_T) \to [0, T-1], \chi_i^l(\{(s_t; \vartheta_{ti}^l), t = 0, \ldots, T-1\}) \\ = \frac{\sum_{t=0}^{T} t\vartheta_{ti}^l}{\sum_{t=0}^{T} \vartheta_{ti}^l} = \beta_i^l \in [0, T-1]\,. \end{aligned} \tag{8}$$

Then its 2-tuple linguistic representation is calculated by the operator Δ:

$$\begin{aligned}&\Delta : [0; T-1] \to S_T \times [-0.5, 0.5), \\ &\Delta(\beta_i^l) = (s_{round(\beta_i^l)}, \lambda = \beta_i^l - \text{round}(\beta_i^l)), \text{ where } \lambda \in [-0.5, 0.5). \end{aligned} \tag{9}$$

Here $S_T = \{s_0 = \text{'}Poor\text{,'}\ s_1 = \text{'}Low\text{,'}\ s_2 = \text{'}Average\text{,'}\ s_3 = \text{'}High\text{,'}\ s_4 = \text{'}Good\text{'}\}$, $T = 5$. $\beta_i^l \in \{0, \ldots, T-1\}$ is obtained using (8). Therefore, applying the Δ function to β_i^l $(i = 1, \ldots, p;\ l = 1, \ldots, q)$ we shall obtain a safety estimate (by the *ith* expert on the *lth* potential cause to a technical failure) whose values are linguistic 2-tuple, e.g., if $\beta_i^l = 1.2$, then its 2-tuple representation is (*Low*, 0.2). There is always a Δ^{-1} function, such that, from a linguisitc 2-tuple it returns its equivalent numerical value $\beta \in [0,\ g]$.

$$\Delta^{-1} \quad : \ S \times [-0.5,\ 0.5) \to [0;\ g],\ \Delta^{-1}(s_i;\ \lambda) = \lambda + i = \beta. \qquad (10)$$

Step 5.2: *Relative weights assignment*

It is highly unlikely for the selected experts to have the same importance, and usually, weights of importance need to be utilised. Each expert is assigned with a weight to indicate the relative importance of his or her judgment in contributing towards the overall safety evaluation process. The analyst must decide which experts are more authoritative. Weights are then assigned accordingly.

In [7, 8], some of the 2-tuple linguistic aggregation operators were presented, such as the Arithmetic Mean operator and the Weighted Mean operator by means of the linguistic 2-tuples. Therefore, to aggregate the linguistic 2-tuples, we shall choose one of these operators and apply it for combining the linguistic 2-tuples, obtaining as a result an aggregation linguistic 2-tuple assessed in S_T for safety synthesis as follows.

Step 5.3: *The synthesis of 2-tuple expression of safety estimates of a specific cause to a technical failure done by a panel of experts by using the 2-tuple weighted mean aggregation operator.*

$$\begin{aligned} \beta^l &= \mathrm{W\_AM}^* \left(\left(w_1;\ \beta_1^l\right), \ldots, \left(w_p;\ \beta_p^l\right) \right), \\ &= \Delta\left(\frac{\sum_{i=1}^p \Delta^{-1}(\Delta(\beta_i^l)) \cdot w_i}{\sum_{i=1}^p w_i} \right) = \Delta\left(\frac{\sum_{i=1}^p \beta_i^l \cdot w_i}{\sum_{i=1}^p w_i} \right). \end{aligned} \qquad (11)$$

$W = \{w_1, \ldots, w_p\}$ is the associated experts' weight vector, Δ and Δ^{-1} are given in (9) and (10) respectively.

Step 5.4: *Ranking and interpretation of the safety synthesis*

The safety estimate results obtained from the approximate reasoning have been transformed into the 2-tuple linguistic representations. Moreover, based on the multi-expert synthesis results on each potential cause from Step 5.3, this step compares the overall 2-tuple representation of the risk level by a panel of experts. Then the identified potential causes are ranked on the basis of their 2-tuple expressions. The ranking results for risks due to various potential causes may help designers understand the anticipated technical problem, so that an improved risk reduction measure can be incorporated or a more innovative design can be carried out in order for higher safety level.

The following are some concepts on the comparison of the linguistic 2-tuples [7, 8] used in the ranking process.

Let $(s_k,\ \lambda_1)$ and $(s_l;\ \lambda_2)$ be two linguistic 2-tuples, with each one representing a counting of information, then

- if $k < l$ then $(s_k,\ \lambda_1)$ is smaller than $(s_l,\ \lambda_2)$
- if $k = l$ then
  (1) if $\lambda_1 = \lambda_2$ then $(s_k,\ \lambda_1)$, $(s_l,\ \lambda_2)$ represent the same information
  (2) if $\lambda_1 < \lambda_2$ then $(s_k,\ \lambda_1)$ is smaller than $(s_l,\ \lambda_2)$
  (3) if $\lambda_1 > \lambda_2$ then $(s_k,\ \lambda_1)$ is bigger than $(s_l,\ \lambda_2)$

Step 5.5: *The synthesis of safety estimate of various causes to a technical failure by using the 2-tuple Arithmetic Mean aggregation operator.*

$$\mathrm{AM}^*(\beta^1, \ldots, \beta^q) = \Delta(\frac{1}{q}\sum_{l=1}^{q}\beta^l). \tag{12}$$

Finally, a multi-attribute-multi-expert safety synthesis can be obtained.

3 Case Study: Collision Risk of FPSO & Shuttle Tanker During a Tandem Offloading Operation

Floating production storage offloading (FPSO) systems combine traditional process technology with marine technology, and thus are dependent on the technical design and the operational safety control [11]. It is essential that the anticipated hazards due to technical factors can be identified, risk control options be proposed, and risk reduction or control measures be taken to reduce the risk to as low as reasonably practical (ALARP). Scenarios involving potential major hazards, which might threaten an FPSO or loss of operational control, are assessed at an early stage in the design of new facilities to optimise technical and operational solutions [13]. Collision between a FPSO and a shuttle tanker in tandem offloading operation has caused a growing concern in the North Sea as well as the rest of the world [11].

In this section, safety assessment is carried out on risks introduced by the collision of FPSO and shuttle tanker during tandem offloading operation. Only the technical failures caused risk is assessed here, though the operational failure has been also recognised as one of the major causes of collision. For the purpose of safety modelling, it is assumed that each antecedent parameter (i.e., **FR, CS**, and **FCP**) will be fed to the proposed safety model in term of any of the four input forms described in Phase #3 of Sect. 2.

According to the literature survey, the technical failures that might cause collisions between an FPSO and a shuttle tanker during tandem offloading operations are malfunction of propulsion systems [3]. The four major causes to these technical failures are:

(1) Controllable pitch propeller (CPP) failure
(2) Thruster failure

(3) Position reference system (PRS) failure
(4) Dynamics positioning system failure (DP)

A panel of five experts from different disciplines participated in risk analyses of the above four identified causes to the technical failures. They used different input forms to describe the collision risk scenario in terms of **FR, CS** and **FCP**.

The safety estimate of each technical failure is assessed by five experts separately. The assessment made by the five experts in terms of **FR, CS**, and **FCP** is depicted in Table 4 for collision between FPSO and shuttle tanker during tandem offloading operation due to controllable pitch propeller (CPP) caused technical failure. Other three kinds of assessments are depicted in Tables 5–7, respectively.

A sample of the 245 rules in the rule base [13] is used in this case study. For illustration, we take CPP for example, Expert # 1 used triangular form to address the inherent uncertainty associated with the data and information

Table 4. Experts' inputs for the technical failure caused by malfunction of the controllable pitch propeller (CPP)

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(6.5, 8, 9.5)	(7.5, 8.5, 9.5)	(5.5, 7, 8.5)
E # 2	Triangular	(5.5, 7.5, 9)	(7, 8.5, 10)	(5, 7.5, 9.5)
E # 3	Closed interval	[6,8]	[7,9]	[6.5, 9]
E # 4	Trapezoidal	{5.5, 6.5, 9, 10}	{5.5, 7, 8, 10}	{5, 7, 8, 8.5}
E # 5	Single deterministic	7.75	8.25	7.6

Table 5. Experts' inputs for the technical failure caused by malfunction of the thruster

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(6, 7, 7.5)	(6.5, 7, 8)	(4.5, 5.5, 6)
E # 2	Triangular	(6, 6.5, 8)	(7, 8, 9)	(6, 7.5, 8)
E # 3	Closed interval	[5.5, 7.5]	[6,8]	[6,8]
E # 4	Trapezoidal	{5, 6, 7, 8}	{5, 7, 8, 9}	{5, 6, 7, 9}
E # 5	Single deterministic	7.15	7.95	7.25

Table 6. Experts' inputs for the technical failure caused by malfunction of the position reference system (PRS)

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(6.5, 7, 7.5)	(8, 8.5, 9)	(5.5, 7, 8)
E # 2	Triangular	(6, 7.5, 8)	(7.5, 8, 9.5)	(5, 6, 7)
E # 3	Closed interval	[6.5, 8]	[7, 7.5]	[6.5, 7.5]
E # 4	Trapezoidal	{6, 7, 8, 9}	{5, 7, 8, 8.5}	{6, 7, 8, 9}
E # 5	Single deterministic	7.5	7.2	7.1

Table 7. Experts' inputs for technical failure caused by malfunction of the dynamics positioning system (DP)

Expert	Shape of input form	FR	CS	FCP
E # 1	Triangular	(7, 7.5, 8)	(7.5, 8.5, 9)	(6, 7, 7.5)
E # 2	Triangular	(6.5, 7, 8)	(6.5, 7, 8.5)	(5.5, 6, 7)
E # 3	Closed interval	[7,9]	[7.5, 9.5]	[7,8]
E # 4	Trapezoidal	{6.5, 7, 7.5, 8}	{6, 6.5, 7, 8}	{6.5, 7, 7.5, 9}
E # 5	Single deterministic	7.95	8.25	7.9

available, while carrying out the assessments on the three input parameters. The **FR** is described triangularly as (6.5, 8.0, 9.5) on the fuzzy scale. The most likely value is 8.0, 6.5 and 9.5 are the lower and upper least likely values, respectively.

The safety estimates made by the five experts for the technical failure caused by malfunction of the controllable pitch propeller (CPP) are performed separately according to the proposed fuzzy-logic-based approximate reasoning approach. The safety estimate assessed by Expert # 1 for the potential cause # 1 (CPP) to a technical failure has the result as follows by using (7):

$$S\left(e_1\left(a_1\right)\right) = \left\{(good;0),(low;0),(average;0),(high;0.0764),(poor;0.1999)\right\}.$$

The output can be interpreted in such a way that the safety estimate of the system is "*high*" with a membership degree of *0.0764* and "*Poor*" with a membership degree of *0.1999*. Furthermore, it can be transformed into a linguistic 2-tuple value in S_T using (8) and (9):

$$\chi_1^1(\{(s_t,\vartheta_{t1}^1),t=0,\ldots,4\}) = \frac{\sum_{t=0}^4 t\vartheta_{t1}^1}{\sum_{t=0}^4 \vartheta_{t1}^l} = 0.2765 = (Poor,\ 0.2765).$$

The similar computations are performed for the safety assessments by all five experts using the proposed fuzzy-logic-based approximate reasoning approach for all four technical failures. The results attained for thrusters, PRS and DP caused technical failures by the five experts are shown in Table 8.

As shown in Fig. 1, the aggregation operators on the 2-tuple linguistic representations are used to synthesise the information thus produced to assess the safety of the whole system. This step is concerned with the safety synthesis of a system at various configurations such as: the first type is multi-attribute synthesis, and the second type is multi-expert evaluation of a particular failure mode. The last one is a multi-attribute-multi-expert synthesis and evaluation.

Table 9 shows the results of multi-expert safety synthesis on the collision risk between FPSO & shutter tanker due to the CPP, thrusters, PRS and DP caused technical failure, obtained using the weighted mean operator on the 2-tuple linguistic representations. The synthesis is carried out with the relative weights assigned to each expert by the 2-tuple weighted mean aggregation operator.

Table 8. Safety estimate by each expert on collision risk between FPSO & shutter tanker due to CPP, the thrusters, PRS and DP caused technical failure

Expert #		E # 1	E # 2	E # 3	E # 4	E # 5
CPP	Safety estimate	{(Poor; 0.1999), (Low; 0.0764)}	{(Poor; 0.3170), (Low; 0.1385)}	{(Poor; 0.9118), (Low; 1)}	{(Poor; 0.4314), (Low; 0.3165), (Average; 0.1309)}	{(Poor; 0.1299)}
	2-Tuple expression	(Poor, 0.2765)	(Poor, 0.3041)	(Low, −0.4769)	(Low, −0.3419)	(Poor, 0)
Thruster	Safety estimate	{(Poor; 0.2571), (Low; 0.1634), (Average; 0.0438)}	{(Poor; 0.3101), (Low; 0.5262)}	{(Poor; 0.6664), (Low; 0.7223), (Average; 0.5005)}	{(Poor; 0.2955), (Low; 0.3435), (Average; 0.2428)}	{(Poor; 0.25)}
	2-Tuple expression	(Low, −0.4594)	(Low, −0.3708)	(Low, −0.0878)	(Low, −0.0526)	(Poor, 0)
PRS	Safety estimate	{(Poor; 0.1222), (Low; 0.0294)}	{(Poor; 0.3635), (Low; 0.2823)}	{(Poor; 0.5), (Low; 0.5003)}	{(Poor; 0.4019), (Low; 0.3907)}	{(Poor; 0.25)}
	2-Tuple expression	(Poor, 0.1939)	(Poor, 0.4423)	(Low, −0.4999)	(Poor, 0.4929)	(Poor, 0)
DP	Safety estimate	{(Poor; 0.125)}	{(Poor; 0676), (Low; 0.0479)}	{(Poor; 0.125)}	{(Poor; 0.4405), (Low; 0.3536)}	{(Poor; 0.125)}
	2-Tuple expression	(Poor, 0)	(Poor, 0.4157)	(Poor, 0)	(Poor, 0.4453)	(Poor, 0)

Regardless of the weight difference between each expert allocated, the potential risk caused by the thruster failure is always the lowest and DP the highest from Table 9. As the relative weights of the panel experts change as $\{W_{\mathrm{E}\#1},\ W_{\mathrm{E}\#2},\ W_{\mathrm{E}\#3},\ W_{\mathrm{E}\#4},\ W_{\mathrm{E}\#5}\} = \{5, 4, 3, 2, 1\}$, DP caused technical failure is ranked first, whereas the potential risk induced by PSR and DP are ranked second and third, respectively. As the relative weights change to {4, 5, 1, 2, 3}, then DP is ranked first, CPP second, PSR third and thrusters last. The results of other weight configurations are depicted in Table 10. The

Table 9. Multi-expert synthesis on each attribute (expert with different weights)

Expert's	Weight				Ranking			
E #1	E #2	E #3	E #4	E #5	CPP	Thruster	PSR	DP
1	1	1	1	1	(Poor, 0.3524)	(Low, −0.3941)	(Poor, 0.3259)	(Poor, 0.1720)
5	4	3	2	1	(Poor, 0.3656)	(Low, −0.3433)	(Poor, 0.3483)	(Poor, 0.1700)
1	2	3	4	5	(Poor, 0.3391)	(Low, −0.4450)	(Poor, 0.3034)	(Poor, 0.1740)
4	5	1	2	3	(Poor, 0.2977)	(Low, −0.4590)	(Poor, 0.2982)	(Poor, 0.1976)
3	4	5	1	2	(Poor, 0.3546)	(Low, −0.3569)	(Poor, 0.3563)	(Poor, 0.1403)

Table 10. Safety ranking (experts with different weights) based on the 2-tuple linguistic representation

Expert's	Weight				Ranking			
E #1	E #2	E #3	E #4	E #5	CPP	Thruster	PSR	DP
1	1	1	1	1	3	4	2	1
5	4	3	2	1	3	4	2	1
1	2	3	4	5	3	4	2	1
4	5	1	2	3	2	4	3	1
3	4	5	1	2	2	4	3	1

Table 11. Multi-attribute-multi-expert safety synthesis by the experts carrying different weights

Expert's	Weight				Safety synthesis
E #1	E #2	E #3	E #4	E #5	
1	1	1	1	1	(Poor, 0.3640)
5	4	3	2	1	(Poor, 0.3852)
1	2	3	4	5	(Poor, 0.3429)
4	5	1	2	3	(Poor, 0.3336)
3	4	5	1	2	(Poor, 0.3736)

ranking results for risks, which are based on various potential causes as assessed by a panel of experts, can lay out a guideline for the designers to enhance the safety level of FPSO.

The results of multi-attribute-multi-expert safety synthesis for other weight variance configurations are depicted in Table 11, which is based on Table 8 using the 2-tuple mean operators on multi-attributes.

4 Conclusions

The framework for modelling system safety proposed in this paper introduced a subjective safety modelling for engineering risk analysis, which is done by combination of the approximate reasoning approach and the ordinal fuzzy linguistic assessment approach.

The safety assessment using the approximate reasoning approach can formulate the domain human experts' experience and the safety engineering knowledge. At the same time, information with different properties from various sources can be transformed into the knowledge base and used in the fuzzy inference process. The safety synthesis approach based on the 2-tuple ordinal linguistic representation is computationally simple and quick.

The results obtained from the case study on collision risk between FPSO and shuttle tanker has shown that such a framework provides the safety analysts and designers with a convenient tool for risk analysis, especially in the initial concept design stages where the related safety information is scanty or with great uncertainty involved. The method described forms a supplement to the methodologies already used in engineering safety assessment.

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A Complex Abstraction Approach to Radioactive Waste Management Policy Decision Making

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Summary. Complex risk-based decisions in radioactive waste management policy are guided by a number of rationalities including probabilistic risk assessments, technical feasibilities, cost-benefit analyses, expert opinions and legal norms. Typically, however, there exists a gap between the risk perceptions of experts and the public, which adversely affects the societal acceptability of these decisions. Eliciting risk-based decision-criteria elements from the elaborate societal argumentation and objectively addressing them in policy decision-making is a complex abstraction issue that will arguably render the decision-making process more transparent and effective in persuading society. In addition, relevant legal elements need to be incorporated objectively for the decisions to be just and equitable to society. This paper proposes a complex Risk–Risk Analysis based socio-legal abstraction approach within a fuzzy decision making framework to support socially persuasive policy decision-making in radioactive waste management. As an illustration, the deep geological repository decision-making problem of ASN, The French Nuclear Safety Authority is abstracted and solved with hypothetical fuzzy rank preferences.

1 Introduction

Decision-Making (DM) in the nuclear domain is complex by nature. In choosing safe options for society, a particular challenge for nuclear safety and policy authorities is DM in the face of scientific uncertainties. This challenge is further deepened by intense public debates/rhetoric surrounding the DM.

The field of nuclear waste management policy involves many complex decisions such as waste storage, transportation, reprocessing etc. In this paper, the policy problem of deciding on a long-term solution for high-level long-lived radioactive waste management (referred to as "the radwaste DM problem" in this paper) is discussed in detail. According to the US Department Of Energy (2000), out of the various possible technical solutions to the radwaste problem, nuclear authorities in the United States, Belgium, Canada, China, Finland, France, Germany, Japan, Russia, Spain, Sweden, Switzerland, and the United

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Kingdom support deep geologic disposal in repositories as a preferred solution for isolating radwastes [1]. However, with the exception of one or two countries, most of the others have been unable to gain public acceptance for siting such repositories despite years of research and societal persuasions. The accumulating radwastes have the nuclear safety authorities increasingly worried about the necessity to act sooner than later on long-term solutions. They are well aware that the radwaste problem is here to stay for the next thousands of years and "must be properly managed irrespective of the fate of nuclear energy" as an energy option for the world in future [2].

In order to improve societal acceptability of long-term solutions for radwaste management, many stakeholder participatory formats are evolving around the world. The mechanisms of how to conduct such participatory processes and gather stakeholder opinions are in itself a field of considerable research and activity. However, the key to the success of these approaches is how effectively various multi-disciplinary inputs and opinions obtained from experts and stakeholder argumentation alike e.g., technical feasibilities, financial feasibilities, expert risk perceptions and public risk perceptions, are abstracted into risk-based decision-criteria elements and objectively integrated into a suitable decision-making framework. Such a wholesome integration would contribute towards the "central route" to societal persuasion, which is considered to be a more durable form of persuasion. (According to social psychologists, societal persuasion can happen via two routes: a "central" route or a "peripheral" route. Central route to persuasion involves an objective focus based on arguments and thinking while the peripheral route occurs when people are influenced by incidental cues e.g., speaker's attractiveness) [3]. Equally important in policy DM is applying the relevant legal basis of the DM objectively so as to offer just and equitable decisions to society.

Addressing the above situation, this paper proposes a new complex abstraction approach to the radwaste DM problem. A combination of Risk–Risk Analysis (RRA) and "intelligent" knowledge representations of legal principles help abstract the necessary socio-legal decision-criteria elements which are then integrated into a fuzzy Analytic Hierarchy Process (Fuzzy AHP) DM framework.

The paper is organized as follows: Sect. 2 provides a brief background of risk perceptions regarding nuclear energy and radwaste management. Section 3 provides a summary of existing approaches of dealing with the radwaste problem. In this context, abstraction and DM methods employed in a case study of the Korean radwaste problem and the work of the Committee on Radioactive Waste Management (CoRWM), UK are discussed. Based on observations emerging from such existing approaches, Sect. 4 first gives imperatives for a new abstraction design. It then outlines a complex abstraction approach comprising of the following three parts:

1. An RRA approach to help extract risk-based decision criteria/sub-criteria elements from societal argumentation.

2. "Intelligent" knowledge representation methods for the legal basis of the decisions to help derive legal decision-criteria elements.
3. A Fuzzy AHP framework to integrate risk-based decision-criteria elements and the legal criteria elements to evolve the most preferred solution to the radwaste problem.

Section 5 presents a case study – the radwaste problem of ASN, The French Nuclear Safety Authority, is solved using the above methodology with hypothetical input values and the results discussed. Section 6 provides an explanatory note on rank reversal phenomenon observed in some AHP cases. Further research directions for the proposed methodology are outlined in Sect. 7. The conclusions are presented in Sect. 8.

2 Nuclear Risk Perceptions: A Background

Underlying the extensive argumentation and rhetoric surrounding nuclear decisions are strong societal perceptions about nuclear risks in general and radwaste risks in particular. E.g., a 2002 joint study of IRSN and SCK [4], based on interviews of over 1,000 members of the public each in France and Belgium presented the following findings as regards the societal risk perceptions concerning nuclear sector:

1. Out of varied technologies including chemical, petroleum, dams etc., nuclear power plants, dangerous transport of nuclear wastes and storage of radioactive waste were ranked as the top three technologies which (according to the people surveyed) had the highest probability to cause a serious accident/disaster.
2. Most people surveyed do not trust that they have been told the truth about the risks involved. Fifty-six percent of the French population believed that they have not been told the "truth" about nuclear power plant risks and 63% believe that they have not been told the "truth" about nuclear waste risks. In Belgium, the corresponding percentages are 60 and 63%.
3. Thirty-seven percent of the French population and 42% of the Belgian population claimed that they don't have confidence in the authorities to protect against the danger of nuclear installations.

Despite such strong feelings about nuclear risks, the above study interestingly found that large fractions of the population were not even familiar with the names of organizations/public nuclear authorities in their respective countries.

2.1 Risk Perceptions and the Radwaste Problem

On the specific issue of radwaste risks, the IRSN-SCK (2002) study found that 82% of the French population ranked nuclear waste risks to belong to the risk category of "medium high" and above.

In France and elsewhere around the world, geo disposal in repositories is a favored policy option. Societal persuasion on radwaste disposal options is typically sought to be achieved by using a combination of Probabilistic Safety Assessment (PSA)/Performance Assessment (PA) studies, expert opinions, cost-benefit analyses and also by taking limited recourse to legal precepts e.g., the Precautionary Principle (PP), ALARA etc. In many countries, participative approaches (limited stakeholder/public consultations) are conducted to incorporate society's views in such decisions. Despite these steps, many members of the public are not yet persuaded of the (urgent) need for geological disposition of wastes [5]. Even if they are, there is a typical Not-In-My-Backyard (NIMBY) societal reaction that stymies most radwaste disposal decisions. One of the key underlying causes for such adverse reactions is a gap in the way geo repository risks are perceived by experts and by public. The average member of public does not understand complex PSA studies, mainly due to the complex risk mathematics and the extremely long time frames involved [6]. Also, the quantitative PAs are audience-dependent i.e., a document that is transparent to a regulator or practitioner of the PA may not be transparent to a member of the public [7]. Such factors widen the gaps in risk perception-between the experts and the public. These are further amplified with media/campaign rhetoric thereby resulting in low social acceptability or even societal rejection of radwaste management decisions.

Various public participatory models are already in vogue (and some are evolving) in order to bridge the expert-stakeholder gap in risk perceptions pertaining to radwaste policy decisions e.g., Cooperative Discourse Approach, Analytic-deliberative approach [8], etc. Such models comprise of two distinctive parts:

1. Mechanisms of public and stakeholder involvement e.g., using Delphi techniques, holding consensus conferences.
2. Abstraction approaches – wherein risk-based decision criteria elements (and other applicable normative elements e.g., ethical elements) are derived from the argumentation/discourse and these are then incorporated into formal Multi-criteria DM approaches.

This paper specifically focuses on the latter part.

Note: The abstraction approach discussed in this paper is generic and is therefore applicable to all models of public/stakeholder participation mechanisms.

3 Existing Abstraction Approaches to Radwaste Management DM

To support the increasing public/stakeholder participation engagements around the world, many abstractions of the radwaste DM problem have been suggested in contemporary research and public participatory action literature. An abstraction method answers the following questions: How and which risk-based decision-criteria elements are extracted from the underlying expert/public discourse? Which legal normative elements are considered as decision-criteria elements in the DM problem and how have they been derived? In what DM framework are the two viz. risk-based decision-criteria elements and legal normative decision-criteria elements integrated?

Before discussing further on current abstraction approaches to the radwaste DM problem, an overview of abstraction is in order.

3.1 What is Abstraction?

Abstraction, from the perspective of the field of computer sciences, could be broadly classified into two types-the process type and the entity type.

Process Type

A process type abstraction denotes the extracting of essential details about an item or a group of items, at the same time ignoring the inessential details. E.g., Out of various details that could be made available on a person, a Human Resources (HR) Manager considers only specific details as per pre-determined criteria e.g., qualifications, experience, etc.

Entity Type

Entity type abstraction denotes a model, a view, or some other focused representation for an actual item [9]. E.g., A map and globe are two different abstractions of geographic data of the physical environment. In the HR example given above, the Manager needs to take a view on how to evaluate the candidates. She might score candidates on each of the parameters and choose the candidate with the highest score. She can also make a pair-wise comparison of candidates using methods like AHP etc. Each of such methods constitutes an abstraction (entity type) of the problem of choosing a suitable candidate.

The process type abstraction helps reduce computational complexities while the entity type abstraction reduces conceptual complexities.

In light of the above discussions, Fig. 1 summarizes the task involved in the radwaste problem abstraction.

3.2 Current Approaches to the Radwaste DM Problem: A Focus on Abstractions

In order to provide an indicative overview of current abstraction approaches to radwaste DM, two cases are summarized below and their results briefly discussed.

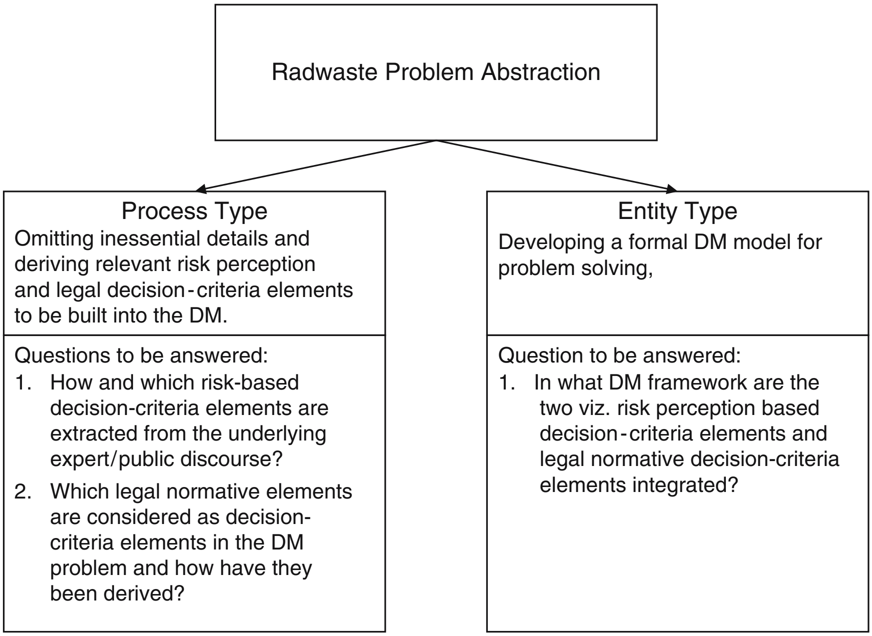

Fig. 1. A generic radwaste problem abstraction

Summary of Korean Case Study on Radwaste DM

Sohn et al. [10] discuss a method of assimilating public opinions in nuclear decision-making using risk perceptions. They have evaluated six options for spent fuel management in Korea based on a fuzzy, AHP and Multi Attribute Utility Analysis (MAUA) based approach.

The following contains a summary of their abstraction methodology in both the process and the entity types.

Abstraction (Process Type). From separate polls conducted to gather public and expert opinions, a total of five attributes were evolved and considered for radwaste DM. Four of these DM attributes viz. *economic cost, safety, technology*, and *international affairs* formed the subject of expert polls while *public risk perception*, a subject of the public polls, was the fifth decision attribute. The *public risk perception* attribute was quantified using a psychometric model of risks proposed by Slovic et al. (The Slovic model is based on the premise that individual risk perceptions are determined by a combination of psychological factors of *voluntariness, dread, control, knowledge, catastrophic potential, novelty* and *equity*.) These factors were trimmed down to four using a factor analysis approach and thus the risk-based decision attribute elements were abstracted.

Abstraction (Entity Type). In the aggregation of expert and public attributes, AHP was used for deriving the attribute weights and Multi-Attribute

Utility Analysis (MAUA) was employed to aggregate expert and public opinion. For uncertainty analysis, a fuzzy set based approach was adopted. The uncertainty ranking of the six-radwaste management options based on fuzzy integrals was compared with the ranking obtained from the utility values of each option.

Results. The Multi-Utility and uncertainty rankings converged and the top three options that emerged for the Korean radwaste problem were (1) AR dry storage (2) Inter-site transshipment of PWR fuels (3) Overseas storage. As regards the specific issue of public risk perceptions, the paper concludes that "when public risk perception was included as one of the DM attributes as in the case studied, the relative importance or ranking of a given option was altered from that based upon cost analysis. The case study suggests that public risk perception could be an important attribute in most nuclear-related DM processes."

Summary of Radwaste DM Methods Adopted by CoRWM (UK)

CoRWM, Committee on Radioactive Waste Management was mandated by the UK Government in 2003 to make recommendations for the long-term management of the UK's higher activity wastes that would both protect the public and the environment, and inspire public confidence [11]. CoRWM undertook extensive public participatory efforts based on the Cooperative Discourse Model of public participation.

The following contains a summary of their abstraction methodology in both the process and the entity types.

Abstraction (Process Type). Engagement with the public and stakeholders, expert knowledge and reflection on ethical issues contributed to the underlying discourse for criteria selection. The committee dealt with seven waste streams, 14 options, 11 head criteria and 27 sub-criteria elements for decision-making. The 11 head line criteria (risk-based decision-criteria) elements abstracted were: *Public safety individual – short term <300 years, public safety individual >300 years, worker safety, security, environment, socio-economic, amenity, burden on future generations, implementability, flexibility* and *costs*.

Abstraction (Entity Type). The committee adopted two complementary assessment methods. An MCDA technique enabled the shortlist of options to be assessed against those criteria judged to be important by citizens of the UK, as identified, e.g., by the Citizens' Panels and other stakeholders. This approach was complemented by a holistic approach in which the options were assessed as a whole rather than breaking them down into their specific attributes. In accordance with a "Cooperative discourse methodology", the MCDA assessments were then compared with the holistic assessments for (in) consistencies and conclusions drawn.

One of the key features of the MCDA model was "swing weighting" of decision criteria/sub-criteria elements. In MCDA, equality of a unit of preference value needs to be established. (Just as 0–100 on a Celsius scale is not equivalent to a 0–100 on a Fahrenheit scale – they need to be correlated). Achieving this equality in scale preferences was established through the swing weighting process. There is a limited explanation of the "swing weighting" method in section "Inter-Criteria Comparisons (Risk Tradeoffs) Are Either Weak or Not Present", however readers are requested to refer to [12] for a detailed discussion on swing weighting methodology.

Findings. CoRWM concluded that overall, disposal options are ranked higher than storage options.

The Committee made a total of 18 recommendations out of which a few are highlighted here.

It recommended "geological disposal as the end point for the long-term management of radioactive wastes" and also called for "robust storage in the interim period, including provision of contingency against delay or failure in reaching the end point". The evaluation of deep geo disposal as the most suitable long-term solution for the radwaste problem was arrived at after a very elaborate process of stakeholder participation and MCDA methodology. Despite this however, the committee interestingly recognized the following in its final recommendations: "recognizes that there are social and ethical concerns that might mean there is not sufficient agreement to implement geological disposal at the present time. In any event, the process of implementation will take several decades. This period could last for as long as one or two generations if there are technical difficulties in siting or if community concerns make it difficult, or even impossible, to make progress at a suitable site." Amongst other recommendations, the committee also recommended a suitable "community package" (financial incentive) in order to make the geo disposal option more acceptable to the host community.

From the above discussion it can be observed that improving societal acceptability of radwaste decisions despite years of expert-public collaboration is not very easy. This makes efforts to re-visit these methods and examine the scope for improvements seem worthwhile.

3.3 Scope for Improvement in Existing Methods

Typically in the existing methods of radwaste DM, (including the two methods discussed in Sect. 3.2), the following observations hold:

The Method of Abstracting Societal Risk Perceptions and Criteria from the Underlying Societal Discourse is Human-Intensive

Further examining the process type abstractions of the cases described in Sect. 3.2:

1. Sohn et al. used a theory-based approach. In this approach, a risk perception theory (Slovic model) was applied to pre-decide on the major lines of stakeholder risk perceptions. Questions to elicit decision-criteria were then designed based on these pre-decided lines of risk perception. Depending

on stakeholder response to questions, risk-based decision criteria elements were abstracted by the analysts.

2. The CoRWM used an approach based on direct inputs. In this approach, the stakeholders were asked to list important criteria that they thought needs to be part of the DM while evaluating options. In a variation of this format, the stakeholders commented on a list of criteria proposed by the authorities. Accordingly the risk-based decision-criteria list was modified and finalized by CoRWM experts.

However, both the above approaches have some scope for improvement – they involve a very high degree of human intervention (facilitation and analysis) in abstracting the risk-based decision criteria. There needs to be a move towards increasing the automation component of this process and minimizing human intervention.

Advantages of Automating the Abstraction Process: With Minimal Human Intervention

1. The abstraction of risk-based decision criteria elements from stakeholder engagements involves a massive volume of linguistic data processing and compilation. Automation would help ease these efforts.
2. Automation can also help increase the effectiveness of the participatory process by facilitating formation of risk-criteria databases. Especially in policy options such as deep geo repositories, decision-makers are aware that "individuals and groups involved in resisting the siting of projects often look for and learn from cases where resistance has been successful in the past". Comparative analysis (between different national experiences) is crucial in developing better theories and models for understanding facility siting processes and outcomes" [13].

In order to make a consistent comparison across national and international risk perceptions and also to learn "intelligently" from past experiences of how these have been dealt with by other nations, it would be helpful to safety authorities and policy makers to possess a database of societal risk perceptions and risk criteria. Populating such a database would be easier if the process of abstraction is automated to the extent possible. This in turn implies the need for an abstraction method that can perform abstractions in a computer-conducive format with minimal human intervention. Such an abstraction method should also be robust enough to abstract risk elements from varied sources including international experience sharing meetings, discussion forums, press articles, position papers, multilateral Institutional reports etc. in a logical manner.

In summary, there is a need for a process type abstraction method that can enable abstraction of risk elements from massive data and also present it in a computer-conducive format. Current abstraction methods do not offer these features.

Inter-Criteria Comparisons (Risk Tradeoffs) Are Either Weak or Not Present

The decision-criteria elements in the existing methods are formulated by the experts and the stakeholders (including members of the public). But this participatory process stops short of providing a suitable mechanism for making rigorous inter-criteria comparisons. Such comparisons are important because they actually reflect expert and stakeholder preferences for risk tradeoffs – ideally, this should be at the core of any complex risk-based policy decision.

Example 1. In the Korean case study (section "Summary of Korean Case Study on Radwaste DM"), out of the five DM attributes used for evaluating the best radwaste solution, four viz. *Economic cost, Safety, Technology* and *International affairs* pertain to expert evaluations and the fifth attribute viz. public risk perception pertains to public opinion. While this method definitely builds in public participation into the formal DM model, the following are some observations:

The expert and public criteria are treated in separate silos. An inter-criteria comparison between the elements of public risk perception and expert criteria is lacking. Choosing a long-term radwaste solution invariably involves such inter-criteria comparison dilemmas.

As a matter of policy, should *risk to next generation* (which is a public risk perception element) be weighted above the *economic cost* consideration (which is an expert category criteria)? Consider the following situation. Radwaste solution A is *economical (expert category)* but does not address the issue of *dread (public risk perception category)* satisfactorily. Radwaste solution B addresses *dread* criteria better, but is quite *uneconomical.* How these two options compare in the model is not clear.

One way of examining whether such tradeoffs are reflected in the methodology is to review the process of how criteria/sub-criteria weights are derived.

Example 2. In the CoRWM case (section "Summary of Radwaste DM Methods Adopted by CoRWM (UK)"), the method of swing weighting is used to derive criteria/sub-criteria weights. This method requires that the sub-criterion with the biggest "swing" under a particular headline criteria category is assigned a weight of 100.The remaining sub-criteria under the same headline criterion will be assigned weights that reflect their values compared to the 100. The sub-criteria weights add up to form weights for the headline criteria elements. A limited pair-wise comparison amongst only those headline criteria elements that appear to be abnormal is then made to moderate the final headline-criteria weights.

However, rigorous inter-criteria tradeoffs are not explicitly considered in this approach either. As an illustration, consider the headline criteria of *public safety for* <300 *years*, *worker safety, security* (vulnerability to terrorist attacks etc.) Each of these criteria has an overall weight derived from their base sub-criteria weights. Inter-criteria tradeoff questions such as these remain: In making radwaste management policy decisions, is *public safety* more important than *worker safety*? Radwaste management Option A scores high on *safety risks to public* on account of radiation but is vulnerable to terrorist attack (low on *security*). Option B is more robust against terrorist attack but is inferior to Option A in terms of *public safety* on account of radiation – Which of these options should be chosen? Are *worker safety* considerations more important than *security* considerations?

Thus in current methodologies as above, it is found that inter-criteria tradeoffs in existing radwaste DM methods are weak/not present.

As is evident from the example discussions above, such tradeoffs encourage decision makers and stakeholders alike to think about the consequences involved while expressing any and every risk preference and hence should ideally form a part of the formal DM model.

Normative Legal Principle Elements: Are Not Explicit Decision-Criteria Elements

Normative legal principle elements are not explicitly and objectively included in current radwaste DM problem abstractions as decision-criteria elements.

Example 1. In the Korean case (section "Summary of Korean Case Study on Radwaste DM"), legal principle elements do not find any explicit mention. However, some public risk perception sub-criteria elements used in the abstraction e.g., "*unknown to science*" are an integral part of legal principles like the Precautionary Principle (PP).

Example 2. In the CoRWM (UK) work (section "Summary of Radwaste DM Methods Adopted by CoRWM (UK)"), precautionary action is identified as one of the "factors relating to the option's performance" under the main criteria of "*implementability*", sub-criteria "*Legal and regulatory acceptability*". In addition, many criterion elements in the value tree correspond to the provisions of PP – however, the principle as such is not explicitly acknowledged and modeled into the DM process using specific legal decision-criteria elements. Based on subjective discourse-based evaluations, the committee in its final recommendation report mentions that environmental principles like the PP have been found to *not* help in discriminating between competing options.

However, legal principles provide binding/non-binding guidance in making decisions that involve societal risks. E.g., the PP "obliges authorities to take a position justifying their decisions. Being obliged to justify their acts in the light of such a principle, the institutions will be able to reflect on the impact of their decisions." [14] Given this legal necessity, presence of the normative elements of the PP (and other relevant legal principle elements) as explicit DM criteria elements will certainly help decision-makers focus on the legal implications of their decision. As is well evident, consideration of such normative legal elements should very much be an inherent part of any multi-criteria decision making process that affects societal welfare – including decisions in radwaste management that have the potential to impact societal welfare for many thousands of years.

4 Designing an "Intelligent" Abstraction Approach for the Radwaste Problem

In order to avoid the lacunae of existing methods as discussed in Sect. 3.3, the solution design for the radwaste problem should ideally comprise of the following features: (see Fig. 2).

1. *A suitable (process type) abstraction paradigm to elicit risk – perceptions and risk trade-offs*. Such an abstraction paradigm should
   a. Be amenable for robust application to a variety of DM inputs e.g., various technical, financial feasibility reports, stakeholder argumentation, etc.
   b. Be able to 'glean' expert and societal risk perceptions from these inputs and help produce a set of risk-based decision-criteria elements (see section "The Method of Abstracting Societal Risk Perceptions and Criteria from the Underlying Societal Discourse is Human-Intensive").
   c. Ideally help the processing of large amounts of linguistic data and eventually pave way for substantial automation of the process with human interventions kept down to the minimum level (see section

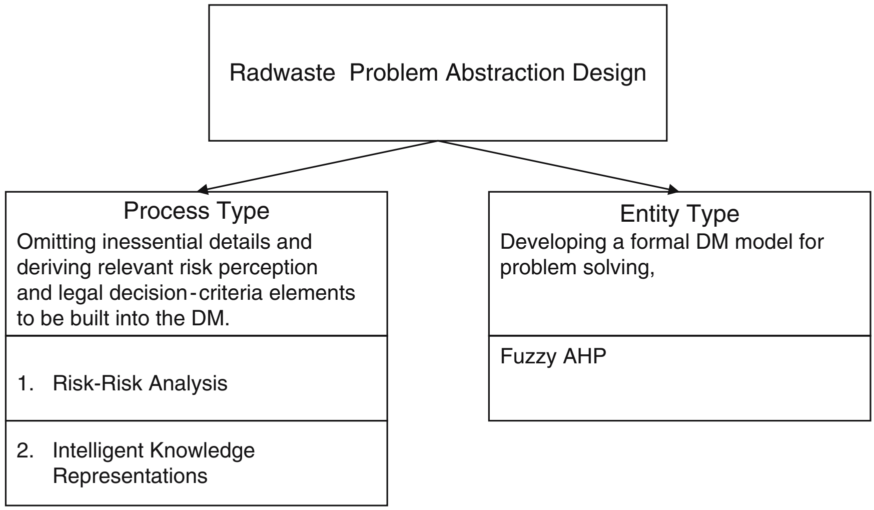

Fig. 2. Radwaste problem abstraction design

"The Method of Abstracting Societal Risk Perceptions and Criteria from the Underlying Societal Discourse is Human-Intensive").

d. Also help highlight the risk tradeoffs involved while making stakeholder preferences (see section "Inter-Criteria Comparisons (Risk Tradeoffs) Are Either Weak or Not Present").

The risk perceptions so obtained from the abstraction paradigm can then be decomposed into suitable risk-based decision-criteria elements.

2. *"Intelligent" representations of the legal basis to abstract normative legal decision-criteria elements.* The 'intelligent' representation method applied on the legal basis (principles, standards etc.) concerning the DM should help abstract normative legal decision-criteria elements relevant for policy DM. The legal basis should be ideally chosen such as to cover all ethical criteria for DM as well) (see section "Normative Legal Principle Elements: Are Not Explicit Decision-Criteria Elements").
3. *A suitable DM Framework – (entity type) abstraction.* The DM framework must successfully integrate (a) and (b) above and help the decision-makers arrive at the "best" solution.

Based on the above imperatives, this paper proposes the following complex abstraction approach:

1. *Risk–Risk Analysis.* As a suitable process type abstraction paradigm to elicit risk perceptions from the underlying societal argumentation.
2. *Concept Nets.* As a suitable intelligent knowledge representation method to abstract normative legal decision-criteria elements.
3. *Fuzzy AHP.* As an entity type abstraction to integrate (a) and (b) above.

Figure 2 gives a summary of the proposed complex radwaste DM problem abstraction design.

4.1 A Suitable Abstraction Paradigm: Risk–Risk Analysis (RRA)

As discussed previously, the first design imperative is to choose a process type abstraction paradigm for abstracting risk-perceptions. Risk-based decision-criteria are then "derived" from these perceptions.

The ensuing discussions first give a background of RRA with examples of risk perception abstractions. This is followed by an examination of whether the RRA is a valid process type abstraction paradigm. The derivation of risk-based decision-criteria elements from the risk perceptions is demonstrated through examples and finally the benefits of using RRA as an abstraction paradigm outlined.

Risk–Risk Analysis (RRA): A Background

RRA is a form of higher-order risk analysis, which is based on the premise that reducing risk in one area can often lead to increases in risk in other areas,

or at other times (such risks are also called countervailing risks). Hence any action should be ideally taken keeping in view the net risks. In other words, an examination of the interactions associated with (overall) risk reduction is called RRA [15]. Comparing the risk trade-offs involved in choosing different decision-alternatives is the backbone of RRA.
Some examples of decisions with Risk–Risk (R–R) issues:

Policy Decision 1: Chlorination of water

R–R issues:

+Reduces risk of waterborne disease
−Increases amount of trace carcinogens in drinking water

Policy Decision 2: DDT Ban

R–R issues:

+Reduces risks to wildlife and human health
−Increases risks to human health by eliminating an effective malaria treatment mechanism.

Some Examples from the nuclear domain:

Policy Decision 3: Nuclear option for energy needs

R–R issues:

+Reduces risks of global warming
−Increases risks of proliferation and is therefore a global security risk

Policy Decision 4: Nuclear fuel reprocessing option

R–R issues:

+Reduces burden of excessive wastes
−Increases risk of proliferation

The "+" signs above denote the expected benefit of the decision and the "−" signs denote countervailing risk concerns expressed by the stakeholders. The number of "+" and "−" issues would vary depending on the specific context of the argumentation.

As a further illustration, the following section shows how R–R issues can be extracted from a piece of societal argumentation rhetoric (for the example *Decision 3*: "Nuclear option for energy needs" outlined above).

Example: In response to the UK government's stance that nuclear energy would benefit society since it was an environmentally friendly energy option, a Green speaker on nuclear issues, said:

Para 1: "The great nuclear PR lobby is in full swing, but don't be deceived. The arguments for nuclear power still don't stand up to scrutiny, and rely on the use of grossly misleading distortions to cover up the gaping holes in the argument. The nuclear option is the worst option to tackle the threat of climate change. More nuclear power is a backward step."

R–R issues: None

Para 2: "It is a fact that nuclear power does create more carbon pollution due to the energy needed in fuel sourcing, transport, processing, construction and disposal. On the grounds of cost, nuclear power is a financial quagmire which will hold back proper investment in renewable energy and energy efficiency – and it will bleed the taxpayer again as it has done for decades.

R–R issues:

– Risk of nuclear power not being environment friendly due to carbon pollution from intermediate stages of fuel sourcing, transport etc.

– Risk of investments for nuclear power jeopardizing investments in other energy sectors and efficiency improvements.

– Risk of benefits of nuclear power being not commensurate with costs to the taxpayer.

Para 3: "It is also an insecure and dangerous game to be playing. Can anyone tell me what energy policy Osama Bin Laden would want the UK to adopt? It seems odd that the Prime Minister who wanted to lock people up for 90 days to fight terrorism is also prepared to create new targets, and to set a dirty example for the rest of the world to aspire to."

R–R issues:

– Risk of nuclear energy increasing nuclear terrorism and proliferation.

In summary,

Policy Decision: Nuclear option for energy needs

R–R issues:

+ Is *environment friendly* and reduces risks of global warming (UK Government)

– Risk of nuclear power not being *environment friendly* (Green Speaker)

– Risk of investments for nuclear power jeopardizing *investments in other energy sectors* and efficiency improvements (Green speaker)

– Risk of *benefits* of nuclear power not *commensurate with costs* to the taxpayer. (Green Speaker)

– Risk of nuclear energy increasing *nuclear terrorism and proliferation* (Green Speaker)

Where the "+" signs denote the expected benefit of the decision and the "−" signs denote countervailing risks expressed as a concern by the stakeholders.

It is important to note that the "−" R–R issues as identified above are indeed the risk perceptions of the stakeholders that need to be addressed specifically in the policy DM and communication.

Is RRA a Valid Process Type Abstraction?

The above discussions establish how argumentative issues in nuclear domains can be viewed objectively from a risks perspective. Clearly, as demonstrated in the above example (section "Risk–Risk Analysis (RRA): A Background"), viewing argumentation using RRA removes redundant rhetoric details and helps focus on the core (societal) risk perceptions. In this respect, RRA serves well as a process type abstraction.

Note: RRA provides a common logic for a focused representation of diverse argumentation issues. This avoids an adhoc approach and enables a firm basis for extracting and incorporating risk perception elements in the DM framework. In addition to being a valid process type abstraction, can RRA also serve as the entity type abstraction for the radwaste problem?

Examining further, it becomes evident that while RRA can fully serve as a useful form of process type abstraction, it cannot be considered fit for an entity type abstraction i.e., RRA cannot be a complete DM model in itself. This is due to the fact that RRA is an incomplete decision-rule. "The advantage of RRA is that it forces decision-makers to look at the behavioral responses to regulations. Once again, however, all other components in a Cost-Benefit Analysis (CBA – which is another important rationality for DM) equation are ignored, so the procedure is not comprehensive." [16]

In summary, RRA emerges as a suitable process type abstraction paradigm for the radwaste DM problem. It cannot, however, serve as an entity type abstraction. A different and suitable framework (Fuzzy AHP in this paper) needs to serve as an entity type abstraction.

Through the "Nuclear option for energy needs" example, it has been demonstrated how RRA, as a process type abstraction, can help glean risk perceptions from societal argumentation rhetoric, objectively. Application of RRA as a process type abstraction for the specific case of radwaste problem DM is demonstrated later in this paper.

Deriving Risk-Based Decision Criteria Elements

Section "Risk–Risk Analysis (RRA): A Background" discussed how the RRA process provides the risk perceptions of the stakeholders as output. The next step is to extract risk-criteria elements based on the risk perceptions so derived from the RRA. In the "Nuclear option for energy needs" example of section "Risk–Risk Analysis (RRA): A Background", the following risk-based

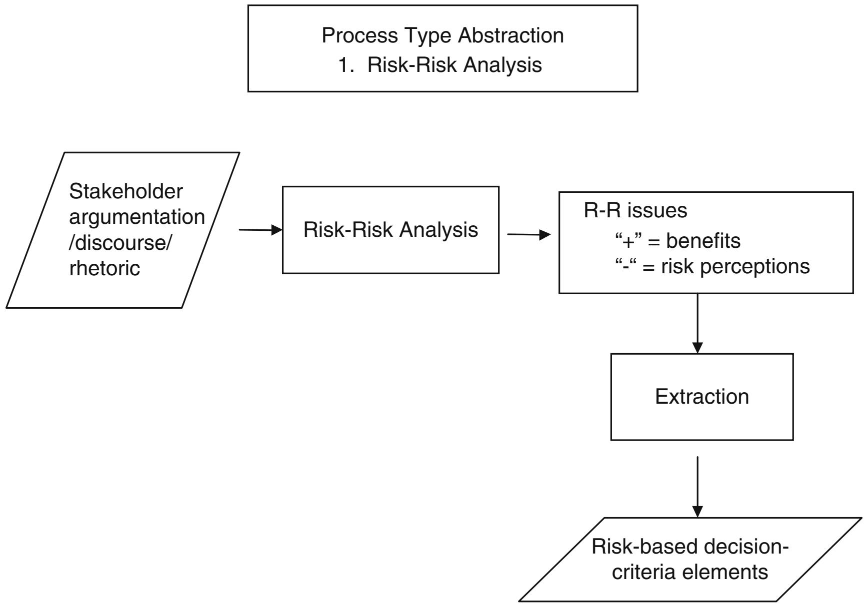

Fig. 3. Risk–Risk analysis: a process type abstraction

decision criteria elements for deciding on the Nuclear option are easily produced (italicized text in section "Risk–Risk Analysis (RRA): A Background" summary): (a) *Environment friendly* (emissions) (b) *jeopardizing investments in other energy sectors (opportunity costs of the decision)* (c) *benefits commensurate with costs* (d) *terrorism and proliferation (security)*. Oftentimes, in the interests of ensuring clarity and transparency in criteria preference rankings, it may not be sufficient for these elements to remain at a high level of granularity. This implies a need to decompose these elements into further constituent criteria elements. In this paper, a simple human-intensive approach is used to derive risk-based decision-criteria elements from the risk perceptions.

However, such extraction of risk-based decision-criteria elements has scope to be "intelligently" extracted using methods like attack graphs.

Figure 3 provides a diagrammatic representation of RRA as a process type abstraction.

Benefits of Using RRA as an Abstraction Method

Sections "The Method of Abstracting Societal Risk Perceptions and Criteria from the Underlying Societal Discourse is Human-Intensive" and "Inter-Criteria Comparisons (Risk Tradeoffs) Are Either Weak or Not Present" discussed scope for further improvement in existing process type abstraction methods in the context of radwaste problems. RRA addresses those issues in the following manner:

1. As demonstrated in the "Nuclear option for energy needs" example, experts or a combination of experts/stakeholders has not 'listed' these decision-criteria elements. Nor are they abstracted based on theory. These have been empirically "derived" from the underlying risk perceptions contained in Stakeholder argumentation/rhetoric. These risk perceptions in turn have been objectively and empirically derived using RRA abstractions on the stakeholder argumentation (despite the rhetoric). Such abstraction logic is the first step towards automation of abstractions as discussed in section "The Method of Abstracting Societal Risk Perceptions and Criteria from the Underlying Societal Discourse is Human-Intensive". Also, the risk criteria elements so derived together with their underlying risk perceptions can be readily built into a risk database to support policy DM of safety authorities/policy makers.
2. RRA facilitates a natural risk tradeoff mechanism which is an abstraction design imperative (see section "Inter-Criteria Comparisons (Risk Trade-offs) Are Either Weak or Not Present").
3. Also RRA responds to the concern raised by legal experts that regulatory and policy making institutions "could potentially do much better" by attending more carefully to "countervailing risks". "Managing Risk–Risk tradeoff is an exercise in judgment" [17]. From this perspective, RRA facilitates a better evaluation of the options from a legal viewpoint as well.

RRA Abstraction Method: Automation Versus Human Intervention

It is important to note that the RRA abstraction method as outlined above does not eliminate the element of human intervention altogether. It is only a first logical step towards automated abstractions. Despite the abstraction logic, the derivation of societal risk perception elements through RRA will still be open to a certain amount of interpretation and will also to some extent be analyst specific. Discussing further nuances of how to automate this process is beyond the scope of this paper – however, in summary it would involve employing soft computing methods with varying degrees of complexity. In the extreme, an intensely objective RRA abstraction might be oriented towards applying mechanized cognition methods on the DM inputs-stakeholder argumentation, feasibility reports, opinions etc. to derive the risk perception elements. But given the complexity of the problem and the arguments, such methods need to be examined for their tediousness, computational complexities, and sufficiency; especially in the light of multinational, multicultural issues. A judicious trade-off between computational complexity and human intervention needs to be worked out while following the path of automating the abstractions.

4.2 Appropriate Legal Basis, Its Intelligent Representation and Abstraction of Legal Decision-Criteria Elements

The next abstraction design imperative (as discussed in Sect. 4.1) is to establish

1. A legal basis for policy DM
2. A suitable method for "intelligent" representation of this legal basis

In deciding on long-term solutions for radwaste management, a wide range of legal principles/standards having safety, environmental and health implications needs to be considered by the nuclear safety/policy-making authorities. The Precautionary Principle (PP) is one of 27 such principles that were enshrined in the Rio declaration of 1992 [18]. Other principles/precepts that are in vogue as regards the (radiation) risks in the nuclear sector are ALARA, BAT, etc. For purposes of simplicity and also because "the PP is in essence an ethical principle which promotes a better use of public participation in risk regulation, where the purely cost/benefit analysis has failed" [19], this paper will limit itself to an evaluation of the Radwaste options using the PP as a legal basis. However, the methodology for treating other legal principles remains the same. Also it is assumed that the legal basis necessarily and sufficiently covers the ethical elements of the DM as well. Hence no separate discussions on ethical elements are made in this paper.

The ensuing discussions give a background of the PP first. This is followed by an examination of how PP is applied in radwaste management decisions – The cases of France and UK are discussed briefly. The usage of concept nets as a method of "intelligently" representing the PP is explained, followed by a note on the importance of "intelligent" gisting of legal documentation. Finally, the normative concept net of the PP is presented together with the abstracted legal decision-criteria elements.

The Precautionary Principle (PP): A Background

The PP had been first spelled out at the EC level in the Maastricht Treaty [20]. It is explained in the Wingspread statement (1998) as "When an activity raises threats of harm to the environment or human health, precautionary measures should be taken even if some cause and effect relationships are not established fully scientifically". In the Rio declaration, the PP is outlined in principle 15 that states "Where there are threats of serious of irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation." However there is no widely agreed single "definition" of the principle. This makes the task of listing out normative elements of the PP challenging. In order to lend more objectivity into the understanding of the principle, which is very much essential before normative elements can be abstracted, suitable knowledge representation methods need to be used. Such methods should facilitate 'intelligent' abstractions of the normative legal concepts/elements concerning the Principle, so that abstraction automations can be effectively supported in future.

Application of the PP in Radwaste Management Decisions

Some examples of how PP is applied in radwaste DM situations is outlined below:

Case of France. The French usage of the PP in explicit terms in radwaste DM seems limited. The PP has been more linked to the repository "reversibility" decision of ASN. Also, responding to a question regarding whether the PP has been considered in radwaste DM, France has said, "The precautionary principle applies if the risk posed by the management of waste is more or less unknown, which should not be the case for existing pathways (radwaste management solutions). The precautionary principle then should apply for the choice of future pathways that need more studies and developments, but the development of these new pathways is submitted to an assessment of their impact from a radiation protection point of view." [21]

Despite this stand it would be interesting to analyze if the PP has been applied indirectly or in an implicit manner through various decision-criteria elements that are in fact part of the principle itself. However, this would require a detailed inquiry into the French environmental and other relevant law provisions under which the ASN decision was made and is as such, beyond the scope of this paper.

Case of UK. In the discussion regarding application of environmental principles in evaluating waste management options, the CoRWM work (discussed earlier in this paper) found that "Most of the well-established environmental principles were discussed and were found not to discriminate between options. For example, the precautionary principle could be argued to support either long-term storage or geological disposal, depending on an individual's views on the nature and scale of the uncertainties and risks associated with each option." [22]

However, the suitability for applying the PP on radwaste decisions is well underscored by a Nuclear Waste Management Organization (NWMO) guiding background paper [23] "Precautionary appraisal explicitly addresses the contending pros and cons of a variety of different options for fulfilling the same ends. The question is not simply "is this acceptable?" but "is this justified?" and "which option offers the greatest societal benefit?" Attention is not confined just to the risks, in a narrow sense, but extends to weighing these up against the countervailing justifications and benefits. The implications for radioactive waste management seem obvious. Where the financial and time commitments envisaged are as large as they are in this sector, and the irreversibilities as pronounced, there seems a particularly strong case for this kind of broad-based precautionary appraisal." This shows clearly both the importance of applying the PP in radwaste management decisions and also underlines the synergy of using RRA abstractions (see Sect. 4.1 above) in dealing with this principle.

Note: Irrespective the official and legal position of France on the PP, in light of the above discussion and also for case study purposes, this paper considers the explicit application of the PP on the French radwaste problem in the abstraction.

Developing an Intelligent Knowledge Representation for the PP

Knowledge Representation for the PP could be achieved using a variety of methods. In this paper the method of concept nets is chosen. Concept nets (also referred to as concept maps in some sections of literature) are used for knowledge acquisition and analysis, and have a useful heuristic nature. Concept nets have the advantage of capturing the contexts as well as the contextual meaning of the PP, and can also be stored in computer-conducive formats and made available for future use. Consequently, they emerge as a suitable process type abstraction for the legal basis of policy DM that effectively addresses the key design imperative of automation friendly abstraction approaches (section "The Method of Abstracting Societal Risk Perceptions and Criteria from the Underlying Societal Discourse is Human-Intensive").

Concept nets can be of different kinds e.g., descriptive, normative etc. However, as the underlying context is legal in nature, the normative concept net appears a more amenable form for PP knowledge representation. Normative concept nets are generally concept nets that converge based on a consensus [24]. As the 2000 'Communication from the European Commission on the Precautionary Principle' [25] has been designed to reflect a common European Union understanding of the PP, it has been chosen as the base document for preparing a 'consensus' normative PP concept net in this paper. In reality however, there are other 'key subordinate principles' and 'associated concepts' of the PP proposed by various authors [26]. In addition, the country-specific (French) interpretation of what constitutes 'precaution' is essential to represent the PP in a more appropriate form. These extensions will give rise to multiple concept nets, which then need merging to form a single normative PP concept net; the legal normative decision criteria elements will evolve accordingly.

Intelligent Summarizing/Gisting of Legal/Regulatory Documents Before Preparing Concept Nets

In the above-mentioned EC 2000 PP communication document, there are approximately 270 sentences (propositions) excluding Annexes. The enormity of the task of developing the concept net for such a complex document of legal understanding can well be imagined. This gets increasingly tedious as the legal basis widens and more principles/legal documentation is added.

With such voluminous legal/regulatory conceptual complexities involved, it is desirable that summarizations of such documents are prepared in advance before concept nets are made. Summarization is the process of condensing a source text into a shorter version preserving its information content.

This could be addressed "intelligently" in various ways. E.g., a general summarization of the EC PP communication (2000) using the Copernic Summarizer Software [27] produced a 25% condensation comprising 15 concepts:

'precautionary principle', 'risk', 'scientists', 'community', 'environment', 'protection', 'commission', 'risk management', 'plant health', 'assessment', 'reasoning', 'agreements', 'recourse', 'review', 'high level'. Other methods of summarization include summarization of legal texts using thematic structures and linguistic markers.

However, it needs to be mentioned that human expert intervention in summarization is definitely desirable for conceptual clarity, given the complexities in legal semantics. In the case of the EC PP communication (2000) a summary reflective of the content is already available in the document itself. Based on this, the author prepared a concept net (conventional directed graph method), the results of which are as follows:

A total of 53 concepts and 51 relations emerged from the summary (This is after omitting a few sentences from the summary, which, being in the nature of establishing the authority of the communication, would not have made any difference to further conceptual discussions as far as DM is concerned.)

Some of the concepts e.g., c_7 (see Table 1 below) have been preserved at a higher level of granularity as the objective is also to ease of reconstruction of the original document from the concept net, in the interests of clarity. This, however, does not affect the problem solving approaches discussed in this paper in any way. The granularity levels will matter when additional legal documents and their corresponding concept nets (as discussed in section "The Precautionary Principle (PP): A Background") begin to get added.

Extracting Normative Legal Decision: Criteria Elements from the PP Concept Net

A partial view of the PP concept net based on the 2000 EC document, is given in Fig. 4.

In Fig. 1, c_i denotes concepts e.g., c_2: "The PP" and r_j denotes the relationships e.g., r_{33}: "need to be aware of". Each sentence from the communication corresponds to a set of relationships as applied on concepts. E.g., "Measures based on the PP should be proportional to the chosen level of protection" – from the PP concept net, this corresponds to:

$$r_{42}(c_{44}, c_2) : r_{43}(c_2, c_{45}) : r_{49}(c_{45}, c_{51})$$

Based on the linguistic marker "should", and the proximity of the concepts to c_2, the key "normative" elements that have been extracted to form L2 level sub-attributes are: "Proportionality" (c_{45}), "Non-Discrimination" (c_{46}) and "Consistency" (c_{47}) and "Benefits commensurate with costs" (c_{48}). In reality, the decision-criteria elements and their "meaning" would evolve as a result of the merged concept net as discussed above, but in this paper, for illustrative purposes, they have been directly assumed from the EC 2000 consensus communication.

1. "Proportionality means tailoring measures to the chosen level of protection."
2. "Examining costs and benefits entails comparing the overall cost to the Community of action and lack of action, in both the short and long term.

Table 1. List of concepts and relations from the PP summary

ci	Concept name	rj	Relationship name
c1	The issue (of when and how)	r1	to use the
c2	Precautionary Principle	r2	is giving rise to
c3	debates, mixed, contradictory views	r3	within the
c4	European Union (and internationally).	r4	are constantly faced with
c5	Decision makers	r5	to balance
c6	Dilemma	r6	with the need to reduce the
c7	the freedom and rights of individuals, industry and organisations	r7	of
c8	risk	r8	with
c9	adverse effects to the environment, human and plant health.	r9	is required so that
c10	structured decision making process	r10	can be taken which is
c11	detailed scientific (and other objective) information	r11	is not defined
c12	action	r12	which prescribes it only once to protect the
c13	transparent	r13	of the
c14	non-discriminatory	r14	is much wider in
c15	proportionate	r15	specifically where
c16	coherent	r16	indicates that there are reasonable
c17	Treaty	r17	that the potentially
c18	Environment	r18	may be inconsistent with the high
c19	The scope	r19	chosen for the
c20	practice	r20	which is essentially used by
c21	preliminary objective scientific evaluation	r21	in the management of
c22	grounds for concern	r22	which comprises
c23	level of protection	r23	is particularly relevant to
c24	community	r24	should not be confused with
c25	risk management	r25	that
c26	risk communication	r26	use in their
c27	risk assessment	r27	to the
c28	the element of caution	r28	presupposes identification of
c29	scientists	r29	does not allow the
c30	data assessment	r30	to be determined with
c31	recourse	r31	based on
c32	potentially dangerous effects of a phenomenon, product or process	r32	(as much as possible), where possible, identifying the
c33	scientific evaluation	r33	need to be aware of
c34	sufficient certainty	r34	what is an accetable level of

Continued

Table 1. (*Continued*)

ci	Concept name	rj	Relationship name
c35	The implementation of an approach/measures	r35	is an
c36	Degree of scientific uncertainty	r36	may not be
c37	The judgement of	r37	is available in the case of
c38	eminent political responsibility	r38	going from
c39	answer (in some cases)	r39	to
c40	Introducing a legally binding measure	r40	should be
c41	A wide range of initiatives	r41	should involve as early as possible and to the extent reasonably possible all
c42	a research project/ recommendation	r42	based on
c43	interested parties	r43	should be
c44	Measures	r44	should be in their application
c45	proportional	r45	should be
c46	non-discriminatory	r46	should be based on
c47	consistent	r47	should be
c48	examination of potential benefits and costs of action (or lack of it)	r48	should be capable of
c49	subject to review	r49	to the
c50	assigning responsibility for producing the necessary scientific evidence	r50	with
c51	chosen level of protection	r51	necessary for a more
c52	similar measures taken		
c53	comprehensive scientific assessment		

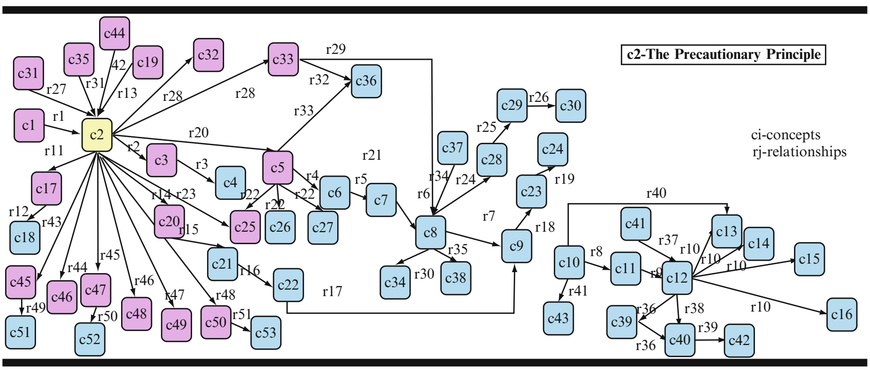

Fig. 4. Normative concept net of the PP based on year 2000 EC communication

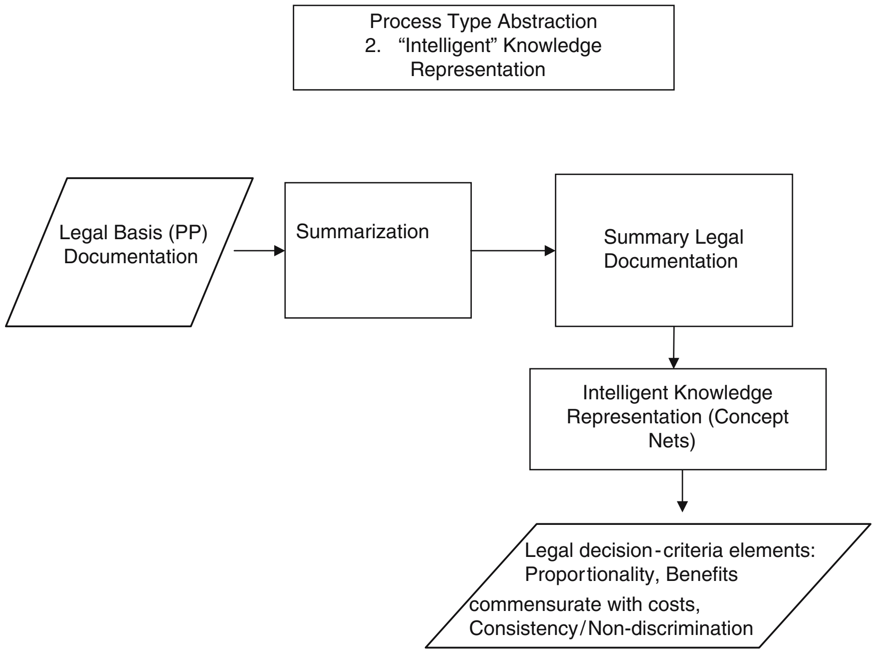

Fig. 5. Intelligent knowledge representation: a process type abstraction

This is not simply an economic cost-benefit analysis: its scope is much broader, and includes non-economic considerations, such as the efficacy of possible options and their acceptability to the public."

3. "Non-discrimination means that comparable situations should not be treated differently, and that different situations should not be treated in the same way, unless there are objective grounds for doing so." "Consistency means that measures should be of comparable scope and nature to those already taken in equivalent areas in which all scientific data are available."

In summary, the legal decision-criteria elements have been chosen based on the PP and these elements are: "*proportionality*", "*Benefits commensurate with costs*" and "*Non-discrimination*" in combination with "*consistency*". Figure 5 gives an overview of the abstraction of the PP through intelligent knowledge representation (concept net).

4.3 A Fuzzy AHP DM Framework: (Entity Type) Abstraction

While many models for Policy DM exist e.g., Cost-Benefit Analysis, Cost-Effectiveness Analysis etc., MCDM techniques have been found to be more appropriate in dealing with analyses where all impacts cannot be quantified into monetary values [28]. Analytic Hierarchy Process (AHP) is one such

MCDM method, which has been widely used in complex DM. Since the underlying human reasoning in DM is "fuzzy", a Fuzzy AHP design is chosen for entity type abstraction of the radwaste DM problem.

The ensuing discussions first give a background of AHP, Fuzzy theory and Fuzzy AHP. Thereafter an outline of how to construct the Fuzzy AHP hierarchy based on the process type abstractions discussed in the previous section is provided. The methodology of solving the Fuzzy AHP problem is briefly outlined.

AHP

AHP was a multi-criteria DM technique developed by Saaty in late 1970s, which has since found application in a variety of DM situations. Analytic Hierarchy Process (AHP) involves converting subjective assessments of relative importance/preferences into a set of overall scores or weights. These preferences are gathered from the answers of experts and stakeholders to a series of questions of the general form; 'How important is criterion A relative to criterion B?' such comparisons are called pair-wise comparisons. These questions establish, within AHP, both weights for criteria and performance scores for options on the different criteria. AHP has the flexibility to process preferences based on both quantitative (e.g., probabilistic) and qualitative premises.

Fuzzy Sets and Fuzzy Theory [29]

Crisp sets are characterized by their membership functions that assign a value of either 1 or 0 to each individual in the universal set, thereby discriminating between members and non-members of the set. In contrast, a fuzzy set is a set whose elements have a continuum of grades of membership. The (characteristic) membership function, in this case, assigns to each element a grade of membership in [0,1]. Fuzzy sets allow better representation of vague concepts as expressed in natural language. Fuzzy sets representing linguistic concepts like Low, Medium, and High are often employed to define states of variable and hence become a natural way of representing fuzzy preferences. Under certain specific mathematical conditions, fuzzy sets become valid fuzzy numbers. One of the most popular categories of Fuzzy Numbers is Triangular Fuzzy Numbers (TFNs).

TFN is typically represented as (l, m, u) where l denotes the smallest possible value, m denotes the most likely value and u denotes the largest likely value of a fuzzy event. Graphical representation of a TFN is given in Fig. 6.

Fuzzy AHP

Fuzzy AHP, as the name suggests, is a fuzzified version of the AHP. Many Fuzzy AHP approaches have been proposed in literature. This paper follows an "extent analysis" approach credited to Chang as elaborated by authors

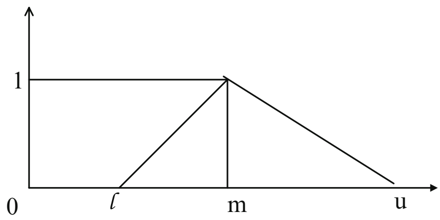

Fig. 6. Triangular fuzzy number

Kahraman et al. [30]. In this, model, the pair-wise comparison scales are fuzzified using TFNs, weights are calculated using the synthetic extent analysis method and final alternative rankings obtained. As the focus of this paper is more on intelligent abstractions, and not on Fuzzy AHP problem solving, a detailed description of the problem-solving methodology has not been given. However, readers can refer to Kahraman et al. paper mentioned above or any such standard reference for detailed explanations on Chang's Fuzzy AHP problem-solving methodology.

Constructing the Fuzzy AHP Hierarchy

The Fuzzy AHP hierarchy has been designed as follows:

1. The top-most level L1 denotes the goal of DM framework
2. The next level L2 consists of normative legal DM criteria elements abstracted from "intelligent" representations (discussed in section "Extracting Normative Legal Decision: Criteria Elements from the PP Concept Net" above).
3. The subsequent level L3 consists of societal risk-based decision-criteria elements, abstracted after applying the RRA approach (as outlined in Sect. 4.1 above)
4. L4 consists of various decision-alternatives.

Solving the Fuzzy AHP Problem

As already discussed briefly in section "Fuzzy AHP", in this paper, Chang's extent analysis method has been chosen for solving the Fuzzy AHP.

Solving the Fuzzy AHP problem based on the above hierarchy and the extent analysis methodology, a socio-legal ranking of various long-term waste management alternatives is obtained and the top-ranking alternative is chosen as the preferred solution.

Such a chosen alternative is the outcome of an elaborate participative DM process, wherein both the societal risk perceptions, as well as legal aspects have been duly incorporated. This will help contribute towards the "Central route to persuasion" of society as discussed in the introduction.

5 Case Study: Nuclear Radioactive Waste Management in France

In France, a research program to study radioactive waste disposal began with legislation enacted in 1991 [31]. In this, The French Nuclear Safety authority ASN played an important role: "with respect to high-level, long-lived waste in particular, ASN's duties notably concerned the examination and supervision of the corresponding projects, (including deep geological disposal) in order to assess whether they offered a *credible* technical solution that was *acceptable* with regard to long-term safety" [32]. With French parliamentary support in early 2006, the deep geological disposal option has been chosen as the reference solution for high-level and long-lived radioactive wastes [33]. Much like other key nuclear risk/safety decisions, this decision has also been subject to intense public argumentation and rhetoric-challenging ASN on the '*credibility*' and '*acceptability*' aspects of the proposed reference solution.

5.1 A Sample of Public Debates/Argumentation in the French Radwaste Case

Table 2 outlines a sample of societal stakeholder arguments and rhetoric revolving around the Bure site (French site chosen for experimental studies of deep geo radwaste disposal in clay formations).

5.2 Designing a Complex Abstraction Approach for the French Radwaste DM Problem

The abstraction design for the French radwaste problem was made combining the process type and entity type abstraction methods as explained in Sect. 4.

L1 Level: Goal of the DM Framework

To select the 'safest' long term management option for High Level and Long Lived radwastes in France. 'Safest' in this context means a '*credible*' technical solution that is '*acceptable*' and '*justifiable*' to both ASN and French society with regard to long-term safety.

L2 Level: Normative Legal Decision: Criteria Elements

Subsequent to the discussion in section "Extracting Normative Legal Decision: Criteria Elements from the PP Concept Net", this paper chooses the normative legal elements of "proportionality", "Non-discrimination/consistency" and "Benefits commensurate with costs".

Table 2. Argumentation of research agencies and stakeholders

Issue	"For" Argumentation	"Against Argumentation"
Issue 1: Technical feasibility [34] of the storage site	IRSN: underground storage technique "appears technically feasible".	Campaign group 'Get out nuclear': Technical feasibility "worse than dubious" and "burying the most dangerous nuclear waste is an absolute crime against future generations".
Issue 2: Economic incentives and development at local site [35, 36]	General Council-Meuse: "an unexpected opportunity for a severely de-populated area to develop its local economy" subject to the reservation that disposal, if any, should be reversible	Local Opposers: Motivation for the economic incentives is not clear-is it a compensation for "hosting" the lab site or "bribery". Also, presence of a "nuclear waste dump" may be dangerous for the local industry like agriculture, Champagne etc.
Issue 3: Sustainable Development (Underground Water Resources) [37]	CNE: Aquifer layers are "little permeable" and part of the water is "very salty". (Different from an earlier CNE statement that said "The Dogger aquifer below the host formation is a potential source of water. The studies ... of the storage site should show how to protect the aquifers that may possibly be exploited"	Nuclear France (Environmentalist): CNE observations are inconclusive as regards the threat of underground water Contamination. Is it not necessary to protect all Aquifers-present & future?

IRSN: French research agency in nuclear and radiation risks; CNE: The French National Scientific Evaluation Committee

L3 Level: Risk-Based Decision-Criteria Elements

The RRA abstraction (as discussed in Sect. 4.1) is applied on the stakeholder argumentation contained in Table 2 to derive the risk perception elements. From these the L3 level risk-based decision-criteria elements are then extracted as discussed in section "Deriving Risk-Based Decision Criteria Elements".

Policy Decision: Deep Geo Repository at Bure Site

R–R Issues:

+ Reduces *safety risks* of radwastes to population and environment in the long-term (IRSN)

+ Creates opportunity for *local economy development* (General Council-Meuse)

+ Risk of *ground water resources* getting adversely affected is minimal (CNE)

– Low *credibility* in *technical feasibility* despite assurances from risk experts (Campaign Group Get out Nuclear) – Risk of *benefits from the decision* not *commensurate with costs* (Local opposers) – Risk of whether the decision is *socially responsible* (Local opposers) – Risk of decision impacting *sustainability* of environment and means of livelihood (Local opposers) – Risk of in*equity to current and future generations* of *people and environment* by contaminating underground water re-sources. (Nuclear France-Environmentalist)

The "+" issues have been derived from the "For" argumentation in Table 2. The "−" issues i.e., the risk perception issues have been derived from the "Against" argumentation (see also column 2, Table 3).

Table 3 summarizes the process type abstraction results and presents the societal argumentation, the abstracted risk perceptions, corresponding legal decision-criteria elements and the risk-based decision-criteria elements for the French radwaste problem.

In this case study, the derivation of risk-based decision-criteria elements (column 4, Table 3) from risk perception elements is based on the limited underlying public argumentation examples used and some assumptions made by the author regarding a general "understanding" of the terms in contemporary usage. As such this derivation was performed for illustration purposes only, in a human-intensive manner. In reality, these elements could be extracted through following "intelligent" methods like attack graphs (section "Deriving Risk-Based Decision Criteria Elements") and with a wider participation of policy makers and various stakeholders.

Also, it is important to consider the contexts while choosing the corresponding L2 element. E.g., in row 1, Table 3 the "dubiousness" or lack of trust of the campaign group Get Out Nuclear has been focused on technical feasibility i.e., safety and levels of protection based on the argumentation context. If the context was not taken into account, "dubiousness" could have also arisen due to reasons of lack of transparency in cost-benefit issues, in which case the corresponding L2 element would be classified under "Examining costs and benefits" (c_{48}).

L4 Level: Decision Alternatives

The three decision alternatives considered are a_1: maintaining Status quo, a_2: opting for a deep geo repository and a_3: opting for participating in a suitable international geo repository.

An AHP Framework of the French Deep Geo Disposal Repository System is given in Fig. 7.

Terms used:

IH Internal hazards; *EH* External hazards; *CH* Cultural hazards; *CBA* Economic cost benefit analysis; *ES* Environmental sustainability; *SR* Social

Table 3. Results of the process type abstraction of the societal argumentation

Societal argumentation 'Against' issues (from Table 1)	"–" Risk–Risk issues identified (Risk perceptions)	Corresponding L2 element	Risk-based decision-criteria elements (L3)
1. Technical feasibility of the deep geo solution 'worse than dubious' and 'a crime against future generations'	*R–R 1*: low 'credibility' in technical feasibility despite IRSN assurances. (Decision not commensurate with desirable levels of protection to society.)	Proportionality (c_{45})	Internal Hazards (IH), External Hazards (EH), Cultural Hazards (CH)
2. Motivation for the economic incentives is not clear-is it a compensation for 'hosting' the lab site or 'bribery'. Also, presence of a "nuclear waste dump" may be dangerous for the local industry like agriculture, Champagne etc	*R–R 2*: Risk of benefits from the decision not commensurate with costs despite Meuse council 'For' arguments. Risk of whether the decision is socially responsible (bribe vs. compensation). Risk of decision impacting sustainability of environment and means of livelihood	Examining Benefits and Costs (c_{48})	Triple Bottom Line elements – Economic Cost Benefit Analysis (CBA), Environmental Sustainability (ES) and Social Responsibility (SR)
3. CNE observations are inconclusive as regards the threat of underground water Contamination. Is it not necessary to protect all Aquifers-present & future?	*R–R 3*: Risk of inequity to current and future generations of people and environment by contaminating underground water resources	Non-discrimination (c_{46})/Consistency (c_{47})	Current Generation People (CGP), Future Generation People (FGP), Current Generation Environment (CGE), Future Generation Environment (FGE)

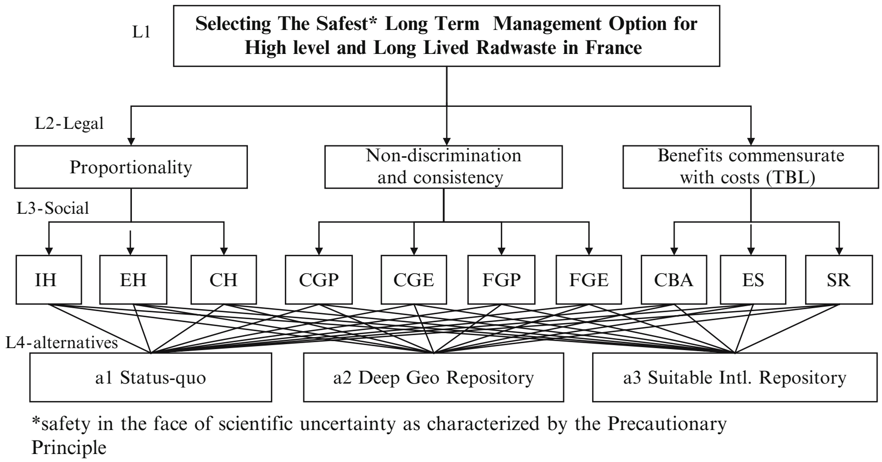

Fig. 7. AHP framework of the french radwaste problem DM

responsibility; *CGP* Current generation people; *FGP* Future generation people (FGP); *CGE* Current generation environment; *FGE* Future generation environment

It needs to be noted that the L4 level alternatives a_1, a_2, a_3 have been assumed for illustration purposes only and are not the actual decision alternatives considered by ASN in its DM. (The actual alternatives are specified in the 1991 French Waste Management Research Act).

5.3 Pair-Wise Comparisons and Rank Preferences

Table 4 provides a few sample questions that may be asked of stakeholders and experts to arrive at the weights.

It is important that the ranking preferences (see Table 4), which are represented as Triangular Fuzzy Numbers (TFNs), are not arbitrary. The preferences used should ideally reflect the consensus of the DM organization (e.g., ASN) and the public on risk perceptions concerning individual decision-attribute elements. However, this may not be so always. As an example, consider the pair-wise comparison of a_3 over a_2 in terms of technical soundness to withstand Internal Hazards (IH). Amongst many stakeholders, the final preference is ideally a consensus preference number comprising of:

1. The policy making/nuclear safety agency's opinion supported by quantitative assessment like PSAs, PAs and
2. The opinion of the stakeholders during consultation.

For discussion purposes, let us assume this consensus does not exist. Suppose ASN experts feel that a_2 is "very strongly preferred" to a_3 in withstanding IH (e.g., they feel that the technical risks are better manageable in French territory than in any international technical collaboration site and the PSAs also

Table 4. Sample questions needed to arrive at weights for the attributes

Q1 (L2)	How important is the criterion of proportionality as compared to the non-discriminatory nature and consistency?	Ranking preferences (TFNs)
Q2 (L3)	How important is the impact of unforeseen Internal Hazards (physical) on safety levels as compared to unforeseen Cultural Hazards?	(7/2,4,9/2) – Absolute, (5/2,3,7/2) – Very Strong/Important/beneficial (3/2,2,5/2) – Fairly Strong/Important/beneficial, (2/3,1,3/2) – Weak/weak importance/weak benefits, (1,1,1) – Equal/Equal Importance/equally beneficial.
Q3 (L4)	How beneficial is a2 over a3 in terms of economic cost-benefits?	

support their belief) but a section of the public, despite the PSAs, strongly perceive that a2 is "very weakly preferred" with respect to a_3 in this dimension (perhaps because a3 helps pacify the NIMBY aspect). As can be observed in this situation, there is a significant divergence in risk perceptions that will result in very different fuzzy ranking preferences. In such cases, the overall aggregated preference could be arrived at using a combination of risk communication – aimed at bridging the risk perception gap and fuzzy consensus methods – aimed at aggregating the fuzzy preferences. However, in this paper, the hypothetical fuzzy ranking preferences have been assumed as consensus numbers, thus not necessitating further modification.

5.4 Solution$_t$ and Key Insights

Each DM hierarchy element 'earns' its priority weight using the hypothetical fuzzy rankings as per Chang's fuzzy extent analysis approach. The evaluation matrix that computes the weights for the DM legal criterion of "proportionality" through pair-wise comparisons is provided in Table 5 for purposes of illustration.

Similar tables have been computed for the other decision criteria/sub-criteria and then the weight vectors worked out. There are a total of 14 such evaluation matrices that provide the weight vectors for the Fuzzy AHP pair-wise comparisons of criteria/sub-criteria elements/alternatives. Table 6 summarizes the weight vectors derived from all the 14 matrices.

Summary tables for the criteria elements of "proportionality", "Non-discrimination/consistency" and "Benefits commensurate with costs" are given below (Tables 7–9).

Table 5. Sub-criteria of "proportionality"

Criteria	EH			IH			CH		
EH	1/1	1/1	1/1	3/2	2/1	5/2	2/5	1/2	2/3
IH	2/5	1/2	2/3	1/1	1/1	1/1	5/2	3/1	7/2
CH	3/2	2/1	5/2	2/7	1/3	2/5	1/1	1/1	1/1

Synthetic Extent values: $S_{EH} = (0.22,\ 0.31,\ 0.43)$, $S_{IH} = (0.29,\ 0.40,\ 0.54)$, $S_{CH} = (0.21,\ 0.29,\ 0.41)$
Using Chang's extent analysis, the weight vector has been derived as $W_P = (0.29,\ 0.47,\ 0.24)^T$

Table 6. Summary of weight vectors from evaluation matrices

Matrix no.	Evaluation matrix	Weight vectors		
1	Goal i.e., (P, NDC, TBL) with itself	0.33	0.33	0.33
2	Sub-criteria with respect to Proportionality	0.29	0.47	0.24
3	Sub-criteria with respect to Non-Discrimination and Consistency	0.41	0.00	0.59
4	Sub-criteria with respect to Benefits commensurate with costs (TBL)	0.32	0.11	0.56
5	Radwaste Mgmt. alternatives wrt EH	0.15	0.70	0.15
6	Radwaste Mgmt. alternatives wrt IH	0.56	0.11	0.32
7	Radwaste Mgmt. alternatives wrt CH	0.43	0.36	0.20
8	Radwaste Mgmt. alternatives wrt CGP	0.56	0.11	0.32
9	Radwaste Mgmt. alternatives wrt CGE	0.56	0.11	0.32
10	Radwaste Mgmt. alternatives wrt FGP	0.00	0.83	0.17
11	Radwaste Mgmt. alternatives wrt FGE	0.00	0.83	0.17
12	Radwaste Mgmt. alternatives wrt CBA	0.00	1.00	0.00
13	Radwaste Mgmt. alternatives wrt ES	0.00	0.50	0.50
14	Radwaste Mgmt. alternatives wrt SR	0.28	0.55	0.17

wrt with respect to

Table 7. The summary combination of weights: proportionality

	EH	IH	CH	Alt. priority wt
Wts	0.29	0.47	0.24	
a_1	0.15	0.56	0.43	0.41
a_2	0.70	0.11	0.36	0.34
a_3	0.15	0.32	0.20	0.24

From the final summary computations (Table 10), it can be seen that Solution_t i.e., the alternative that ranks highest (safest) based on risk-based decision-criteria and normative legal criteria elements at time t is a_2 – *a deep geological repository option for radwastes.*

Table 8. The summary combination of weights: nondiscrimination/consistency

	CGP	CGE	FGP	FGE	Alt. priority wt
Wts	0.41	0.00	0.59	0.00	
a_1	0.56	0.56	0.00	0.00	0.23
a_2	0.11	0.11	0.83	0.83	0.54
a_3	0.32	0.32	0.17	0.17	0.23

Table 9. The summary combination of weights: triple bottom line

	CBA	ES	SR	Alt. priority wt
Wts	0.32	0.11	0.56	
a_1	0.00	0.00	0.28	0.16
a_2	1.00	0.50	0.55	0.69
a_3	0.00	0.50	0.17	0.15

Table 10. The summary fuzzy evaluation matrix of alternatives

	P	NDC	TBL	Alt. priority wt
Wts	0.33	0.33	0.33	
a_1	0.41	0.24	0.16	0.25
a_2	0.34	0.53	0.69	0.51
a_3	0.24	0.23	0.15	0.20

6 A Note on Rank Reversals in AHP

The AHP has been widely applied in science and industry for many decisions. However, one of the criticisms of this approach has been the occurrence of rank reversals when other alternatives or criteria are introduced. The possibility of this occurring in the AHP approach has been ignored in this paper because:

1. It is assumed that the alternatives such as a_1, a_2 and a_3 discussed in this paper and also the various decision criteria elements have been arrived at after extensive stakeholder engagement and abstractions; the time span of such engagement might last months or even years. Therefore it is highly unlikely that any practical alternative or decision-criteria, however remote, has been omitted in the DM analysis before announcing/publishing such a formal and expensive public decision. By design and default this fact reduces the practical chances of rank reversal.
2. All alternatives and pair-wise comparisons occur in the problem formulation on the basis of best available information at time t. Any additions at time t + 1: either of a new criterion, e.g., introduction of a new regulatory precept, or new alternative e.g., a radwaste management option based on break-through success in transmutation research, will have to be

considered in a fresh abstraction and Fuzzy AHP calculation. Assume a situation where a break-through transmutation/waste reprocessing option has emerged at time t+1 (gap between t, t+1 may well be 20–30 years say year 2037). It is perhaps not useful to examine if this causes any historic rank reversals e.g., ranking of a_2 as compared to a_1 or a_3 at time 2007. Even if it does, ASN and society cannot be held responsible for having chosen a_2 "wrongly" at time t (2007), as this decision was made on the basis of best available information at that time. However, if the repository is still technologically "reversible", the new transmutation option can be analyzed afresh in pair-wise comparison with a_2.

In summary, changes/new additions in criteria/alternatives should be viewed as a fresh DM situation, warranting a fresh abstraction and problem solving leading to solution $_{t+1}$. Construing the addition of temporally spaced criteria/alternatives as possibly challenging the historic solution$_t$ decisions from the viewpoint of rank reversals would not be meaningful.

7 Further Research Directions

Further directions/improvement in the abstraction methodology as discussed in this paper could involve the following:

1. Using an action research framework to fine-tune the RRA abstraction. The field of action research is in itself quite vast. Within this domain, one of the key tools used to improve acceptability of decisions is Force Field Analysis. According to Kurt Lewin, a key early contributor to the field of action research, "An issue is held in balance by the interaction of two opposing sets of forces – those seeking to promote change (driving forces) and those attempting to maintain the status quo (restraining forces)" [38]. In order for any change to occur, the driving forces must exceed the restraining forces, thus shifting the equilibrium. The Force Field Diagram (FFD) developed by Lewin provides a weighted diagrammatic representation of 'for' and 'against' issues concerning a decision. In order for a planned decision to be successfully implemented, the weight of the favorable forces should exceed the weight of the unfavorable forces. Either strengthening the favorable forces or weakening the unfavorable forces achieves this, strategically.

In the context of Radwaste repository rhetoric, FFD can be used as a tool complementing the risk dialogue process at every stage of discussions and analysis. Rather than a sequential listing of 'For'/'Against' arguments as in Table 3 above, a diagrammatic representation of these arguments can be made on a FFD together with perceived/estimated weightages. This would enable calculation of a "balance of power" between driving and restraining forces, which can then be analyzed and worked upon to support the efforts towards increasing the social acceptability. Using FFD in this manner has the following advantages:

(a) It helps prioritize stakeholder arguments for further analysis and strategic action.
(b) It improves the transparency and objectivity in the decision-making organization's strategic efforts at risk perception management.
(c) It helps highlight which risk perception elements the decision-making organization should focus on in its risk communication with stakeholders. This 'targeted' risk communication will arguably lead to a better influence on these target stakeholder groups rather than a general one-size-fit-for-all type of risk communication.

2. Fuzzy Clustering and Classification. The current method of classifying decision criteria elements at L2/L3 levels has been undertaken manually. As already discussed, there is scope for automation of the abstraction process. Once the risk-based decision-criteria elements begin to get captured in databases, fuzzy clustering and classification methods can be adopted to integrate them into the Fuzzy AHP framework.

3. Improving Legal Normative Elements Extraction. As discussed in section "Developing an Intelligent Knowledge Representation for the PP", the PP has been chosen to form the legal normative basis and in particular, the EC 2000 communication on the PP has been assumed to form a consensus concept net. In reality, the legal normative elements might involve multiple principles/standards and different interpretations of principles, leading to multiple concept nets. A robust methodology needs to be developed and employed in order to 'intelligently' merge the multiple concept nets. This will enable objective incorporation of a more comprehensive legal normative understanding for the L2 level elements.

4. Fuzzy Consensus Methods. As discussed in Sect. 5.3 above, there may be situations when there is a lack of consensus between the DM organization and the stakeholders on preference rankings. This would then involve adopting suitable fuzzy consensus methods to minimize the dissimilarity between the group and individual stakeholder preference opinions.

8 Conclusions

One of the biggest challenges for decision-making in the field of radioactive waste management policy has been managing stakeholder risk perceptions. Various stakeholder participatory formats have evolved to help engage stakeholders actively in such policy decisions. However, efforts so far in persuading society about these decisions, especially for siting deep geo repository for radwastes have met with only limited success. One of the key success factors in making policy decisions socially persuasive is incorporation of risk perceptions/criteria underlying the societal argumentation explicitly and objectively into the policy DM framework. As a complement to this, the legal criteria in the decision should also be considered objectively. Such complex issues require suitable socio-legal abstractions of the radwaste problem.

After a brief consideration of existing methods, this paper proposed a new complex socio-legal abstraction of the radwaste problem based on Risk–Risk Analysis and intelligent knowledge representation within a Fuzzy AHP framework. Practical applicability of this abstraction was demonstrated using a combination of actual facts of the French deep geo repository DM case of ASN with hypothetical fuzzy preference rankings.

The results show the complex abstraction approach as indeed addressing the key challenge of objectively extracting stakeholder risk perception/risk-criteria elements from underlying rhetoric and incorporating them transparently into the policy DM framework. Such an approach also facilitates explicit incorporation of normative legal criteria in the DM objectively. In addition to supporting socially persuasive radwaste policy DM by enabling risk tradeoff considerations, this abstraction logic can also serve as a first step towards automation of such processes in future participatory mechanisms.

> "The purpose of all computing is insight, not numbers" – Richard Hamming

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Fuzzy-Set Decision Support for a Belgian Long-Term Sustainable Energy Strategy

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Summary. This chapter addresses the methodological challenges of developing relevant scientific knowledge for a sustainable energy system transition in an innovative way. We argue that scientific contributions to sustainable development do not follow the 'linear' procedure from empirical knowledge production to policy advice. Instead, they consist of problem-oriented combinations of explanatory, orientation- and action-guiding knowledge. Society and policy makers not only have to be 'provided' with action-guiding knowledge, but also with an awareness of the manner in which this knowledge is to be interpreted, and where the inevitable uncertainties lie. Since the sustainability question is inherently multi-dimensional, participation of social groups is an essential element of a strategy aimed at sustainable development. Multi-criteria decision support provides a platform to accommodate a process of arriving at a judgment or a solution for the sustainability question based on the input and feedback of multiple individuals. At the same time in practice, multi-criteria problems at tactical and strategic levels often involve fuzziness in their criteria and decision makers' judgments. Therefore, we argue in favor of the use of fuzzy-logic based multi-criteria group decision support as a decision support tool for long-term strategic choices in the context of Belgian sustainable energy policy.

1 Introduction

It is difficult to imagine our lives (i.e. the lives of people in rich, industrialized countries) without all the services made possible by the provision of commercial energy: the heating of our houses, electricity for our appliances, fast

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transportation modes (train, tram, bus, car, airplane), the industrial manufacture of consumer goods, and so on. All of these technologies have completely changed our way of life, but they rely on the uninterrupted supply of huge amounts of energy. And energy consumption is still on the rise – in Belgium, Europe, and certainly on a global scale. Especially our dependence on fossil fuels (oil, gas, coal) – supplied from the four corners of the world if necessary – is growing. Our 'addiction to energy' comes at a heavy price. Next to the obvious problems of long-term energy security and geo-political risks, there are also risks for the safety and health of people and the environment all the way from the extraction of oil, gas, coal and uranium, to the final consumption. Problems can be local (e.g. noise pollution from airplanes), regional (e.g. acid rain), or even world-wide (e.g. anthropogenic climate change, proliferation risks). And besides the environmental problems and security risks, there are also social problems. Access to clean energy is a fundamental right for everyone in order to satisfy basic needs such as shelter, food and hygiene. Hence, the global energy situation raises a number of ethical questions, such as: '*What would happen if everyone in the world used as much energy as we do in rich, industrialized countries*?'; '*Can we guarantee access to clean, reliable and affordable energy sources for the next generations*?'; and '*Will the resource depletion, pollution and other risks remain manageable*?'. By now, the recognition that development should become more sustainable is widespread.

The realization of sustainable development is a monumental challenge, not only for politics and society. Strategic scientific information is needed to support opinion formation and decision-making processes. However, the services which science has to provide to support the transition to a sustainable energy system have – in part – other characteristics than the 'traditional' scientific outputs (e.g. technological innovations, new explanatory knowledge about causal processes, etc.). The normative character of sustainability, its inseparable connection with deep-rooted societal structures and value patterns, the long-term nature of many relevant developments, as well as the necessary inclusion of societal actors, result in specific demands on scientific policy support [7]. Scientific knowledge for sustainable development has to consist of targeted and context-sensitive combinations of **explanatory knowledge** (i.e. energy system knowledge or knowledge of the interactions between societal activities, energy service demands, energy technologies – supply and demand – and the resulting impacts); **orientation knowledge** (i.e. knowledge of justification arguments which operate with normative premises); and **knowledge for action** (i.e. scientific contributions to the 'therapy' of unsustainable situations). Furthermore, this kind of knowledge will always be provisional and incomplete in its descriptive aspects, as well as dependent on changing normative expectations [9]. Therefore, science for sustainability needs to be **reflexive** – i.e. sensitive to the conditions of knowledge production. Society and policy makers not only have to be 'provided' with action-guiding knowledge, but also with an awareness of the manner in which this knowledge is to be interpreted, and where the inevitable uncertainties lie. In other words, strategic knowledge for sustainability needs to be **transparent** (i.e. all decision criteria should *a priori* be presented in their 'original' form, without converting them to frequently used common measurement rods such as energy inputs/outputs or money).

In order to meet these challenging conditions for strategic knowledge production, a PhD research project was carried out at the Belgian nuclear research centre (SCK•CEN) and the University of Leuven (KULeuven) which aimed at innovative methodological developments in the field of policy support for a long-term sustainable energy strategy in Belgium [12]. The project put an emphasis on the following essential aspects of 'knowledge for sustainability':

- **Long-term energy foresight from a normative perspective** by using a 'back-casting' approach;
- **Planetary scope** in the sense that the global universalizing perspective is an essential element of the sustainability logic;
- **Feasibility as part of a governance process** in the sense that, if embedded in an appropriate institutional context, the required knowledge should be developed in such way that it can play a role in a more open-ended learning approach to energy policy – i.e. strategic knowledge should be flexible and adaptive in nature, in response to changing assessments regarding the political relevance of items, alternatives or impacts. Furthermore, the development of knowledge should not be too demanding (e.g. in terms of the theory behind it), expensive to implement, unduly protracted, etc.;
- **Integrated assessment** in the sense that all life-cycle stages of energy technologies – from energy services to primary energy demands – should be taken into account;
- **Interdisciplinarity** in the sense that strategic knowledge should not put any artificial boundaries on the type of issue or measurement that can be taken into account in the analysis – i.e. the analysis needs to support arguments coming from technological, economic and sociological perspectives;
- **Uncertainties in the long run** in the sense that strategic knowledge should incorporate some form of uncertainty management.

At this point, if we accept the multi-dimensional nature of the sustainability question, we also have to accept that the evaluation of strategic policy options has to be based on procedures that explicitly recognize the integration of a broad set of (possibly conflicting) points of view, taking into account the principles set out above. Elsewhere, we have argued that multi-criteria evaluation techniques can in principle (i.e. providing certain conditions are met) provide an appropriate policy framework for setting long-term strategic priorities [14]. This chapter sets out a proposal to use a fuzzy multi-criteria group decision support system (FMCGDSS) as a possible framework for the application of strategic choice to an intractable policy problem such as sustainable development. Fuzzy multi-criteria decision making has been one of the fastest growing areas in decision making and operations research during the last three decades [18,23,29,35]. A major reason behind the development of fuzzy multi-criteria decision making is due to the large number of criteria that decision makers are expected to incorporate in their actions and the difficulty of expressing decision makers' opinions by crisp values in practice [30–32]. Group decision making takes into account how people work together in reaching a decision. Uncertain factors often appear in a group decision process, namely with regard to decision makers' roles (weights), preferences (scores) for alternatives, and judgments (weights) for criteria. We will illustrate some of the main points of interest in the application of the FMCGDSS by drawing upon our case-study of Belgian long-term energy policy. First, we set out the policy context and the positions of major energy policy stakeholders at the time when the multi-criteria evaluation took place (Sect. 2). Next, we discuss the application of the FMCGDSS according to the principal phases in any multi-criteria evaluation: identification of the stakeholders to take part (Sect. 3); generation of decision alternatives (Sect. 4); selection of evaluation criteria (Sect. 5); and scoring, weighting and application of an aggregation convention (Sect. 6). We conclude with general observations on the use of multi-criteria decision aiding methods (and the application of the FMCGDSS in particular) in the context of sustainability (Sect. 7). As our main aim in this chapter is to discuss the methodological issues of multi-criteria decision support in the context of sustainable energy policy, we will not discuss in detail the substantive results of the 'Belgian case'. For this, we refer the interested reader to Laes [12].

2 The (Nuclear) Energy Debate in Belgium

Of course, policy making for sustainability is not a one-shot activity. On the contrary, policy measures are shaped by a highly dynamic process taking place at multiple levels (e.g. international guidelines, European directives, national legislation) and crossing the boundaries of institutionally separated policy domains (e.g. fiscal measures impacting on consumer behavior, liberalization of European energy markets and the rules of the 'free market', climate change policy, environmental regulations, etc.). Furthermore, policy making is inevitably bound to the normal rules of the democratic game, so that political judgments regarding the salience of certain problems or impacts may change (sometimes drastically) over time. Therefore, before entering into the details of the particular application of a multi-criteria decision aid to the development of strategic knowledge for a sustainable energy strategy, it is necessary to give some more details about the policy-making context at the time when this multi-criteria exercise was organized (Oct.–Dec. 2003). At that time, the Belgian parliament had only just voted a law entailing the gradual phase out of nuclear energy (Sect. 2.1). This decision roused quite some contestation between a number of historically active social groups on the Belgian energy policy scene. The resulting debate stretched the scope of arguments outside the boundaries of political (parliamentary) decision making, as it opened up to (sometimes highly ideologically colored) arguments about the strategic direction of Belgian energy system development involving at the same time a discourse about the cognitive (i.e. concerning the availability and use of existing scientific knowledge), reflexive (i.e. concerning the issue of framing and interpreting scientific knowledge in a policy-making context) and planning (i.e. concerning the organization of a politico-scientific debate) dimensions of the policy process configuration at the time [13] (Sect. 2.2).

2.1 Policy-Making Context

In Belgium – as in many other industrialized countries – the energy sector has been shaped in the past (roughly before 1990) by the dominant importance accorded to the diversification of energy sources (in order to minimize the geo-political risks of dependence on oil-exporting countries) and security of supply at a reasonably competitive price for all concerned. This post-war 'social pact' formed the core of energy policy: representatives of both employers and employees recognized the need for a growing economic output in order to maximize welfare, and direct state intervention in the energy sector was encouraged. From a historical point of view, the bargaining process among the interested parties has led to a low priority for measures to promote a rational use of energy (because this interest was not directly advocated, or even implicitly opposed). From the 90s on, the policy-making context was gradually changed mainly by the combined forces of an increasing prominence of environmental issues on the (international, regional and national) political agenda (e.g. climate change) and the liberalization of European energy markets.

The attitude of the Belgian political class towards nuclear power in the 90s was generally characterized by a great deal of reticence. Starting from 1988, subsequent governments upheld the moratorium on the construction of new nuclear capacity; options preferred by the nuclear sector which were taken earlier (e.g. reprocessing and use of mixed-oxide fuel in Belgian power plants) were questioned and revised; and decisions regarding rather pressing nuclear issues ran into a complete gridlock and were postponed (e.g. the siting of a waste disposal for low-level wastes). All in all, it seemed as if the safest political strategy for the major political parties (Liberals[5], Socialists, Christian-democrats) was to be as quiet as possible about nuclear issues. This is not surprising as more than 30 years of nuclear controversy resulted in deeply polarized positions and an almost complete gridlock[6]. Under these circumstances, it is safe to assume then that the nuclear phase out (as opposed

[5] In the European-continental sense of the word – i.e. central-right on socio-economic issues and more progressive on moral issues.

[6] Gridlock can, in this sense of the word, be characterized as a condition where technological policy has faced major obstacles, due to an emphasis on hardware and technological fixes to the neglect of citizen or political concerns. When one

to a continuation of the moratorium on new nuclear construction) was directly placed on the political agenda as a result of the participation of the Green parties (AGALEV/ECOLO) in the 1999–2003 federal government (a coalition of Liberal, Socialist and Green parties)[7]. These parties have, since their origins in the early 80s, consistently rejected the reliance on nuclear power as an element of energy policy. The other partners in the coalition (Liberals and Socialists) apparently were not willing to turn the proposed nuclear phase out into a breaking point in the political negotiations preceding the formation of the new government[8].

In the context of profound change provoked by the Kyoto commitments and the (at that moment still embryonic) liberalization of the electricity market, the nuclear phase out was first announced as an intention in the government policy statement of 7 June 1999 (at the beginning of the legislature of the previous government), together with a confirmation of the political willingness to comply with the Kyoto agreements. The phase-out scenario means that the Belgian nuclear power plants would effectively be taken out of service in the period 2015–2025 (after 40 years of operation), whereas Belgium now provides for some 55% of its electricity needs by nuclear power generation. It took almost four years before the original government intention was translated into law. During this period, some policy documents were published which provide a deeper insight in the political negotiation of problem structuring and the justifications given to support the decision. In Laes [12] we argue that these justifications were based on an attempt to **recast the policy problem in a well-structured technical mould**. This was evident from a self-proclaimed reliance on expert opinion, limitations on the possibilities for ethical debate, treatment of the policy question within the mandate of existing bureaucratic organizations, etc. A detailed analysis showed however that this technical treatment could only be achieved by leaving some ‘white spots’ and/or ambiguities in the justifications given. Conflict rather than mutual exchange was the dominant dynamic in the debate surrounding

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encounters gridlock, or in other words an almost complete loss of trust, co-operation on any issue involving the technology in question seems almost impossible [25].

[7] Other political parties never went further than advocating an enlarged moratorium, concerning as well other activities in the nuclear sector (i.e. not only the production of electricity, but also e.g. the production of mixed-oxide fuel elements) as the foreseen duration of such moratorium.

[8] The present government (2003–2007) – a coalition of Liberals and Socialists (without the Green parties) – has not altered the nuclear phase-out law. Nuclear power again figures prominently in the electoral campaign at the time of writing this chapter (May 2007), with the Socialist and Green parties proposing to stay on a nuclear phase-out course, the Liberal party agreeing to maintain the phase-out agreement for the present power plants whilst advocating increasing research efforts into new nuclear reactor concepts (the so-called ‘GenIV’ initiative), and the Christian-democrat party in favor of keeping the present power plants open longer than foreseen in the phase-out law.

the phase-out decision. Exclusive relations between the different perspectives were caused by competing rationalities on the one hand and the governance framework on the other. Our analysis revealed that social learning was mainly hindered by the following issues:

- Different **methodological approaches** (bottom-up vs. top-down analysis of the energy system);
- **Lack of data** (to perform the bottom-up analysis);
- Different perceptions of **relevant time scales** (or how to link short-term issues with long-term issues);
- Different **framing of the problem** (studying only the electricity system vs. embedding electricity needs in the wider energy system);
- **Institutional barriers** (e.g. to develop a much needed long-term vision);
- **Lack of communication** (between political decision makers and scientists, between scientists and stakeholders);
- **Strategic use** of scientific assessments by different stakeholders, or
- **Insufficient knowledge of scientific assessments**.

As a result, sustainable energy (and the role of nuclear power therein) proved to be an essentially contested concept, and furthermore there were virtually no 'connecting' or 'translating' links between the divergent concept and problem framings. This finding suggested that other possible views on the role of nuclear power in a sustainable development perspective existed which had to be actively 'suppressed' or 'blurred' (in order to proceed 'as if' there was a consensus). In the following section the major positions in the debate are reconstructed.

2.2 Patterns of Argumentation on a Sustainable Energy Strategy

To understand if other courses of action were possible then the highly discordant ones described above, an institutional analysis was carried out and consequently representatives of most of the organizations having a seat in the Belgian 'Federal Council for Sustainable Development' (FCSD) were invited for a personal interview session. For purposes of clarity, we made an attempt to reconstruct the different arguments used in the interviews into some coherent and consistent argumentation schemes. These argumentation schemes thus differ from each other in the assessment of different aspects of the sustainable energy policy question and in the resulting will to change the course of development. They are meant simply as frameworks for analysis and thus, essentially, as 'ideal' reconstructions. This implies that although participants will certainly recognize parts of their reasoning, they are not to be identified with the vision of a particular societal actor. This analytic approach is only meant to guide the process of reflection, by drawing particular attention to some aspects of the problem and by systematically positioning the collective choices between different options against each other. We have labeled the three perspectives the '**management**', '**controllist**' and '**reformist**' perspective.

These perspectives have been reconstructed in their structural dimensions, i.e. their communicated images of self and others (with respect to relevant actors), valid forms of communication, main problem focus, and main principal references. Boltanski and Thévenot's 'commonwealth model' [5] has served as an aid in identifying them.

The **manager** for a large part frames his arguments within the confines of industrial and market arguments. He sees economic growth and technological advance as the most important component of sustainable development, to the extent that actions that might seriously endanger possibilities of growth or competitiveness in general must be discouraged. Furthermore, economic growth will most likely be driven by higher demands for energy and electricity. The *manager* is quite content for the market for electric power to stand as a surrogate for societal consent. To be sure, he is of course worried about safety and health issues; however, these are considered to be part of a technical design. It is the government's responsibility to ensure standards and norms, based on 'objective' scientific rationality. Hence, sustainable development is at risk when the necessary long-term stability is undermined by a lack of (respect for) expert knowledge as an indisputable basis for the legitimacy of state action. Governments should set up a stable framework; business will then take up its responsibilities through 'sustainable entrepreneurship', ensuring relationships based on trust and consent with concerned parties (labor unions, stockholders, employees, local residents, etc.). There is no reason why electricity generators owning nuclear power plants could not be part of this.

The **controllist** seems to be caught in a paradox. His position on the role of nuclear power in sustainable development was perhaps best phrased by one interviewee: "*...As long as there is no real commitment to the development of a vision on long-term alternatives for nuclear power, a phase-out scenario is nonsense. But, if society does not want to consider the phase out of nuclear energy, the motivation to think about alternatives will also be very weak* ...". The *controllist* is not so much interested in the 'pro or contra' discussion about nuclear power; rather, attention should be given to the institutional embedding of this technology is society. Fear exists that in the future, nuclear power will be 'inevitable' if one wants to respect post-Kyoto commitments and still foster economic growth. Rather, acceptance (or rejection) should be based on a democratic debate with the representatives of concerned parties, under conditions of full transparency. For now, according to this position, these conditions have not been fulfilled as too much is left in the dark: costs of decommissioning, costs of high-level waste management, the real costs of the business-as-usual scenario, etc. – all 'great unknowns'. In other words, the *controllist* is mainly concerned with the maintenance of the democratic system of 'checks and balances'. Thus, more attention is given to the necessary framing of 'industrial' and 'market' values within the logic of a civic argumentation. The *controllist* prefers a real balance between economic, social and environmental development – for now, economic growth is too strongly favored. This perspective deplores the risk that in a liberalized market, the government's power of intervention could be limited.

The **reformist** sees the evolution of the Belgian electricity sector as an ongoing social process in which scientific knowledge, technological innovation (or the lack thereof in renewable energy technologies) and corporate profit reinforce each other in deeply entrenched patterns, patterns that, according to this perspective, bear the unmistakable stamp of political and economic power. In terms of Boltanski and Thévenot's commonwealth model, people and objects are artificially kept in a state of permanent 'misery': perfectly valid technical options (e.g. renewable energy options) are underdeveloped and 'rational' behavior (e.g. energy saving) discouraged, the true costs of energy use are being concealed, and people are kept in a state of political apathy. For the *reformist*, nuclear power is not merely the symbol of this social order; it is a true embodiment of that order. The concerns are broad and directed at ethical and socio-cultural levels for which even regulatory environments might not be suited. Moreover, this perspective challenges and stretches the limits of the established argumentations towards long-term and global ethical considerations. The *reformist*'s explicit agenda calls for a new social order that would make the current distribution of resources more equitable. Resources must be understood in the broadest sense: not only in a physical (e.g. distribution of health and environmental risks) or monetary sense (e.g. distribution of benefits from nuclear power generation), but also culturally, involving democratic and governance issues. Consent for a technological or development option must be based on explicitly revealed preference in a dialogical form of democracy. Small-scale participatory institutions are regarded with more trust than central government. The *reformist* also feels that, as a result of this socio-technological nexus centered on nuclear power, his perspective on sustainable energy has not been addressed sufficiently and calls for a new research agenda: there is no culture of long-term reflection, there are no sufficient scientific data to perform a bottom-up analysis of electricity demand, energy issues in general are not high on the political agenda, etc.

Once these general perspectives were identified the problem has to be structured in a multi-criterion framework. This means to identify stakeholders, generate strategic decision alternatives and to choose evaluation criteria. The next sections illustrate the multi-criterion approach used (i.e. the FMCGDSS) and the results obtained.

3 Identification of Stakeholders

The value of the so-called 'extended peer communities' [7] for the formulation of public policy measures is increasingly recognized, especially in contentious policy fields such as sustainable development. Such extended peer communities (e.g. citizen juries, focus groups, deliberative conferences, etc.) all have one thing in common: they assess the quality of policy proposals, not only by adding 'public values' to the mix, but crucially also by assessing the technical and scientific component of these proposals [4]. Banville et al. [3]

offer a convincing argument on the need to extend theoretical thinking about multi-criteria decision aid frameworks towards their role in upholding dialogue processes among many stakeholders – individual and collective, formal and informal, etc. While we agree that stakeholder participation is a *necessary* condition for a multi-criteria decision aid, we do not agree that it is a *sufficient* one. As we will explain in Sects. 4 and 5, we cannot simply take stakeholder perspectives for granted in the formulation of decision alternatives and criteria.

For the operation of our particular multi-criteria decision aid framework, we have chosen to continue our participation with selected members of the FCSD. In a way, the multi-criteria exercise can thus be regarded as a more mathematically formalized sequel to the interview sessions discussed in Sect. 2.2, with however a shift in focus towards future-oriented scenarios (whereas the interviews mainly discussed present problems). The individuals taking part in the multi-criteria exercise were approached on the basis of their wider interest in both sustainable development and energy (governance) issues. Often, this meant that they were representatives of protagonists in the current energy debate with large stakes in its outcomes. However, this was not always the case, as we also explicitly strove to involve other actors than the 'traditional' interest groups in the discussions. As such, each participant could be expected to hold a general knowledge of the issues raised in contemplating energy options and their general implications, whilst also sometimes holding specialist knowledge on particular issues. As a group, it was important to include a sufficient number of perspectives, so that no point of view would be excluded *a priori*. At least one representative of the major stakeholder categories (environmental NGO's, labor unions, employers' organizations, electricity generators, academia and advisory bodies) has participated in the multi-criteria exercise, with the exception of development NGO's[9]. However, due to busy schedules or other exigencies, most organizations did not participate in all research steps (interviews, generation of decision alternatives and assigning weights and scores). Also, in some cases different representatives from the same organization participated in the different research steps. Maintaining full participation by the same representatives would have been more desirable though, in view of ensuring participants' understanding of the logic behind each of the steps. In any case, this particular selection of participants for the limited 'pilot exercise' reported in this chapter should not be seen as a definite choice in favor of these groups for representing 'societal views' on sustainable energy. Deciding which groups should be involved in a concrete governance initiative would be a matter of further research and – above all – political negotiation. Also, in more realistic political settings, different individuals will

[9] The representative of the development NGO made it clear after the first interview session that he really did not consider his organization to be involved in the questions that were of interest to us (i.e. the role of nuclear power from a sustainable development perspective in Belgium), so he declined further participation.

have different degrees of influence for the selection of satisfactory strategies. This means that the relative importance of each stakeholder may not be equal in the group. Therefore, the FMCGDSS foresees the possibility to assign a weight to each stakeholder. Formally, these weights are described by linguistic terms $\widetilde{v}_k,\ k = 1,\ 2, \ldots,\ n$ (*normal, important, more important*, and *most important*) which could be arrived at through group discussion or assigned by a higher policy level (e.g. a minister in charge of developing a strategy for sustainable energy development).

4 Generation of Strategic Alternatives

One crucial part of decision-analytic methods is how the decision problem under scrutiny is constructed, and as a consequence, the alternatives for solving the problem. In the context of a long-term policy for sustainable energy development, however, it is clear that there is no ‘single’ decision involved, but rather a set of interlinked decisions, none of which taken on its own constitutes the policy, but which in combination produces a process which we could describe as a ‘strategy’. Nevertheless, in order to use a decision-analytic procedure, we need to represent clearly distinctive ‘alternatives for action’ in a way that would allow participants in the exercise to choose between them. Hence, a possible conflict emerges between the ‘complexity of the real world’ and the ‘simplicity’ required for the purposes of decision-analytic modeling. In principle, there is no ‘right’ solution to this dilemma; one can only try to propose an acceptable (pragmatic) solution [8].

For instance, in a multi-criteria application to energy policy, Stirling [28] proposes to limit the selection of decision alternatives to a “*...conventionally recognized and highly aggregated set of options...*” (fossil fuels, nuclear power and renewable energy), whilst leaving the ‘framing assumptions’ for assessing these options open to the participants involved in the exercise. Stirling’s view appears to be motivated by a concern that the multi-criteria analysis should not be unduly constrained or biased by an externally imposed framework. While this concern may be legitimate, it is also clear that leaving the framing assumptions entirely open to the participants’ insights leaves the door wide open to strategic behavior – i.e. a participant simply assumes that ‘the framing assumptions’ function in accordance with the requirements for his/her preferred decision alternative performing optimally. While Stirling would of course contend that the purpose of a multi-criteria aiding technique is precisely to make such framings more transparent (and hence also possibly open to discussion at a later stage), we nevertheless see two fundamental objections. The first is that without at least proposing some scenarios as a common framework for communication and discussion, the multi-criteria exercise is likely to simply reproduce existing positions and statements. Hence, it is unclear to us what the precise added value of a multi-criteria exercise might then be in this case. Secondly, simply accepting these framing assumptions at face value implies that there is no possibility to check whether these assumptions are applied consistently and coherently to all options under scrutiny – an important advantage offered by a reliance on formal modeling. Jones et al. [11] offer another interesting solution to the dilemma. In their decision-analytic model, these authors propose the use of five contrasting energy policy scenarios (in their case developed for the UK), drawn from the publications of a variety of different organizations engaged in energy policy. Using existing scenarios has the advantage that participants in the exercise will likely already be familiar with these scenarios, thus greatly facilitating communication and discussion. However, as mentioned before, at the time we organized our multi criteria exercise (Oct.–Dec. 2003) long-term energy scenarios for the Belgian context were simply not yet available, so we had to develop our own scenarios.

Therefore, our solution has been to develop four broadly conceived technological options – namely (a) a continued reliance on nuclear power; (b) development of carbon capture & storage technology; (c) increased import of electricity; or iv) more energy conservation combined with renewables and/or cogeneration technology – and subsequently 'test' these options against a background of two different (summarily narrated) 'worlds' – (a) the 'market world' which imposed some barriers to the penetration of energy efficiency measures and renewable energy into the energy system; and (b) the 'rational world' where energy efficiency measures and renewable energy could penetrate more easily. The eight resulting scenarios were simulated with the aid of an energy system model (MARKAL). Figure 1 gives an example of the long-term evolution of the Belgian electricity sector under the assumption that nuclear energy is not phased out, and that market functioning continues to impose

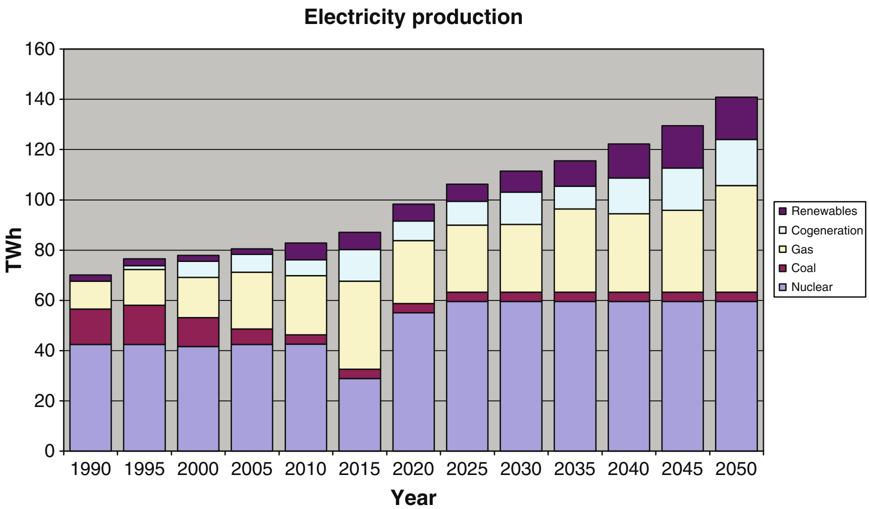

Fig. 1. Evolution of electricity production (TWh) in the case of a 'Market' scenario with continued reliance on nuclear power

barriers upon the penetration of renewables and energy conservation measures. A further characteristic of the scenarios under scrutiny is that although the principal focus concerned the relative merits of nuclear power, this option was nevertheless put in the context of alternative options for meeting the energy (and not only the electricity) needs of the future in a sustainable way. Our intention was thus not to make a specific pronouncement on the sustainability of the nuclear option as such, but rather to evaluate its relative (i.e. in comparison with other possible long-term options) performance under a number of different perspectives.

5 Selection of Decision Criteria

As argued by Munda [20–22], an effective application of policy support techniques should consider not merely the measurable and contrastable dimensions of the simple parts of a complex system, but should also deal with the 'higher dimensions' – e.g. those dimensions in which power relations, hidden interests, social participation, cultural constraints and other 'soft' variables become relevant. In practice however, the criteria in a multi-criteria appraisal exercise are often established according to the requirements of 'quantitative' sciences (e.g. ecology or economics). This approach often seems to be motivated by a concern for avoiding deep-seated value conflicts. For instance, multi-criteria discussions on sustainable development are often framed in terms of 'technical' criteria such as 'environmental impacts', 'social impacts', 'economic impacts', etc. (see e.g. Haldi et al. [10], Afgan et al. [1]). However, as demonstrated by Rauschmayer [24], establishing comparisons on a technical basis reflects in itself a deep link to a value system concerned only with efficacy, performance, and functional exigencies. If one wants to avoid scientific reductionism of this kind, there is a clear need to take into account policy dimensions using different 'languages' coming from different representations of the same system. It is clear that a multi-criteria approach, being inherently multi-dimensional in nature, seems an interesting framework to make this basic idea operational.

The decision criteria used in the FMCGDSS were derived from the interviews with members of the FCSD and a range of publications and policy documents in the field of (sustainable) energy policy. However, it is important to note that these criteria are a **technical translation** of the stakeholders' preferences and needs, operated by the research team. Such translation is a necessity since the technical formulation of decision criteria needs to show properties such as 'non-redundancy', 'legibility', etc. which cannot simply be 'extracted' from the rough material contained in interviews [6]. Decision criteria were subsequently structured into a 'combined value tree'. This combined value tree includes four important issues (high-level criteria): (a) 'Environmental and human health & safety', (b) 'Economic welfare', (c) 'Social, political, cultural and ethical needs', and (d) 'Diversification'. Just for the first dimension, seven aspects were defined (intermediate-level criteria):

(1) 'Air pollution', (2) 'Occupational health', (3) 'Radiological health impacts', (4) 'Aesthetic', (5) 'Other environmental impacts', (6) 'Resource use', and (7) 'Other energy related pressures'. Each aspect had one or more low-level criteria.

For instance, the aspect of air pollution has both mid- and long-term impacts. Figure 2 shows the combined value tree for environmental and human health & safety, whilst Fig. 3 shows the main interface of the FMCGDSS with the left part representing the two top levels of the decision structure. In any case, this classification of the criteria does not affect the final results of the multi-criteria exercise, but is simply a matter of convenience: the possibility was left open to participants to choose between a smaller selection of criteria at a higher level of abstraction at any time in the exercise. For the purposes of a multi-criteria appraisal exercise, it is important that individual criteria are independent in the sense that, although different criteria might be related in various ways (e.g. policies aimed at reducing carbon dioxide emissions generally also lower emission of other air pollutants), the associated assessments of

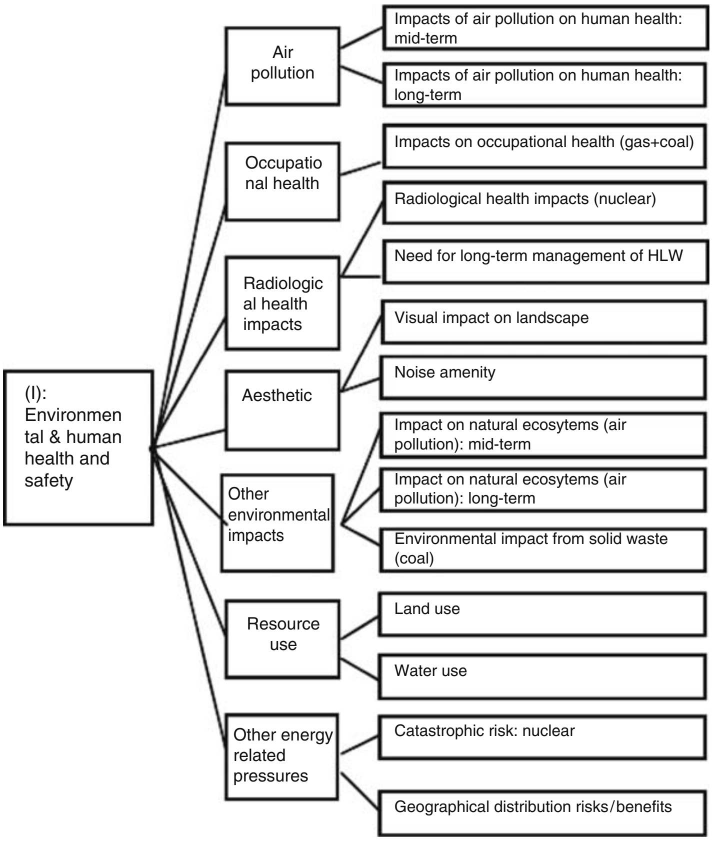

Fig. 2. Structured value tree 'Environmental & human health and safety'

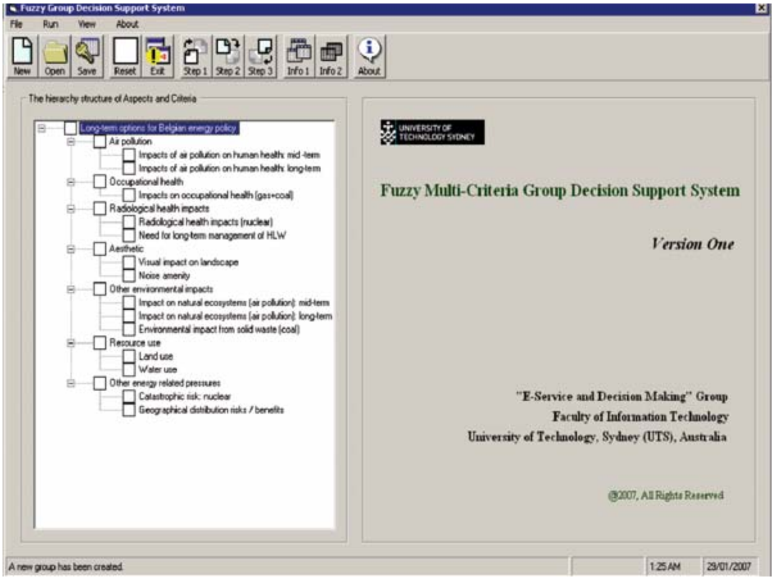

Fig. 3. Problem structure as represented in the FMCGDSS interface

performance do not depend on judgments of performance under other criteria (e.g. measuring carbon dioxide emissions can be done entirely independently of the measurement of any other air pollutant). We have tried to structure the 'combined value tree' in such way that this requirement was met. However, since the 44 bottom-level criteria were still phrased in a rather general way (particularly those relating to the 'social, political, cultural and ethical needs'), some degree of overlap could probably (at this stage) not be avoided[10]. Because working with 44 criteria at the same time would be generally unfeasible, we asked participants in the exercise to select from this list about 10–15 criteria which seemed to be most important to them. During the exercise, participants could also add new criteria or criticize chosen measurements for some of the criteria (and possibly even suggest others).

6 Scoring, Weighting and Application of an Aggregation Convention

The actual operation of the multi-criteria decision aiding system was framed in the context of individual interviews. Interviews usually lasted between 1 and 2 h. During the interview, an iterative process was undertaken, comprising: (a) a discussion of the scenarios developed for the multi-criteria exercise;

[10] Also as a result of the different framings of the same criterion adopted by participants in the exercise (as became apparent when questioned what a criterion precisely meant for them).

(b) a discussion of the combined value tree developed for the multi-criteria exercise (with possibilities for clarification and specification of new criteria); (c) the scoring of the performance of each scenario under a selection of criteria; and (d) the weighting of the criteria in terms of their relative importance as 'matters of concern' to the interviewee. The entire interview was organized in an iterative and reflexive way, so that participants were for instance able to add further comments on the scenarios while they were scoring criteria, or add new criteria along the way. In the context of this chapter, which deals mostly with methodological considerations, we will focus on the issue of scoring and weighting the decision criteria and aggregation procedures – since these often raise fundamental ethical questions (Sect. 6.1) – and explain how these issues have been dealt with formally (i.e. in a fuzzy-logic framework – Sect. 6.2).

6.1 Considerations on the Ethics of Scoring, Weighting and Aggregation

Since the aim of multi-criteria decision support is – obviously – to support (political) decisions, it is clear that procedural questions ('who is making the decisions and how?') in MC decision support carry an important ethical/political component which should be part and parcel of the reflection. These ethical considerations are discussed in depth in Laes ([12], Chap. 7); within the confines of this chapter we simply want to raise some of the most important questions and indicate the responses, without going into the details of the reasoning behind them.

With regard to scoring, we have already stressed that a policy support tool which aims to fulfill – at least up till a certain degree – standards of procedural fairness, must be able to integrate all sorts of interests and judgments of those stakeholders who stand to gain or loose from the outcomes of the decision. For a complex problem such as deciding on long-term strategies for sustainable energy, different legitimate representations of 'the same' system – using different (scientific) languages – co-exist. Engineers, economists, and stakeholders dealing with the 'messiness' of energy policy decisions in real-world political contexts will each have strongly divergent opinions on the framing of the decision problem[11]. Therefore, for the scoring of strategic options it is important to keep in that the 'descriptive' representation of a real-world system always depends on very strong assumptions about e.g. the purpose of the representation, the scale (local, regional, global) judged to be

[11] We might consider the example of nuclear safety (or conversely, the risk of a catastrophic accident in a nuclear power plant): the engineer will likely base his/her 'scoring' of this criterion on probabilistic considerations; the economist could base his/her opinion on the insurance premiums for nuclear power plant operation; while a politician or representative of a stakeholder organisation might base his/her opinion on e.g. testimonies from trusted sources, experiences with the effectiveness (or lack thereof) of regulatory organisms, social indicators such as the safety culture in nuclear power plants, etc.

relevant, and the set of dimensions used for the evaluation process. The experience in the context of Belgian long-term options for sustainable energy policy has shown that a multi-criteria framework can be a very effective tool for to implement a multi- or interdisciplinary approach. This is because the structuration of the decision problem in a multi-criterion fashion allows to set up a hierarchy of values (the decision value tree) coming from mixed information of the widest type (cf. Sect. 2.2) in which each stakeholder can recognize his/her perspectives and ability to pronounce meaningful scores on the different criteria. This also implies that stakeholders might very well be ignorant or indifferent about certain criteria scores (not each dimension will be equally relevant to all stakeholders), and that this aspect of the 'real-world' decision-making setting should also be addressed in the formal representation of it (cf. next section). Figure 4 gives the example of one particular stakeholder's input on all strategic alternatives under all criteria by linguistic terms. 'Cannot be determined' is a linguistic terms which is also accepted by the system.

The issue of criteria weighting is also hotly debated in the relevant scientific literature (see e.g. [2,20,26,27]. Broadly speaking, the debate often turns around the issue of 'commensurability'. Full commensurability means that an actor is able to rank all decision criteria using a principle of compensation showing an intensity of preference. This intensity of preference is revealed by indicating how much of an advantage on one criterion is sufficient for the

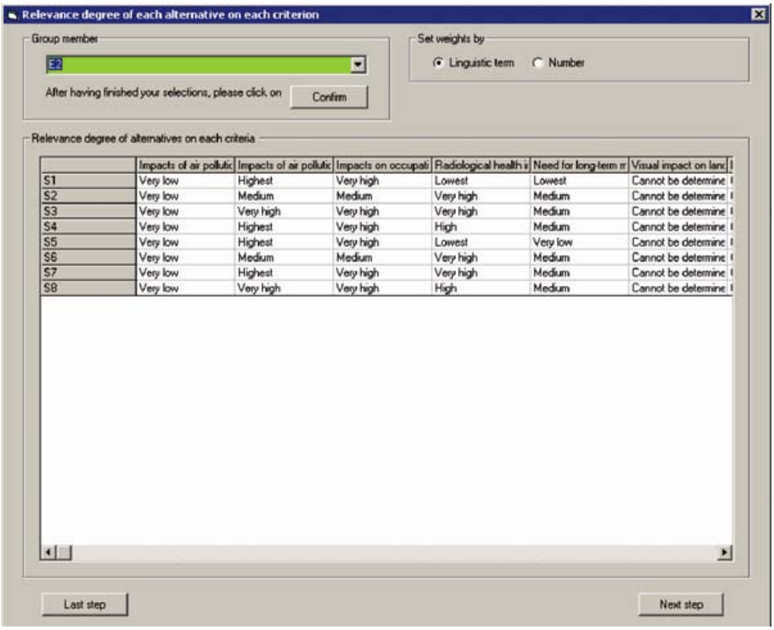

Fig. 4. Example of stakeholder 'belief matrix' (i.e. scores for all alternatives under all criteria)

actor to compensate a disadvantage on another criterion (one example might be the willingness to accept some health impact if it is compensated by a sufficiently high economic benefit). Incommensurability means that an actor is cannot be expected to attribute weights to criteria in any meaningful way, simply because the decision criteria are incomparable. Following Munda [21], we agree that full commensurability has to be rejected as a formal decision support principle. This is because any measurement of the 'intensity of preferences' (even in the sense of 'weak comparison' – e.g. pair-wise comparison of criteria as sometimes practiced in multi-criteria decision support) already implies an acceptance of the non-preferred, and therefore excludes deontological arguments of right or wrong which are omnipresent in our everyday ethical vocabularies (e.g. killing a person for most people is a matter of 'right or wrong') [24]. On the other hand, strict incommensurability also cannot be upheld in an ethically meaningful way, because in any act of decision making it is simply unavoidable to weigh different criteria, however implicitly this weighing might occur [19]. The position adapted in the framework we are proposing implies that weights can only be meaningful as 'importance coefficients'. In contrast to the trade-off approach, importance coefficients originate from non-compensatory elicitation procedures as they indicate how important a criterion is according to a particular actor without referring to compensation by means of another criterion. Figure 5 gives an example of the input of weights for different stakeholders and different levels of criteria.

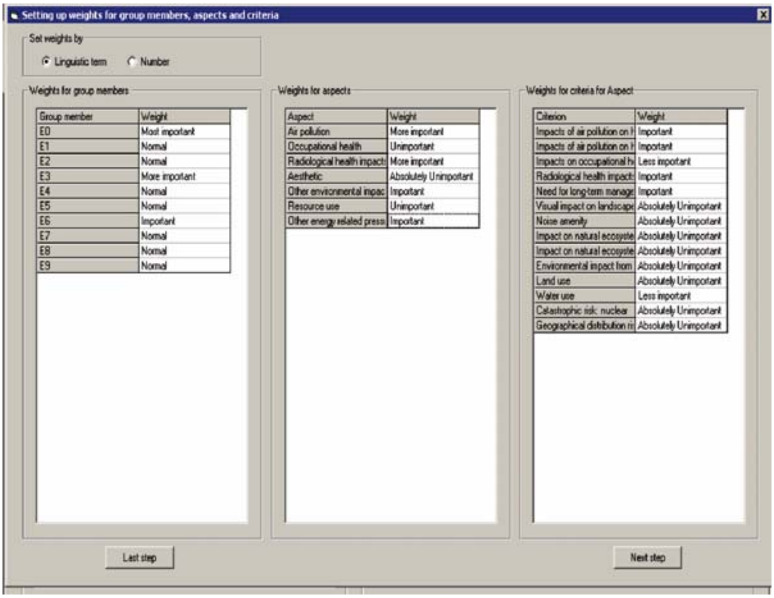

Fig. 5. Setting weights for stakeholders, aspects and criteria

Finally, the issue of ranking the decision alternatives is at least as contentious as the issue of deriving weights. Again, we can identify some 'extreme' positions in the debate. At one extreme, one might use decision support techniques to derive one 'most preferred' alternative, based on averaging scores and weights from all stakeholders. Having followed the argument in the previous sections, it will be clear to the reader that for pragmatic (since strong conflicts among various stakeholders are likely to occur) and ethical (since arriving at a 'most preferred' option necessarily relies on strong presumptions regarding the full commensurability of all criteria and stakeholder positions) reasons, presenting the results of the decision analysis *only* in these terms is less than desirable. On the other hand, one could also refrain from any analysis on the group (aggregate) level and just take each stakeholder position (as revealed in the criteria weightings and scores) separately. This kind of analysis can for instance reveal the structure of stakeholder reasoning, and can be used to check argumentative patterns for consistency and coherence. But of course, using a multi-criteria framework in this sense prevents one from tapping the potential wisdom of *group* decision making – the reason to use a group decision support tool in the first place! In view of the difficulties presented by both 'extreme' alternatives, we advocate a 'middle' position on the issue of ranking alternatives. This position includes: (a) a presentation of ranking results obtained by comparing the major ethical positions in the debate (e.g. the three 'narratives identified in Sect. 2.2) rather than presenting a single 'group result' or individual results for each stakeholder; (b) a check for possible 'social compromises' between different stakeholder positions[12]; and (c) sensitivity and robustness analysis based on the checking of the consequences on the final ranking of changing importance of criteria based on some clear ethical positions and not of all possible combinations of weights.

6.2 Formal Mathematical Representation in the FMCGDSS

This section discusses how the ethical requirements raised in the previous section are met by the formal representation of the decision-making process in a fuzzy multi-criteria group decision method. This method is developed based on previous studies in this field [15–17, 33, 34]. Put very briefly, 'fuzzy' multi-criteria group decision support is distinguished from more 'traditional' forms of multi-criteria analysis mainly because it uses fuzzy membership sets instead of crisp ones. Crisps sets are characterized by membership functions which assign a unique value to each individual member of a 'set' (e.g. members of the Belgian population can be either 'adult' or 'not adult' based on the 'crisp' criterion that they are either younger or older than 18 years). In contrast, a fuzzy set is a set whose elements have a continuum of grades of

[12] This can be done in formal mathematical terms by using a 'distance function' as a conflict indicator between different stakeholder positions for all possible pairs of stakeholders.

membership. In this case, the membership function assigns to each member of the set a grade of membership (e.g. based on more 'fuzzy' evaluation criteria prevalent in vernacular understandings of 'adultness' based on e.g. observable behavior, attitude, maturity etc. people anywhere between 0–30 years could conceivably be called 'non-adults'). It is clear that fuzzy sets allow for a better representation of vague concepts as expressed in natural language. Based on this philosophy, the FMCGDSS applied in the present case of long-term strategic options for the Belgian energy system can accept decision makers (group members)' input data (from interviews, questionnaires, databases, and direct entry) with or without uncertainties: numerical, linguistic, or missing values from a group of experts whose views may not agree with each other. It can also allow decision makers to give their evaluation criteria, which can be under a multi-level hierarchy structure. In a formal-mathematical sense, FMCGDSS's functioning is described as follows[13]:

Let $\boldsymbol{P} = \{\boldsymbol{P}_1, \boldsymbol{P}_2, \ldots, \boldsymbol{P}_n\},\ n \geq 2$, be a given finite set of decision makers to select a satisfactory alternative or identify a number of important issues with raking for a decision problem. The proposed method consists of 12 steps[14]:

Step 1: Generate Strategic Options

When a decision problem is proposed in a group, each group member can raise one or more possible strategies or alternative solutions. Let $S^* = \{S_1^{p_1}, S_2^{p_1}, \ldots S_{m_{p1}}^{p_1}, \ldots\ldots S_1^{p_n}, S_2^{p_n}, \ldots\ldots S_{m_{pn}}^{p_n}\}$, where $S_j^{p_i}$ is the jth alternative for the decision problem raised by group member p_i'. Through a discussion and summarization, $\boldsymbol{S} = \{\boldsymbol{S}_1, \boldsymbol{S}_2, \ldots, \boldsymbol{S}_m\},\ m \geq 2$ is selected from S^* as alternatives for the decision problem.

Step 2: Set up Weights for Stakeholders

As group members play different roles in an organization and therefore have different degrees of influence for the selection of the satisfactory group solution. That means the relative importance of each decision maker may not equal in a decision group. Some members are more important than others for a specific decision problem. Therefore, in the method, each member is assigned with a weight that is described by a linguistic term $\widetilde{v}_k,\ k = 1,\ 2,\ \ldots,\ n$.

[13] For illustrative purposes, here we discuss only the basic decision-making problem of arriving at a 'group satisfactory conclusion'. However, as discussed in Sect 6.1, other types of analysis (looking for social compromises, sensitivity and robustness checks, etc.) are for this type of decision problem at least as important. The FMCGDSS software is capable of supporting these kinds of analysis as well [16].

[14] Steps 1 and 2 - deciding on the strategic options for the decision problem at hand and deciding on the weights of the members of the decision-making group – have already been discussed in previous sections (Sects. 3 and 4); however we repeat them here for the sake of completeness.

These terms are determined through discussions in the group or assigned by a higher management level (say, the leader denoted as E0) before or at the beginning of the decision process. Possible linguistic terms used in the factor are *Normal, Important, More important*, and *Most important.*

Step 3: Set up Weights for All Aspects and Related Criteria

Referring to a set of aspects $F = (F_1, F_2, \ldots, F_n)$, let $WF = (WF_1, WF_2, \ldots, WF_n)$ be the weights of these aspects, where $WF_i \in \{$*Absolutely unimportant, Unimportant, Less important, Important, More important, Strongly important, Absolutely important*$\}$. Those weights are described by fuzzy numbers $\widetilde{a}_1, \widetilde{a}_2, \ldots, \widetilde{a}_n$.

For an aspect F_i, let $C_i = \{C_{i1}, C_{i2}, \ldots, C_{it_i}\}, i = 1, 2, \ldots, n$ be a set of the selected criteria with respect to the aspect F_i. Let $WC_i = \{WC_{i1}, WC_{i2}, \ldots, WC_{it_i}\},\ i = 1, 2, \ldots, n$, be the weights for the set of criteria, as shown in Table 1, where WC_{ij} will be signed a value from the same linguistic term list as WF_i above, which are described by fuzzy numbers $\widetilde{c}_1, \widetilde{c}_2, \ldots, \widetilde{c}_t$. For the example given in Fig. 2, '*Air pollution*' is an aspect of performance, two criteria to evaluate it are '*Impacts of air pollution on human health: mid-term,*' and '*Impacts of air pollution on human health: long-term.*'

Step 4: Set up the Relevance Degree of Each Alternative on Each Criterion

Let $A = (A_1, A_2, \ldots, A_m)$ be a set of alternatives, $AC_i^k = \left\{AC_{i1}^k, AC_{i2}^k, \ldots, AC_{it_i}^k\right\}$ be the relevance degree of alternative A_k on criterion $C_i,\ i = 1, 2, \ldots, n, k = 1, 2, \ldots, m$, where $AC_{ij}^k \in \{$Lowest, Very low, Low, Medium, High, Very high, Highest$\}$, as shown in Table 2, which are described by fuzzy numbers $\widetilde{b}_1, \widetilde{b}_2, \ldots, \widetilde{b}_k$.

Table 3 further describes the relationships among these aspects, criteria, alternatives, their weights, and decision makers' evaluation values (scores).

Table 1. Linguistic terms and related fuzzy numbers for describing the weights of aspects and criteria

The importance degrees	Membership functions
Absolutely unimportant	a_1
Unimportant	a_2
Less important	a_3
Important	a_4
More important	a_5
Strongly important	a_6
Absolutely important	a_7

Table 2. Linguistic terms for preference of alternatives

Linguistic terms	Fuzzy numbers
Very low (VL)	b_1
Low (L)	b_2
Medium low (ML)	b_3
Medium (M)	b_4
Medium high (MH)	b_5
High (H)	b_6
Very high (VH)	b_7

Table 3. The relationships among the aspects, criteria, alternatives, their weights, and evaluation values

				A_1	$\dots$	A_m
		C_{11}	WC_{11}	AC_{11}^1	$\dots$	AC_{11}^m
F_1	WF_1	$\dots$	$\dots$	$\dots$	$\ddots$	$\dots$
		C_{1t_1}	WC_{1t_1}	$AC_{1t_1}^1$	$\dots$	$AC_{1t_1}^m$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\ddots$	$\dots$
		C_{n1}	WC_{n1}	AC_{n1}^1	$\dots$	AC_{n1}^m
F_n	WF_n	$\dots$	$\dots$	$\dots$	$\ddots$	$\dots$
		C_{nt_n}	WC_{nt_n}	$AC_{nt_n}^1$	$\dots$	$AC_{nt_n}^m$

Step 5: Normalize the Weights for Criteria

The weights for the criteria $WC_i = \{WC_{i1},\ WC_{i2}, \cdots, WC_{it_i}\},\ i = 1, 2, \dots, n$ are normalized and denoted as $WC_{ij}^* = \frac{WC_{ij}}{\sum_{j=1}^{t_i} WC_{ij_0}^R}$, for $j = 1, 2, \dots, t_i,\ i = 1,\ 2, \dots, n.$, where the $C_{ij_0}^R$ is the right end of 0-cutset.

Step 6: Calculate the Relevance Degrees

The relevance degree FA_i^k of the aspect F_i on the alternatives $A_k,\ i = 1, 2, \dots, n,\ k = 1, 2, \dots, m$, are calculated by using $FA_i^k = WC_i^* \times AC_i^k = \sum_{j=1}^{t_i} WC_{ij}^* \times AC_{ij}^k,\ i = 1, 2, \dots, n,\ k = 1, 2, \dots, m.$

Step 7: Normalize the Relevance Degrees

The relevance degrees FA_i^k of the aspect F_i on the alternatives $A_k,\ i = 1, 2, \dots, n,\ k = 1, 2, \dots, m$ are normalized based on $FA^k = \left\{FA_1^k,\ FA_2^k, \dots, FA_n^k\right\},\ k = 1, 2, \dots, m.$

$$\overline{FA}_i^k = \frac{FA_i^k}{\sum_{i=1}^{n} FA_{i\ 0}^{k\ R}}, \text{ for } i = 1, 2, \dots, n, k = 1, 2, \dots, m.$$

Step 8: Calculate the Aspect Relevance Degrees

The relevance degree S_k of the aspects F on the alternatives A_k, $k = 1, 2, \ldots,\ m$ is calculated by using $S_k = \overline{FA}^k \times WF = \sum_{i=1}^{n} \overline{FA}_i^k \times WF_i\ k = 1, 2, \ldots, m$. Here, S_k is still a fuzzy number.

Step 9: Normalize Weights for Decision Makers

Each member $\boldsymbol{P}_k$ has been assigned with a weight already that is described by a linguistic term $\widetilde{v}_k,\ k = 1,\ 2, \ldots, n$ as shown in Table 3. A weight vector is obtained:

$$V = \{\widetilde{v}_k, k = 1, 2, \ldots , n\}.$$

The normalized weight of a decision maker $\boldsymbol{P}_k$ $(k = 1,\ 2, \ldots,\ n)$ is denoted as

$$\widetilde{v}_k^* = \frac{\widetilde{v}_k}{\sum_{i=1}^{n} v_{i\ 0}^{R}},\ \text{for}\ k = 1, 2,\ \ldots , n.$$

Step 10: Construct the Normalized Fuzzy Decision Vector

Considering the normalized weights of all group members, we can construct a weighted normalized fuzzy decision vector

$$(\widetilde{r}_1, \widetilde{r}_2, \ldots, \widetilde{r}_m) = (\widetilde{v}_1^*, \widetilde{v}_2^*, \ldots, \widetilde{v}_n^*) \begin{pmatrix} \bar{b}_1^1 & \bar{b}_2^1 & \ldots & \bar{b}_m^1 \\ \bar{b}_1^2 & \bar{b}_2^2 & \ldots & \bar{b}_m^2 \\ \vdots & \vdots & \ddots & \vdots \\ \bar{b}_1^n & \bar{b}_2^n & \ldots & \bar{b}_m^n \end{pmatrix},$$

where $\widetilde{r}_j = \sum_{k=1}^{n} \widetilde{v}_k^* \bar{b}_j^k$.

Step 11: Calculate the Positive and Negative Solution Distances

In the weighted normalized fuzzy decision vector the elements $\widetilde{v}_j$, $j = 1, 2,\ \ldots , m$, are normalized as positive fuzzy numbers and their ranges belong to the closed interval [0, 1]. We can then define a fuzzy positive-ideal solution (FPIS, r^*) and a fuzzy negative-ideal solution (FNIS, r^-) as:

$$r^* = 1 \text{ and } r^- = 0.$$

The positive and negative solution distances between each $\widetilde{r}_j$ and r^*, $\widetilde{r}_j$ and r^- can be calculated as:

$$d_j^* = d(\widetilde{r}_j, r^*) \text{ and } d_j^- = d(\widetilde{r}_j, r^-),\ j = 1, 2,\ \ldots , m,$$

where d (.,.) is the distance measurement between two fuzzy numbers.

Step 12: Calculate the Closeness Coefficient

A closeness coefficient is defined to determine the ranking order of all alternatives once the d_j^* and d_j^- of each $\boldsymbol{S}_j(j = 1, 2, \ldots, m)$ are obtained. The closeness coefficient of each alternative is calculated based on:

$$CC_j = \frac{1}{2}\left(d_j^- + (1 - d_j^*)\right), \ j = 1, 2, \ldots, m.$$

The alternative $\boldsymbol{S}_j$ that corresponds to the $Max(CC_j, \mathrm{j} = 1, 2, \ldots, m)$ is the best satisfactory solution of the decision group, and the top N issues that correspond to the top N higher raking CC_j are the critical issues to consider for the decision problem.

7 Conclusions

Decision support tools for a complex policy problem such as the assessment of long-term strategic options for sustainable energy has to face a number of complex challenges. On the empirical side, the tool has to face conditions of imperfect knowledge (e.g. lacking data), different problem framings, strained relations between major stakeholders involved in the policy issue, uncertainties over long-term evolutions, etc. On the normative side, the tool has to support basic principles of sustainability, e.g. developing a global long-term view, supporting meaningful participation by stakeholder groups, enabling transparency and accountability, etc. In this chapter, we argue that the software tool FMCGDSS is able to meet these fundamental methodological requirements. It can accept input data (from interviews and questionnaires from various sources) with or without uncertainties: numerical, linguistic, or missing values from a group of experts whose views may not agree with each other. From the input data, FMCGDSS can generate overall evaluation and any individual expert evaluation in any category or subcategory. All the outcomes can be displayed graphically. If there are different weights assigned to criteria, alternatives, and stakeholders, the FMCGDSS software can automatically deal with all conflict situations. We strongly believe the FMCGDSS tool will be useful for the sustainability impact assessment of energy systems in particular and for any complex decision problem in general.

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On the Constructive Role of Multi-Criteria Analysis in Nuclear Emergency Management

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Summary. In this chapter we argue that multi-criteria analysis, as an iterative process, can be a useful instrument for improving decision-making in complex societal problems. As a possible application, we focus on the management of contaminated milk following an accidental radioactive release to the environment. We describe a stakeholder process for the development of a multi-criteria decision aid model and we show that the related problem structuring has led to the exploration of some new research topics, in order to gain more insight in the factors that can contribute to a successful countermeasure strategy. Such results have on the one hand a clarifying role in a comprehensive multi-criteria analysis and, on the other hand, they highlight practical implications for decision-making, including communication on potential countermeasure strategies both between various stakeholders and with the general public.

1 Introduction

The lessons learnt from a number of nuclear and radiological events, ranging from nuclear power plant accidents to loss of radioactive sources with subsequent contamination episodes, have emphasized the need to develop better structured and coherent decision-making procedures for protective actions. Some of these events had widespread consequences and proved that psychological and social factors are at least as important as the health hazard [1, 12]. A recent report of the International Atomic Energy Agency [19, p. 86] emphasizes that a robust and practicable restoration strategy should take into account alongside with radiological and feasibility criteria also the "acceptability of the countermeasures, ethical and environmental considerations, requirements for effective public communication, spatial variation and the contrasting needs of people in urban, rural and industrial environments". The need to address all these different factors highlights multi-criteria decision aid (MCDA) as particularly suitable. MCDA methods help overcome the shortcomings of traditional decision support tools used in economy, such as Cost-Benefit Analysis, especially when dealing with values that cannot

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be easily quantified (e.g. environmental issues), even less, translated in monetary terms due to their intangible nature (e.g. social, cultural or psychological issues). The related methodology promotes "a good decision-making process" [22] by a clearer illustration of the different types of data and information items that go into decision-making, being able to deal in a structured way with multiple, conflicting objectives and value systems.

Past attempts of implementing MCDA in nuclear emergency management (e.g. [11,15,16],) confirm its added value in stimulating discussions and achieving a common understanding of the decision problem and the stakes involved. Nevertheless, the results show the need for a better interaction with decision-makers and other relevant stakeholders from the early phases of designing a decision aid model. The value of such a process has been pointed out in [3] where it is argued that the socio-political context of the decision making process must be sufficiently integrated in the models developed for decision support.

In Sect. 2 we discuss about the use of multi-criteria analysis in decision-making at governmental level, with focus on the strengths and difficulties as stemming from case studies reported in the literature. This will set the framework for Sect. 3 in which we elaborate on a stakeholder process carried out in Belgium with a number of key stakeholders in order to set up a theoretical and operational framework for an MCDA model for the management of contaminated milk. We first take a close look at potential actions, evaluation criteria and inter-criteria information and then we proceed with a discussion on suitable aggregation procedures and robustness of results.

Conclusions and lessons learnt are summarised in the final section.

2 Multi-Criteria Analysis in Governmental Decision-Making

Multi-criteria decision aid (MCDA) has emerged from the operational research field as an answer given to a couple of important questions encountered in complex decision problems. Firstly, as decision aiding tools, MCDA methods do not replace the decision-maker with a mathematical model, but support him to construct his solution by describing and evaluating his options [29]. Secondly, instead of using a single criterion capturing all aspects of the problem, in MCDA one seeks to build multiple criteria, representing several points of view. Comprehensive descriptions of various types of MCDA methods, often classified as multi-attribute value/utility methods, outranking methods and interactive methods, can be found in [5, 7, 9, 37].

The case studies in the recent literature prove that MCDA has seen a widespread decision support function in the last decades (see e.g. [14]). Where not legally prescribed -which is still seldom the case-, it is being applied following an initiation by analysts as support for their local, regional or even national governments or even government officials themselves (e.g. [6, 26]). Alternatively a MCDA research study might afterwards become relevant for actual public decisions (e.g [2]). Decision-makers generally choose multi-criteria analysis in order to gain an insight into the complexity of public good decisions and their consequences that are felt not only on one, but on multiple dimensions: economic, social, environmental and institutional. They are also more likely to choose such tools when they face decisions coupled with uncertainty, which is typically the case for sustainability decisions that concern the quality and quantity of future resources.

The problem structuring in the framework of a MCDA is generally recognized as a useful learning process [25] that stimulates discussion between the various stakeholders [13] and helps decision-makers to better comprehend the decision problem, as well as the values and priorities involved [5]. However, the technical complexity brought by multi-criteria methods is sometimes a limiting factor: the determination of parameters such as criteria weights and the - often lengthy - process required are frequently identified as major shortcomings. As pointed out in [40], decision-makers may prefer taking exemplary decisions rather than having to explain them in terms of specific model parameters. In addition, political decision-makers may not wish to openly express their priorities or may have own hidden agendas.

The openness to divergent values and opinions brought by MCDA certainly facilitates stakeholder involvement, but a difficult question is the choice of stakeholders and the timing of their participation. It can be observed that there are still predominantly more cases in the literature where a holistic approach to stakeholder analysis is being dispensed with. Besides making technical information understandable to all stakeholders, one has to ensure that technical specialists become aware of the social and political dimensions of the problem they face [4, p. 19]. Decision-support tools in general, and MCDA in particular, might be regarded as challenging the expert's prerogatives [20] when the decision process develops at higher decision levels. Contrary to that, integration of multi-criteria decision-aiding tools seems easier and is increasingly used at regional and local level, e.g. for environmental decision making [8], possibly as replacement for the standard procedures in use at a national level.

In conclusion, a number of strengths and difficulties need to be considered regarding the use of MCDA for decision-making at governmental level (see [14], for a detailed analysis). An early involvement of stakeholders can certainly give a more pragmatic dimension to MCDA and contributes to an increased acceptance of the final result. This motivation has been the grounds for developing the stakeholder process summarised in the following section.

3 Key Elements of a MCDA Model Derived from a Stakeholder Process

In this section we highlight the key elements of the multi-criteria decision aid model developed for the management of contaminated milk and we underline the constructive dimension brought by the use of MCDA.

For the stakeholder process [34], we opted for individual interviews in order to allow sufficient time for discussions, to cover in a consistent way a range of stakeholders as complete as possible and –since hierarchical relations may hamper this– to facilitate free expression of opinions. In this process, 18 governmental and non-governmental key actors in the management of contaminated milk were interviewed: decision-makers, experts and practitioners. This included various areas of activity: decision making (Ministry of Interior); radiation protection and emergency planning; radioecology; safety of the food chain; public health; dairy industry; farmers' association; communication; local decision making; social science; and management of radioactive waste.

3.1 Potential Actions

The possible decisions temporarily considered as realistic by at least one of the actors, or assumed as such by the analyst [31], that shall be explored during a given decision process constitute the set of potential actions. Several individual or combined countermeasures can be employed for the management of contaminated milk [18], for instance disposal of contaminated milk; prevention or reduction of activity in milk (clean feeding, feed additives) and/or storage and processing to dairy products with low radioactivity retention factors. The need to make available a more flexible way to generate potential actions, requirement which came out from the stakeholder process, led to the development of a prototype tool allowing the integration of various types of data, as illustrated in Fig. 1.

Such a data fusion tool [33] can also be used for a fast calculation of e.g. the amount of production in the selected zone, the implementation costs for the selected countermeasure, the collective doses and maximal individual doses due to ingestion of contaminated foodstuff (the dose is an objective measure of the detriment to health), helping the decision makers or advisers in choosing the set of potential actions to be further evaluated.

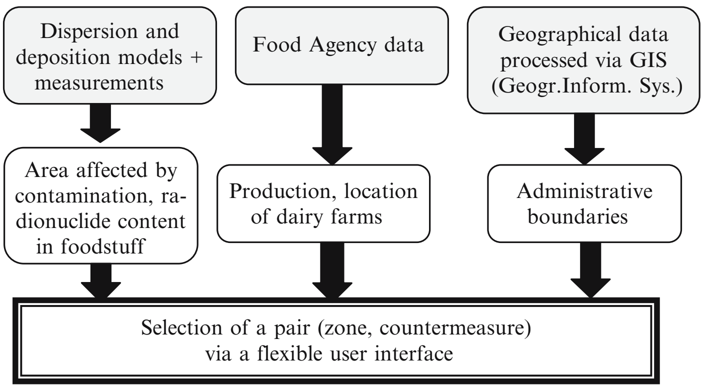

Fig. 1. Generation of potential actions by integration of various data

The problem adds in complexity when we take into consideration the geographical zoning of the affected area in view of application of -possibly different- countermeasures. Two cases could be distinguished, depending on whether geographical dispersion is considered or not. In the first case, the application of countermeasures is homogeneous, i.e. in the single zone $\mathrm{Z_1}$ selected for countermeasures, one has to decide on the countermeasure or combination of countermeasures $\{\mathrm{C_{1,1}}, \ldots, \mathrm{C_{1,k1}}\}$ to be applied. In the second case, the affected area is divided in a number of zones $\mathrm{Z_1}, \ldots, \mathrm{Z_m}$, while for each zone $\mathrm{Z_i}$ the countermeasures applied are, respectively, $\{\mathrm{C_{i,1}}, \ldots, \mathrm{C_{i,ki}}\}$. Since the number of feasible combinations of countermeasures is in practice rather small, we have assumed for simplification that $k_i = 1,\ \forall i = 1, \ldots, m$. We shall come back to this in Sect. 3.5.

3.2 The Evaluation Criteria

An evaluation criterion allows evaluating potential actions from a given point of view -in a qualitative or quantitative way- and also expressing preferences between them. For our application, the evaluation criteria were built through a process combining a top-down and a bottom-up approach.

In order to stimulate free thinking [21], the stakeholders interviewed were first asked to identify all the relevant effects/attributes/consequences of potential actions. Subsequently, they commented on a list of evaluation criteria derived from the literature and amended it, if felt necessary. This resulted in a number of elementary consequences [30] which were then synthesized in the evaluation criteria illustrated in Fig. 2. The latter was done taking account, as much as possible, of the properties of exhaustiveness, cohesiveness and non-redundancy (see [30] for a description of these concepts), in order to arrive at a consistent set of evaluation criteria.

The preferences on each criterion were modelled be means of the "double threshold" model [37]. A criterion is thereby represented by a real-valued

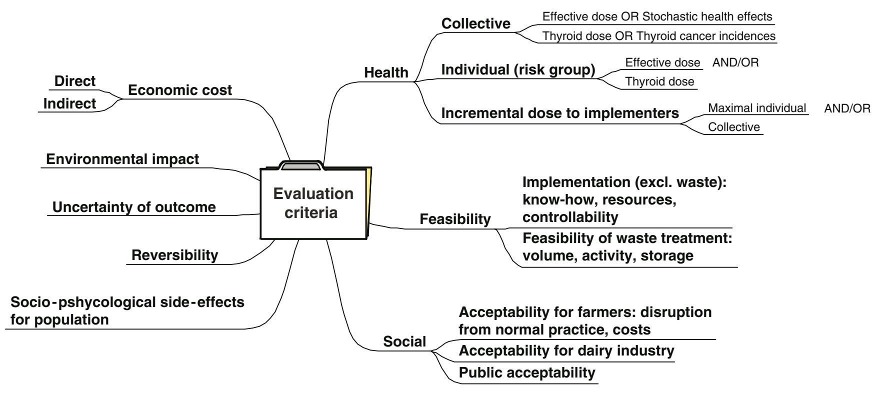

Fig. 2. Evaluation criteria

positive function, associated with two types of discrimination thresholds: an indifference threshold $q(\cdot)$ and a preference threshold $p(\cdot)$. For a criterion g to be maximised and two actions a and b, we say that:

$$\begin{aligned}
&a \text{ I } b \text{ } (a \text{ indifferent to } b) \Leftrightarrow g(a) \leq g(b) + q(g(b)) \text{ and} \\
&\qquad\qquad\qquad\qquad\qquad\quad g(b) \leq g(a) + q(g(a)); \\
&a \text{ P } b \text{ } (a \text{ strictly preferred to } b) \Leftrightarrow g(a) > g(b) + p(g(b)); \\
&a \text{ Q } b \text{ } (a \text{ weakly preferred to } b) \Leftrightarrow g(b) + q(g(b)) < g(a) \text{ and} \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\quad g(a) \leq g(b) + p(g(b)).
\end{aligned}$$

The triplet of binary relations (P, Q, I) represents the preference structure associated to criterion g. Under certain consistency conditions for p and q, this criterion model corresponds to what is called a pseudo-criterion [28].

It is interesting to note that discrimination thresholds can be related to the uncertainty in the evaluation of a criterion value $g(a)$. If this uncertainty can be modelled by a dispersion interval $[c^-(a),\ c^+(a)]$, with $g(a) = c(a)$ being the best estimate, one way to model the strict preference, indifference and weak preference, if for instance g has to be maximised, is the following [31, p. 58]:

$$\begin{aligned}
&a \text{ P } b \Leftrightarrow c^-(a) > c^+(b) \\
&a \text{ I } b \Leftrightarrow c(a) \in [c^-(b), c^+(b)] \text{ and } c(b) \in [c^-(a), c^+(a)] \\
&a \text{ Q } b \Leftrightarrow c(b) < c^-(a) \leq c^+(b)
\end{aligned}$$

Let us assume that the set of potential outcomes with respect to g is bounded, i.e. there exist g_* and g^* such that $g_* \leq g(a) \leq g^*$ for any potential action a. If $c^-(a) = c(a) - \alpha_{\mathrm{m}} - \beta_{\mathrm{m}} \cdot c(a)$ and $c^+(a) = c(a) + \alpha_{\mathrm{M}} + \beta_{\mathrm{M}} \cdot c(a)$, with $\alpha_{\mathrm{m}} + g^* \cdot \beta_{\mathrm{m}} \geq 0,\ \alpha_{\mathrm{m}} + g_* \cdot \beta_{\mathrm{m}} \geq 0,\ \alpha_{\mathrm{M}} + g^* \cdot \beta_{\mathrm{M}} \geq 0,\ \alpha_{\mathrm{M}} + g_* \cdot \beta_{\mathrm{M}} \geq 0$, and $\beta_{\mathrm{m}} < 1,\ \beta_{\mathrm{M}} \geq -1$, the preference structure defined above is equivalent [28, pp. 268–269] to that induced by a pseudo-criterion $g(a) = c(a)$ having the discrimination thresholds given by:

$$p(g(a)) = \frac{c^+(a) - c^-(a)}{1 - \beta_m} \text{ and } q(g(a)) = \min\left\{c^+(a) - c(a), \frac{c(a) - c^-(a)}{1 - \beta_m}\right\}$$

The choice of the double threshold model is motivated by the fact that for certain criteria (e.g. economic cost) it might not be possible to conclude a strict preference between two actions scoring similar values, e.g. due to the uncertainties involved, while an intermediary zone exists between indifference and strict preference. On the other hand, the double threshold model is a general one, easy to particularise for other types of criteria. For example, by setting both thresholds to zero, one obtains the traditional, no-threshold model.

In order to account for both the situations when a fixed or a variable threshold could be better fitted we have assumed that, for any criterion g_i and any potential action a, the discrimination thresholds are given by

$$q_i(g_i(a)) = \max\{q_i^{ref}, q_{0i} \cdot g_i(a)\} \text{ and}$$
$$p_i(g_i(a)) = p_0 \cdot q_i(g_i(a)),$$

with $p_0 > 1$, a fixed value, and $q_i^{ref} \geq 0$ and $0 \leq q_{0i} < 1$ parameters depending on the criterion g_i.

The structuring process of the decision problem on the management of contaminated milk has also pointed out that certain criteria need further study. For instance, public acceptance has been highlighted as an important criterion, but little is known a priori on the acceptance of the various countermeasures. In order to get some insight, we included this topic in a public opinion survey on risk perception issues organised by the Belgian Nuclear Research Centre, SCK•CEN [36]. In this survey, the public acceptance of various milk countermeasures was measured on a 5-point qualitative scale, ranging from "strong disagreement" to "strong agreement" with respect to the implementation of a given countermeasure after a radiological contamination in the environment. The resulting distributions of acceptance degrees on the sample of respondents can be further used in a MCDA context in several ways (see [35] for details):

- an outranking relation S (with the meaning "at least as good as") can be defined for the various countermeasures, e.g. based on stochastic dominance:
$$a\ S\ b \Leftrightarrow \sum_{j \leq i} a_j \leq \sum_{j \leq i} b_j + \theta, \forall i = 1, \ldots, 5$$
where $a_j,\ b_j$ are the percentages of respondents using the j-th qualitative label to evaluate countermeasures a and b, respectively, and θ is parameter linked to the uncertainty in the evaluation of a_j and b_j. Further on, a strict preference P and an indifference I can be defined as the asymmetric and, respectively, the symmetric parts of S or;
- an overall score can be derived based on e.g. the percentage of respondents agreeing (or disagreeing) with a countermeasure.

3.3 Inter-Criteria Information

In order to derive comprehensive preferences, taking into consideration all evaluation criteria, priorities have to be set, i.e. the relative importance of criteria has to be considered. This notion can be interpreted differently [32], depending on the parameters and the type of preference aggregation method used. In particular, in our stakeholder process we investigated the adequacy for our application of four types of inter-criteria information:

- substitution rates (tradeoffs) between criteria, which are for instance used in the additive multi-attribute value models or some interactive methods;
- criteria weights as intrinsic importance coefficients, as in e.g. outranking methods of ELECTRE type;

- criteria ranking with possible ties, like in lexicographic aggregation;
- a partial ranking on subfamilies of criteria.

For each of the above we investigated if the stakeholders interviewed think that such a way to express priorities is suitable and, most importantly, if they are willing and accept to provide/receive such information. Our discussions revealed a higher acceptance of the qualitative approaches, which indicates that outranking methods might be better suited. The concept of weights as intrinsic importance coefficients proved hard to understand, but still encountered a smaller number of opponents than weights associated with substitution rates. The main argument against the latter was based on ethical motivations, e.g. the difficulty to argue for a value trade-off between the doses received and the economic cost.

3.4 Aggregation of Preferences

The exploration of an outranking methodology is motivated by some particularities of our decision problem. Firstly, the units of the evaluation criteria (e.g. averted dose, cost, and public acceptance) are heterogeneous and coding them into one common scale looks difficult and not entirely natural. Secondly, the compensation issues between gains on some criteria and losses on other criteria are not readily quantifiable. Kottemann and Davis [23] suggest that the degree to which the preference elicitation technique employed requires explicit trade-off judgements influences the "decisional conflict" that can negatively affect the overall perception of a multi-criteria decision support system. Finally, the process of weighting and judging seems in general more qualitative than quantitative.

Methods of outranking type that can exploit a qualitative expression of inter-criteria information are for instance the MELCHIOR method [24] or ELECTRE IV [30].

A way of coping with the case when the inter-criteria information is incomplete -because the decision-maker is not able or not willing to give this information- is the following. Let's suppose that the information about the relative importance of criteria is available in the form of a function:

$$\begin{aligned}&\imath:\ \mathrm{G}\times\mathrm{G}\to\{0,1\},\ \text{such that}\\&\imath(g_m,\ g_p)=1\Leftrightarrow \text{criterion } g_m \text{ is "more important than" criterion } g_p,\end{aligned}$$

where G is the set of evaluation criteria.

If g_m is not "more important than" g_p, or if no information is available, then $\imath(g_m,\ g_p)=0$. Let us assume that $\imath$ is irreflexive and asymmetric, i.e.

$$\begin{aligned}&\imath(g_m,g_p)=0,\forall\ g_m\in\mathrm{G},\ \text{and}\\&\imath(g_m,g_p)=1\Rightarrow\imath(g_p,g_m)=0,\forall\ g_m,g_p\in\mathrm{G},\ \text{with } p\neq m.\end{aligned}$$

The function ι, comparing the relative importance of individual criteria, can be extended to subsets of criteria in a manner similar to the MELCHIOR method.

A mapping $\iota^* : \wp(\mathrm{G}) \times \wp(\mathrm{G}) \rightarrow \{0, 1\}$ will be defined recursively as:

$$\begin{aligned}
&\iota^*(\mathrm{F}, \emptyset) = 1,\ \forall \emptyset \neq \mathrm{F} \subset \mathrm{G},\\
&\iota^*(\emptyset, \mathrm{F}) = 0,\ \forall \mathrm{F} \subset \mathrm{G},\\
&\iota^*(\{g_m\},\ \{g_p\}) = 1 \Leftrightarrow \iota(g_m, g_p) = 1,\\
&\iota^*(\{g_m\} \cup \mathrm{F},\ \mathrm{H}) = 1,\ \text{with } \{g_m\} \cup \mathrm{F} \subset \mathrm{G} \text{ and } \mathrm{H} \subset \mathrm{G} \Leftrightarrow\\
&\qquad \iota^*(\mathrm{F},\ \mathrm{H}) = 1 \text{ or } \exists\ g_p \in \mathrm{H} :\ \iota(g_m, g_p) = 1 \text{ and } \iota^*(\mathrm{F},\ \mathrm{H}\backslash\{g_p\}) = 1.
\end{aligned}$$

A binary relation R representing comprehensive preferences can be further defined on the set of potential actions A as follows:

$$\begin{aligned}
&\forall\ a,\ b \in\ \mathrm{A},\ R\ (a,\ b) = \iota^*(\mathrm{F},\ \mathrm{H}),\ \text{where}\\
&\qquad \mathrm{F} = \{g_i\ \in\ \mathrm{G} \mid a\ \mathrm{P_i}\ b\},\ \mathrm{H} = \{g_i\ \in\ \mathrm{G} \mid b\ (\mathrm{P_i} \cup \mathrm{Q_i})\ a\} \text{ and}\\
&\qquad (\mathrm{P_i},\ \mathrm{Q_i},\ \mathrm{I_i}) \text{ is the preference structure associated with } g_i.
\end{aligned}$$

In particular, if $\iota(g_m,\ g_p) = 0,\ \forall\ g_m,\ g_p \in \mathrm{G}$, i.e. no information on the relative importance of criteria is given, then $\iota^*(\mathrm{F},\ \mathrm{H}) = 1 \Leftrightarrow \mathrm{F} \neq \emptyset$ and $\mathrm{H} = \emptyset$. In this case, R is reduced to:

$$R = \{(a, b) \in \mathrm{A} \times \mathrm{A} \mid a\ (\mathrm{P_i} \cup \mathrm{Q_i} \cup \mathrm{I_i})b,\ \forall\ i = 1, \ldots, n \text{ and } \exists\ j : a\ P_j\ b\}.$$

Let us consider an example of a limited scale contamination where the potential actions have been defined as in Table 1, and the evaluation criteria are modelled as illustrated in Table 2. Table 1 does not include the criteria for which all potential actions have the same impact, but the complete set of evaluation criteria considered is listed in Table 2.

When choosing discrimination thresholds for a criterion such as collective dose (person · Sv) (see Table 2), one can for instance take into consideration that a collective dose of 20 person · Sv roughly corresponds to 1 health effect expected in the whole population; therefore when the difference in the impacts of two actions is below this value one cannot express strict preferences in favour of one or another action.

When no inter-criteria information is given, on the basis of the aggregation method given above, the resulting comprehensive preferences are illustrated in Fig. 3. For instance, the arrow 4 → 3 means that action 4 outranks action 3.

We can see that there are also actions which are incomparable, for instance actions 4 and 6; the situation changes however, when some information is given concerning the relative importance of criteria.

As an example, let us assume that the decision-maker states that the maximal individual dose is more important than any other criterion and that public acceptance is more important than the cost of implementation and

Table 1. Impact of potential actions

Action\Criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Area & Countermeasure	person · Sv	mSv	k€	t	-	-	-	-
1 DoNothing	4	100	0	0	0	1	0	3
2 Sector (100°, 119°, 25km): CleanFeed	0.1	3.6	240	16	3	1	2	1
3 Deposit > 4000Bq/m^2: CleanFeed	0.3	4.6	17	16	3	1	2	1
4 Deposit > 4000Bq/m^2, extended to full administrative zones, CleanFeed	0.3	4.6	27	16	3	2	2	1
5 Deposit > 4000Bq/m^2: Storage(32days)	0.8	20	1.3	0	2	1	1	2
6 Deposit > 4000Bq/m^2, extended to full administrative zones, Storage (32days)	0.8	20	2.5	0	2	2	1	2

Table 2. Evaluation criteria and discrimination thresholds*

Criterion	Variable indif. threshold (q_{0i})	Minimal indif. thresh. (q_i^{ref})	Optimis. direction
C_1 = Residual collective effective dose (person · Sv)	10%	10 person · Sv	min
C_2 = Maximal individual (thyroid) dose (mSv)	5%	0.5 mSv	min
C_3 = Implementation cost (k€)	10%	20 k€	min
C_4 = Waste (tonnes)	10%	1 t	min
C_5 = Public acceptance	0	0	max
C_6 = Geographical feasibility	0	0	max
C_7 = Acceptance of dairy industry	0	0	max
C_8 = Uncertainty of outcome	0	0	min
C_9 = Acceptance of farmers	0	0	max
C_{10} = Environmental impact	0	0	min
C_{11} = Reversibility	0	0	max

*$p_0 = 2$ for all cases.

the geographical feasibility. We then obtain the results presented in Fig. 4, highlighting both actions 4 and 2 as interesting choices.

In case several zones and possible countermeasures are considered, a combination of interactive-outranking methodologies can be used to cope with the potentially large number of actions. Performing a final step including qualitative criteria by making use of an outranking method allows bypassing the difficulty of introducing qualitative criteria in outranking methods. For instance, one can use a number of quantitative criteria such as collective and

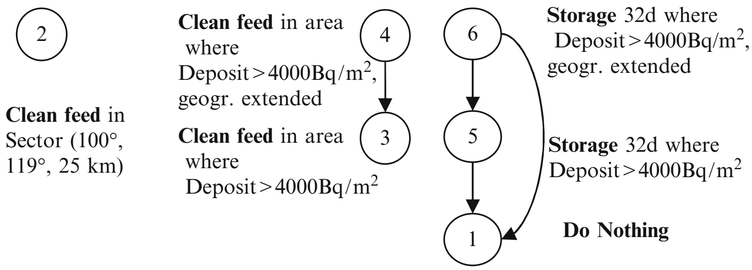

Fig. 3. Comprehensive preferences when no inter-criteria information is given

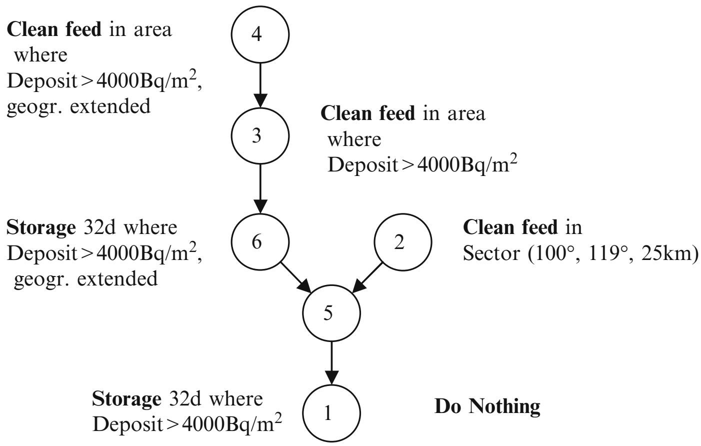

Fig. 4. Comprehensive preferences with inter-criteria information

individual doses and financial cost and search for promising solutions (i.e. potential actions) among the non-dominated ones.

Let P be the payoff matrix, whose n rows are the criterion vectors obtained by individually optimising each criterion $g_1, \ldots, g_n$. Perny and Vanderpooten [27] have proposed using the following scalarising function derived from the augmented Chebyshev norm, the solutions obtained by its minimisation corresponding to non-dominated feasible points:

$$F(g_1(a), \ldots, g_n(a); \widetilde{z}) = \max_{j=1,\ldots,n} \{\lambda_j(\widetilde{z}_j - g_j(a))\} - \varepsilon \sum_{j=1}^{n} \lambda_j g_j(a), \ \forall\ a \in A$$

where:

A = the set of actions;
$g_1, \ldots, g_n$ = the quantitative criteria;
$\lambda_j = 1/(z^*_j - z_{*j})$, with z^* and z_* being the ideal and the nadir points;

$\widetilde{z}$ = reference point representing aspiration levels, e.g. $\widetilde{z} = z^*$;
ε = small positive value.

In the above, z^* consists of the elements of the main diagonal of matrix P (i.e. is the optimal value reached individually for each criterion g_j), whereas z_* consists of the worst criterion values (e.g. minimal in case the criterion is to be maximised) in each column of matrix P.

In a later phase, qualitative criteria -such as public acceptance- that cannot be evaluated in an automated manner could be introduced and an outranking method could be employed to compare the potential actions selected.

3.5 Robustness of Results

Naturally, results such as those presented in the previous section depend on the specific values chosen for the parameters used in the model, i.e. discrimination thresholds. A classical way to deal with the uncertainty in model parameters is sensitivity analysis. This type of analysis may seek to determine the parameters which contribute most to the variance in a model's output or to determine how much the parameters may vary such that the conclusion of interest (e.g. that an action holds the best rank in a ranking problem) still holds. An additional way to address uncertainty and imprecision is robustness analysis. For a given model M and a domain D of possible values for model M's parameters (e.g. weights, thresholds, etc), Roy and Bouyssou [31] use the term "robust" to denote a result or conclusion that is not "clearly invalidated" for any parameter instance belonging to D. Connected to that, the robustness analysis is the process of elaborating recommendations founded on robust conclusions.

In fact, in the optimisation and decision aid domains, the notion of robustness may have different interpretations; see details in [9] or [17]. For example in strategic decisions involving sequential decision-making (Rosenhead et al. 1972), the robustness of a decision is a measure of flexibility, expressing the potential of decision taken at a given time to allow achieving near-optimal states in the future in conditions of uncertainty. A robust outranking method [38] has the property that its solutions derived from different admissible method-specific parameter sets do not contradict each other. In turn, a robust solution [39] is always near, or does not contradict solutions corresponding to other admissible parameter instances.

Let us assume in the framework introduced in the previous section that p_0 has a fixed value and that for $\forall i,\ 1 \le i \le n$ (n being the number of criteria), the admissible domain for q_{0i} is $\mathrm{D_i} = [{q_{0i}}^L,\ {q_{0i}}^U]$, while the admissible domain for q_i^{ref} is $\mathrm{D_i^{ref}} = [q_i^{Lref},\ q_i^{Uref}]$. We can determine which of the assertions of the type "$a\ R\ b$" are robust with respect to this parameter domain as follows:

Step 0. $\widetilde{q} \leftarrow q_0$; $\widetilde{q}^{ref} \leftarrow q^{ref}$;

Step 1. For $i = 1$ to n, $Sg(i) = 1$, if g_i has to be maximised; -1 else.

Step 2. For $i = 1$ to n

If $Sg(i) \cdot (g_i(a) - g_i(b)) > 0$ then

$\widetilde{q}_i \leftarrow q_{Oi}^U$; $\widetilde{q}_i^{\,ref} \leftarrow q_i^{Uref}$;

ElseIf $Sg(i) \cdot (g_i(a) - g_i(b)) < 0$ then

$\widetilde{q}_i \leftarrow q_{Oi}^L$; $\widetilde{q}_i^{\,ref} \leftarrow q_i^{Lref}$;

End

End

Step 3. If "$a\ R\ b$" holds for $\widetilde{q}$ and $\widetilde{q}^{\,ref}$ then "$a\ R\ b$" robust

Else "$a\ R\ b$" non-robust

End

Furthermore, let us take a closer look to the case when no inter-criteria information is given. The conditions that must be imposed on the parameters in order to ensure that "$a\ R\ b$" is valid in a certain parameter setting can be expressed by means of a logical formula *F(a R b)* involving a conjunctive part (necessary conditions that appear when transforming weak or strong preferences of b over a to indifferences) and a disjunctive part (sufficient conditions, i.e. at least one criterion has to yield a strict preference in favour of a):

$$F\ (a\ R\ b) = C(a\ R\ b) \wedge D(a\ R\ b) = C_1 \wedge \cdots \wedge C_m\ \wedge\ (D_1\ \vee \cdots \vee\ D_t)$$

For simplification of the discourse let us also assume that only q_{0i} is subject to variation, i.e. q_i^{ref} being a fixed at a minimal value for the indifference threshold. Then, if "$a\ R\ b$" is a non-robust conclusion, with respect to the domain $\mathrm{D_i} = [{q_{0i}}^L,\ {q_{0i}}^U]$ for q_{0i}, we have:

$$C(a\,R\,b) = \bigwedge_{i \in G_1} (q_{0i} \geq l_i), \text{ with}$$

$$G_1 = \{i | Sg(i) \cdot (g_i(a) - g_i(b)) < 0 \text{ and } \min(g_i(b),\ g_i(a)) > 0\} \text{ and}$$

$$l_i = \frac{|g_i(a) - g_i(b)|}{\min(g_i(a), g_i(b))}, \forall i \in G_1.$$

Similarly,

$$D(a\ R\ b) = \bigvee_{i \in G_2} (q_{0i} \leq u_i), \text{ with}$$

$$i \in G_2 \Leftrightarrow$$

$$Sg(i) \cdot (g_i(a) - g_i(b)) > 0 \text{ and}$$

if $\min(g_i(b),\ g_i(a)) = 0$ and $|g_i(b) - g_i(a)| > p_0 \cdot q_i^{ref}$ then $u_i = {q_0}_i^U$;

else if $\min(g_i(b),\ g_i(a)) > 0$ and $|g_i(b) - g_i(a)| > p_0 \cdot q_i^{ref}$

$$\text{and } \frac{|g_i(a) - g_i(b)|}{p_0 \min(g_i(a), g_i(b))} > q_{0i}^L,$$

$$\text{then } u_i = \min\left\{ \frac{|g_i(a) - g_i(b)|}{p_0 \min(g_i(a), g_i(b))} - \varepsilon, q_{0i}^U \right\}, \text{ with}$$

$\varepsilon > 0$ small.

As can be seen from the above, the terms appearing in $F(a\ R\ b)$ can be translated to lower and upper bounds on q_0. In case q_i^{ref} also varies, additional conditions on q_i^{ref} have to be included.

In the given parameter domain, if $\{$"$a_1\ R\ b_1$", ..., "$a_p\ R\ b_p$"$\}$ is the set of non-robust conclusions, suppose we would like to test if a given combination e.g. $(a_1\ R\ b_1) \wedge \neg(a_2\ R\ b_2) \wedge \cdots \wedge \neg(a_p\ R\ b_p)$, is possible or not. The validity of this combination can be expressed by a logical formula which, in turn, yields certain bounds on q_0 (and possibly q^{ref}), [33]. If these bounds are compatible, then the combination of non-robust conclusions is possible. Such an analysis may serve for determining the minimal and maximal rank of each action, when applying one or another ranking method starting from relation R.

For the example illustrated in Tables 1 and 2 let us suppose that the acceptable domain of values for the parameters used to model indifference thresholds are $[0,\ 2 \cdot q_{0i}]$ and $[q^{ref},\ 2 \cdot q^{ref}]$, respectively, q_0 and q^{ref} being the initial values as given in Table 2. In this parameter domain, if for instance, $q_2^{ref} = 1\,\text{mSv}$ -instead of 0.5 mSv as initially-, while the rest of the parameters remain at their initial value, both actions 4 and 3 would outrank action 2 (as non-robust arcs). An examination of Fig. 5 suggests that action 4 is in fact our best choice.

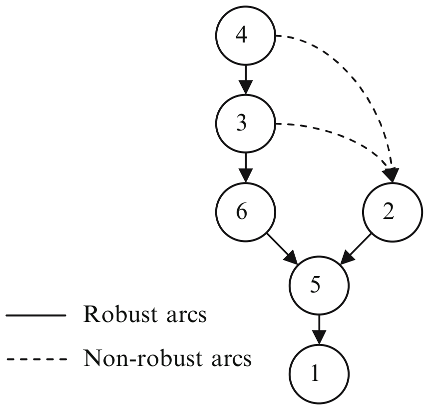

Fig. 5. Robust and non-robust arcs with inter-criteria information

4 Conclusions

In this chapter we showed that multi-criteria decision aid can have a constructive role in a real-life application. The study of MCDA application in decision-making at governmental level has shown that there are still predominantly more cases with limited stakeholder participation, but inclusion of opinion diversity from an early stage of a decision aid model's design can certainly give a more pragmatic dimension and presumably lead to an increased acceptance. The stakeholder process initiated led to a better understanding of the many aspects of the problem considered. As Dodgson et al. [10] note, the ideal way to structure the process is in an iterative fashion. In a first phase, it triggered further research on two main directions: flexible tools for generating potential actions and social research in the field of public acceptance of food chain countermeasures. The multidisciplinary dimension of MCDA helps thus bridging between decision science, radiation protection, radioecological modelling, social science and economy. Further validation in exercises and workshops will contribute to improving the proposed methodology according to the decision-makers needs. The increased transparency and traceability of the decision process will provide a good basis for training and discussions, which are key factors in emergency preparedness.

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Index