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Multi-criteria Group Decision Support with Linguistic Variables in Long-term Scenarios for Belgian Energy Policy

Da Ruan[1]
(Expertise Unit of Society and Policy Support
Belgian Nuclear Research Centre (SCK•CEN)
Boeretang 200, 2400 Mol, Belgium
druan@sckcen.be)

Jie Lu
(Lab of Decision Systems and e-Service Intelligence, Center of Quantum Computation and Intelligent Systems, Faculty of Engineering and Information Technology
University of Technology, Sydney (UTS)
PO Box 123, Broadway, NSW 2007, Australia
jielu@it.uts.edu.au)

Erik Laes
(Unit Transition Energy & Environment (TEM)
Flemish Institute for Technological Research (VITO)
Boeretang 200, B-2400 Mol, Belgium
erik.laes@vito.be)

Guangquan Zhang, Jun Ma
(Lab of Decision Systems and e-Service Intelligence, Center of Quantum Computation and Intelligent Systems, Faculty of Engineering and Information Technology
University of Technology, Sydney (UTS)
PO Box 123, Broadway, NSW 2007, Australia
{zhangg, junm}@it.uts.edu.au)

Gaston Meskens
(Expertise Unit of Society and Policy Support
Belgian Nuclear Research Centre (SCK•CEN)
Boeretang 200, 2400 Mol, Belgium
gmeskens@sckcen.be)

Abstract: Real world decisions often made in the presence of multiple, conflicting, and incommensurate criteria. Decision making requires multiple perspectives of different individuals as more decisions are made now in groups than ever before. This is particularly true when the decision environment becomes more complex such as sustainability policies study in environmental and energy sectors. Group decision making processes judgments or solutions for decision problems based on the input and

[1] Corresponding author

feedback of multiple individuals. Multi-criteria decision and evaluation problems at tactical and strategic levels in practice involve fuzziness in terms of linguistic variables vis-à-vis criteria, weights, and decision maker judgments. Relevant alternatives or scenarios are evaluated according to a number of desired criteria. A fuzzy multi-criteria group decision software tool is developed to analyze long-term scenarios for Belgian energy policy in this paper.

Keywords: Fuzzy numbers; Multi-criteria decision making (MCDM); Linguistic variables; Group decision support; Energy policy, Evaluation model
Categories: F.4.3, J.5, H.5.3, M.4

1 Introduction

The Belgian parliament in 2003 enacted a law to progressively phase out existing nuclear power plants. Decision has caused contestation among a number of historically active social groups in the energy policy debate. Referring to this relatively controversial climate, the research reported in [Laes, 2006] stretches the scope of the debate outside the boundaries of political (parliamentary) decision making. Among many interesting issues related to nuclear energy and sustainable development, Laes [Laes, 2006] attempted to shed some light on the question whether nuclear electricity generation can contribute to the transition towards a sustainable energy future for Belgium, and, if so, under which conditions. Laes argued 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 decision problems at tactical and strategic levels often involve fuzziness in their criteria and decision makers' judgments. Due to the multi-dimensional nature of the sustainability question, we believe 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. Multi-criteria evaluation techniques can in principle provide an appropriate policy framework for setting long-term strategic priorities [Laes, 2006].

Multi-criteria decision making (MCDM) with linguistic variables, commonly known as fuzzy multi-criteria decision making (FMCDM), has been one of the fastest growing areas in decision making and operations research during the last three decades [Marimin et al, 1998, Nishizaki et al, 1994, Yager and Zadeh, 1992, Zimmermann, 1987]. The motivation for the development of FMCDM is 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 [Zadeh, 1975a, 1975b, 1975c]. Group decision making takes into account how experts 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 (scenarios), and judgments (weights) for criteria (indicators) [Lu et al, 2007, Marimin et al, 1998]. In this paper, we argue in favor of the use of a fuzzy-logic based multi-criteria group decision support tool for long-term scenarios of Belgian energy policy. The paper is organized as follows. In Section 2, we briefly outline the problem statement of long-term scenarios of Belgian energy policy. In Section 3, we present a fuzzy multi-criteria group decision making (FMCGDM) algorithm. In Section 4, we illustrate an application of the FMCGDM algorithm on a case-study of Belgian long-term energy policy support. In Section 5, we further compare the result obtained from the proposed FMCGDM method with the one from earlier methods from [Laes, 2006]. Finally in Section 6, we conclude the use of the FMCGDM algorithm in the context of Belgian sustainable energy policy.

2 Problem Statement of Long-term Scenarios for Belgian Sustainable Energy Policy

This paper aims to discuss the methodological issues of multi-criteria decision support in the context of sustainable energy policy. For details about the substantive results of the Belgian case, we refer to [Laes, 2006].

The decision criteria used in the multi-criteria decision exercise were derived mainly from the substantive results of the Belgian case [Laes, 2006] and related 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 preferences and needs of those experts or stakeholders (who participated in the multi-criteria decision exercise), operated by the research team within [Laes, 2006]. 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 [Bouyssou, 1990]. Decision criteria were subsequently structured into a *combined value tree*. This *combined value tree* includes four important issues (high-level criteria): i) Environmental and human health & safety, ii) Economic welfare, iii) Social, political, cultural and ethical needs, and iv) Diversification. Just for the first dimension (see Figure 1), 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. For the first dimension alone, each aspect had one or more low-level criteria.

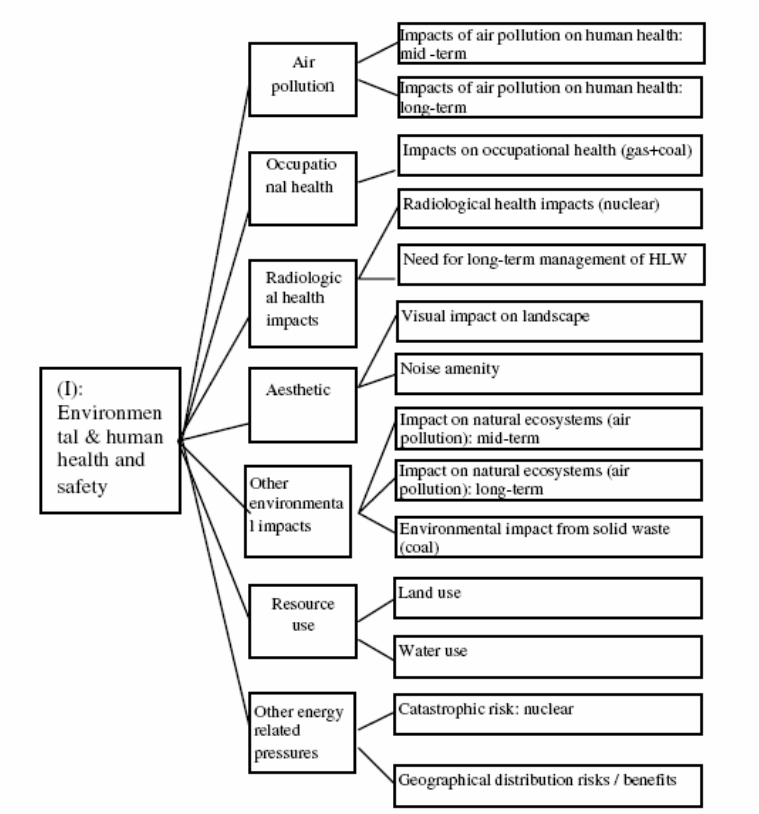

Figure 1: Structured value tree for 'Environmental & human health and safety' issues

As reported in [Laes et al, 2008]: 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, clearly, 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 among 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 [Guitouni and Martel, 1998].

For the scenarios/alternatives, Laes [Laes, 2006] used two different *worlds* (assumptions about how the market, political institutions and consumers behave): the *Market* world (M) and the *Rational Perspective* world (R). M denotes higher economic discount rates, lower penetration levels for renewable energy and less

possibilities for energy saving; R indicates lower discount rates, higher penetration levels for renewable and more possibilities for energy-saving behaviour.

The codes each describe the dominant energy supply strategy used within a particular *world* (all scenarios assume that a reduction of greenhouse gases will be imposed upon energy policy). Basically, the possibilities are nuclear, carbon capture & storage, import of electricity (up to 30%), and renewable & cogeneration. Each scenario looks at what happens if one suppresses one strategy, e.g., no nuclear, low carbon capture & storage, no import. This is described by the letter codes: P - nuclear phase out; LCS - low carbon capture and storage; I - import of electricity. So the scenario MPLCS is a scenario using the *Market* assumptions, and assuming a nuclear phase out, no import and low potential for carbon capture & storage (e.g., investments will be necessarily placed in renewable & cogeneration). RLCS uses the *Rational Perspective* assumptions, and assumes a low potential for carbon capture & storage and no import (so this scenario will invest in nuclear). In this study, we assume eight scenarios (S_1, S_2, …, S_8) as (MLCS, MPCS, MPLCS, MPLCSI, RLCS, RPCS, RPLCS, RPLCSI).

There are many ways to evaluate this policy option study. Standard multi-criteria decision support and group decision support systems are typically suitable for such a study [Chen, 2000, Dubois et al, 2001, Zimmermann, 1987]. Due to the complexity of this study, different experts will have different views under various uncertain information for different scenarios (S_1, S_2, …, S_8). Expert views are often expressed in certain linguistic variables and some undetermined values during the evaluation procedure. In the original multi-criteria exercise in [Laes, 2006], Laes used only crisp values for weights and criterion scores. In the current paper, we have softened those crisp values into certain fuzzy numbers that better reflect perception based views from experts. Hence the integration of multi-criteria decision making, group decision making and fuzzy logic systems is recommended to carry out for this study. By giving a rational-political group decision model [Lu et al, 2007, Marimin et al, 1998], we mainly identify three uncertain factors involved in a group decision-making process: decision makers' roles (weights), preferences (scores) for alternatives (scenarios), and judgments (weights) for criteria.

The next section presents an FMCGDM algorithm to deal with the three uncertain factors to a multi-level, multi-criteria decision to generate a group satisfactory decision. The solution is in the most acceptable degree of the group for this study. With the help of the FMCGDM algorithm, a software package designed to assist multi-criteria decision analysis under uncertainties, a long-term scenarios study for Belgian energy policy has being carried out as a result of the cooperation between the Belgian Nuclear Research Centre (SCK•CEN) and University of Technology, Sydney (UTS).

3 Fuzzy Multi-Criteria Group Decision Making Algorithm

In this section, a proposed FMCGDM algorithm, based on the previous study [Lu et al, 2006, Zhang and Lu, 2003] is developed for evaluating different long-term scenarios of Belgian energy policy.

Outline of the algorithm

Input:
scenarios S,
experts E with weights $WE=\{we_j, j=1, 2, \ldots, n\}$,
criteria C with weights $WC=\{wc, c\in C\}$,
relevance scores of scenarios for leaf nodes in C
Output:
ranking of scenarios S
Algorithm:
1. for each s_k in S
2. for each c_i in C calculate relevance degree CS_i^{yk}
3. calculate relevance degree S_k^y
4. normalize S_k^y, $k=1, \ldots, m$
5. calculate normalized weights of experts we^*_y, $y=1, 2, \ldots, n$.
6. calculate group decision $\tilde{r}_k$
7. calculate closeness coefficient CC_k of scenario s_k
8. ranking scenarios

This FMCGDM algorithm is composed of three stages: (a) determination of weights for experts and criteria, (b) preference aggregation for individual experts and (c) aggregation of group experts.

Stage (a): determination of weights of experts and criteria

Step 1: Identify experts, scenarios, and criteria

Let $E = \{e_1, e_2, \ldots, e_n\}$ ($n \geq 2$) be a set of experts. Let $S = \{s_1, s_2, \ldots, s_m\}$ ($m \geq 2$), be a set of identified scenarios for evaluation by E. Also suppose a three-level criteria model is identified within a tree structure. Without loss of generality, we use c_{jk} to indicate the k-th sub-criterion of criteria c_j, and use C_i the set of criteria at level i, $i=1, 2, 3$. By this notation, suppose criteria at level 1 are $c_1, c_2, \ldots, c_t$, each c_i has j_i sub-criteria and each c_{ij} has k_{ij} sub-criteria. An example of the criteria tree for assessing the set of S is shown in Figure 2.

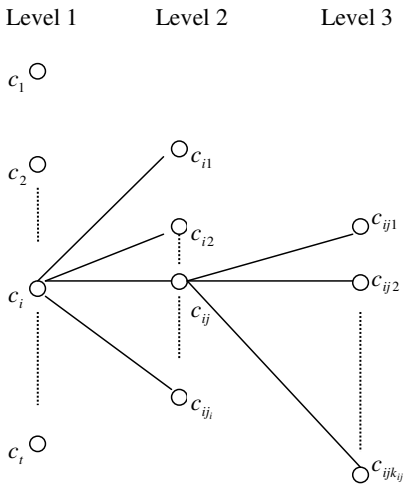

Figure 2: A three-level criteria evaluation model

Step 2: Identify weights for experts

As these experts play different roles in the evaluation, they have different degrees of influence for the evaluation results. Therefore, in the proposed algorithm, each expert is assigned a weight denoted by a linguistic term we_k, $k = 1, 2, \cdots, n$. These linguistic terms are determined through discussions in the group or assigned by a higher management level at the beginning of the evaluation process. Possible linguistic terms are listed in Table 1.

Linguistic terms	Fuzzy numbers
Normal	$\tilde{c}_1$
Important	$\tilde{c}_2$
More important	$\tilde{c}_3$
Most important	$\tilde{c}_4$

Table 1: Linguistic terms and related fuzzy numbers for describing weights of experts

Step 3: Identify weights for all criteria within the three evaluation levels

For any $c \in C$, denote wc the weight of c, where $wc \in$ {*Absolutely unimportant, Unimportant, Less important, Important, More important, Strongly important, Absolutely important*} that are described by fuzzy numbers $\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_7$ in Table 2.

Note that these linguistic terms can be symmetrically distributed, as default, but are also allowed to be asymmetrically distributed based on users' specific requirements.

Linguistic terms	Fuzzy numbers
Absolutely unimportant	$\tilde{a}_1$
Unimportant	$\tilde{a}_2$
Less important	$\tilde{a}_3$
Important	$\tilde{a}_4$
More important	$\tilde{a}_5$
Strongly important	$\tilde{a}_6$
Absolutely important	$\tilde{a}_7$

Table 2: Linguistic terms and related fuzzy numbers for the aspect weights, criteria and sub-criteria

Stage (b): Preference aggregation of individual expert

Step 4: Set up the relevance degree (score) of scenarios on each leaf criterion.
All criteria construct a tree. Evaluation data are collected for all leaf nodes, called leaf criteria, of the tree. Leaf criteria include two different types: the subjective criteria, whose values are given by experts, and objective criteria whose values are obtained through certain instruments, such as statistic reports or databases of existing studies.
To set up the relevance degrees of these scenarios on each leaf criterion, we use the linguistic term set B = {*Very low, Low, Medium low, Medium, Medium high, High, Very high*} in Table 3.

Linguistic terms	Fuzzy numbers
Very low (VL)	$\tilde{b}_1$
Low (L)	$\tilde{b}_2$
Medium low (ML)	$\tilde{b}_3$
Medium (M)	$\tilde{b}_4$
Medium high (MH)	$\tilde{b}_5$
High (H)	$\tilde{b}_6$
Very high (VH)	$\tilde{b}_7$

Table 3: Linguistic terms and related fuzzy numbers for evaluation scenario scores

For a subjective criterion c, denote $SC^{yk} \in B$ the relevance degree (score) of a scenario s_k on c given by an expert e_y.
For an objective criterion c, suppose U_C is the universe of discourse of c. According to the domain expertise knowledge of a given problem, there is a corresponding relationship between U_c and the used linguistic term set B. Suppose the corresponding

relationship can be described as a transformation mapping $f_C : U_C \to B = \{\tilde{b}_1,...,\tilde{b}_7\}$. By using this transformation mapping, an objective value $u \in U_C$ is labeled with a linguistic term $f_C(u)$ which is denoted by SC^{yk}. The linguistic term SC^{yk} will be taken as the relevance degree of s_k on c. For example, suppose c is a criterion that records the number of a kind of social sectors (e.g., transportation, agriculture, and insurance) and the possible value of it falls in $U_c = \{0,1,...,27\}$, that is, the range is [0, 27]. Moreover, suppose the corresponding relationship f_{c1} is defined as follows.

$$f_{c1}(u) = \begin{cases} \tilde{b}_1 & if\ 0 \le u < 3 \\ \tilde{b}_2 & if\ 4 \le u < 7 \\ \tilde{b}_3 & if\ 8 \le u < 11 \\ \tilde{b}_4 & if\ 12 \le u < 15 \\ \tilde{b}_5 & if\ 16 \le u < 19 \\ \tilde{b}_6 & if\ 20 \le u < 23 \\ \tilde{b}_7 & if\ 24 \le u \le 27 \end{cases}$$

Without loss of generality, let the number of social sectors be 4, i.e., u=4. Then the corresponding linguistic term $\tilde{b}_2$ is obtained by f_{c1} (i.e., the relevance degree (score) on the criterion c is *Low*). Obviously, this corresponding relationship f_{c1} is within a symmetrical distribution. If an evaluation task has a specific requirement for the distributions of these linguistic terms, the distribution of those linguistic terms may be not symmetrical. This step allows defining an asymmetrical corresponding relationship such as the following example f_{c2}:

$$f_{c2}(u) = \begin{cases} \tilde{b}_1 & if\ 0 \le u < 2 \\ \tilde{b}_2 & if\ 3 \le u < 5 \\ \tilde{b}_3 & if\ 6 \le u < 8 \\ \tilde{b}_4 & if\ 9 \le u < 11 \\ \tilde{b}_5 & if\ 12 \le u < 16 \\ \tilde{b}_6 & if\ 17 \le u < 21 \\ \tilde{b}_7 & if\ 22 \le u \le 27 \end{cases}$$

The above two examples show the possibility of mapping objective values to linguistic terms. In real applications, such a mapping is conducted by domain experts to meet the requirements of real world evaluation tasks.

Hence, the relevance degrees of a scenario on all leaf criteria can be obtained.

Step 5: Calculate the relevance degrees of each criterion at the first level.

The relevance degree CS_i^{yk} of the $c_i \in C_1$ on scenario s_k (i=1,2, …, t; k=1, 2, …, m; y=1, 2,…, n) is calculated by

$$CS_i^{yk} = \sum_{j=1}^{j_i} wc_{ij} \times SC_{ij}^{yk}$$

where $SC_{ij}^{yk} = \sum_{z=1}^{k_{ij}} wc_{ijz} \times SC_{ijz}^{yk}$. The operation "×" for fuzzy numbers is defined by $\tilde{a} \times \tilde{b} = \bigcup_{\lambda \in [0,1]} \lambda \left[\tilde{a}_\lambda^L \times \tilde{b}_\lambda^L, \tilde{a}_\lambda^R \times \tilde{b}_\lambda^R \right]$ in here and in Step 6 as well, and the operation "+"

is defined by $\tilde{a}+\tilde{b}=\bigcup_{\lambda\in[0,1]}\lambda\left[\tilde{a}_\lambda^L+\tilde{b}_\lambda^L,\tilde{a}_\lambda^R+\tilde{b}_\lambda^R\right]$, where $\tilde{a}_\lambda^L,\tilde{b}_\lambda^L,\tilde{a}_\lambda^R,\tilde{b}_\lambda^R$ are the left and right end points of $\lambda-$cut set of fuzzy numbers $\tilde{a}$ and $\tilde{b}$, respectively.

***Step 6*:** Calculate the relevance degrees of all criteria at the first level

The relevance degree S_k^y of scenarios s_k (k=1, 2,…, m) on all criteria at the first level by expert e_y, is calculated by $S_k^y=\sum_{i=1}^{t}CS_i^{yk}\times wc_i$.

***Step 7*:** Normalize the relevance degrees of all scenarios

The normalized relevance degrees of the k-th scenario evaluated by expert e_k, are

$$\overline{S}_k^y=\frac{S_k^y}{\sum_{i=1}^{m}(S_k^y)_0^R},\quad k=1,2,\cdots,m. \tag{4}$$

where S_k^y is the relevance degree obtained in Step 6.

Stage (c): *Aggregation of group evaluation*

***Step 8*:** Normalize each expert's weights

Each expert e_y, is assigned a weight denoted by a linguistic term we_y (y= 1, 2, …, n) as shown in Table 3. A weight vector is obtained:

$$WE=(we_1, we_2, \ldots, we_n). \tag{5}$$

The normalized weight of an expert e_y is denoted as

$$we_y^*=\frac{we_y}{\sum_{i=1}^{n}(v_i)_0^R},\quad \text{for } y=1,2,\cdots,n. \tag{6}$$

***Step 9*:** Obtain the group decision vector

Considering the normalized weights of all experts, a weighted normalized fuzzy decision vector is obtained by

$$(\tilde{r}_1,\tilde{r}_2,\cdots,\tilde{r}_m)=\left(we_1^*, we_2^*,\cdots, we_n^*\right)\begin{pmatrix}\overline{S}_1^1 & \overline{S}_2^1 & \cdots & \overline{S}_m^1\\ \overline{S}_1^2 & \overline{S}_2^2 & \cdots & \overline{S}_m^2\\ \vdots & \vdots & \ddots & \vdots\\ \overline{S}_1^n & \overline{S}_2^n & \cdots & \overline{S}_m^n\end{pmatrix}, \tag{7}$$

where $\tilde{r}_k=\sum_{j=1}^{n}we_j^*\times\overline{S}_k^j$.

***Step 10*:** Calculate the distance between the evaluation result and positive- and negative-ideal solution

In the weighted normalized fuzzy decision vector the elements $\tilde{r}_k$ $(k=1,2,\cdots,m)$ are normalized as positive fuzzy numbers and their ranges belong to the closed unit interval. We define a fuzzy positive-ideal solution (FPIS, r*) and a fuzzy negative-ideal solution (FNIS, r^-) as $r^*=1$ and $r^-=0$.

The positive and negative solution distances between each $\tilde{r}_j$ and r*, $\tilde{r}_j$ and r- can be then calculated as:

$$d_k^*=d(\tilde{r}_k, r^*)\quad\text{and}\quad d_k^-=d(\tilde{r}_k, r^-),\quad k=1,2,\cdots,m, \tag{8}$$

where d (.,.) is the distance measurement between two fuzzy numbers such as

$$d(\tilde{a},\tilde{b}) = \int_0^1 \frac{1}{2}((\tilde{a}_\alpha^L - \tilde{b}_\alpha^L)^2 + (\tilde{a}_\alpha^R - \tilde{b}_\alpha^R)^2)^{1/2} \mathrm{d}\alpha$$

***Step 11*:** rank scenarios

A closeness coefficient is defined to determine the ranking order of all scenarios once both d^*_k and d^-_k of each s_k (k = 1, 2, ..., m) are obtained. The closeness coefficient of each scenario is calculated by:

$$CC_k = \frac{1}{2}\left(d_k^- + (1 - d_k^*)\right) \tag{9}$$

The top N scenarios that correspond to the top N max$\{CC_k, k = 1, 2, \ldots, m\}$ are the preferred scenarios.

The research team at UTS has implemented this method in a decision support software tool, which will be applied to a case-study of long-term scenarios of Belgian energy policy in the next section.

4 A Case-study of Long-term Scenarios of Belgian Energy Policy

In our early study [Ruan et al, 2007], we only considered one of the four important issues, namely, environmental & human health and safety for long-term scenarios of Belgian energy policy. As the complete case-study of this project, we now illustrate the use of the FMCGDM algorithm to the whole range of the four important issues as briefly mentioned in Section 2. In this study, we aim to rank eight scenarios as defined in Section 2 as (S_1, S_2, …, S_8) = (MLCS, MPCS, MPLCS, MPLCSI, RLCS, RPCS, RPLCS, RPLCSI) by integrating 10 experts' evaluation results that are expressed by linguistic variables. Here are the main stages for this case-study.

Stage (a): Determination of weights of experts and criteria

We first identify 67 evaluation criteria that are grouped in three levels in Table 4.

Level 1	**Level 2**	**Level 3**
Environment & human health and safety	Air pollution	Impacts of air pollution on human health: mid-term
		Impacts of air pollution on human health: long-term
	Occupational health	Impacts on occupational health (gas+coal)
	Radiological health impacts	Radiological health impacts (nuclear)
		Need for long-term management of HLW
	Aesthetic impacts	Visual impact on landscape
		Noise amenity
	Other environmental impacts	Impact on natural ecosystems (air pollution): mid-term
		Impact on natural ecosystems (air pollution): long-term
		Environmental impact from solid waste (coal)

	Resource use	Land use
		Water use
	Other energy related pressures	Catastrophic risk : nuclear
		Geographical distribution risks / benefits
Economic welfare	Overall economic benefit	Intensity of energy use
		Security of energy supply
		Distribution of economic benefits / burdens
		Economic risks
		Overall cost energy system: 2010
		Overall cost energy system: 2030
	Producer need/benefit	Overall cost energy system: 2050
		Ability to provide specialist market
		Marginal cost electricity: mid-term
	Consumer need/benefit	Marginal cost electricity: long-term
	International cooperation	Strategic factors for export
		Compatibility with international R&D agenda
	Need for government intervention	Amount of direct or indirect subsidies needed
Social, political, cultural and ethical needs	Individual/consumer choice/benefit	Consumer choice
		Citizen participation
		Contribution to rational energy use
	Institutional needs	Degree of decentralisation
		Need for intermediary storage of spent fuel
		Control and concentration of power
		Influence on political decision-making
		Need for socio-political stability
		Need for direct political intervention
		Reversibility of technology choice
		Knowledge specialisation
		Need for institutional non-proliferation measures
	Development opportunities	Potential for technology transfer
		Leaving resources for development
		Equity (general)
	Jobs	Job opportunities
Diversification		

Table 4: All three-level evaluation criteria for Belgian Energy policy

Based on the identified criteria, the criteria tree is shown in Figure 3. For each criterion, we input the related information such as strength (weight), and data type, etc. into the program through interface. Similarly, we obtain the related information

about experts and scenarios and input them into the program. Experts can set transformation functions and input their assessments of relevance degree on the leaf indicator for each alternative.

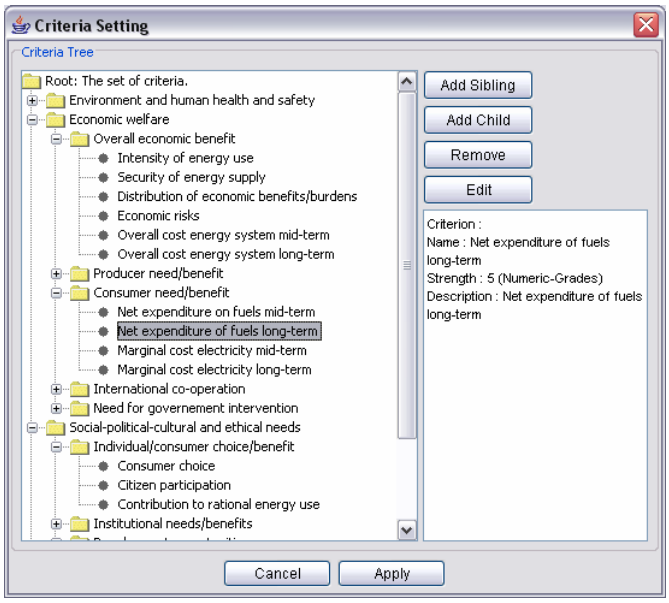

Figure 3: Criteria tree for the project.

Stage (b): Preference aggregation of individual experts
For each expert, the individual evaluation on each scenario is aggregated through the proposed algorithm. Figure 4 shows Expert e1's evaluation result for all criteria, i.e., the sixth scenario (i.e., RPCS) is the preferred scenario by Expert e1.

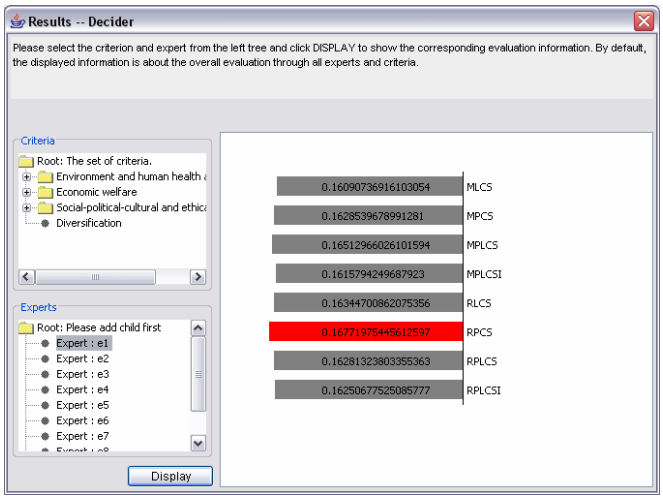

Figure 4: Evaluation result of Expert e1 on all criteria.

Stage (c): *Aggregation of group evaluation*

Based on the proposed algorithm, we aggregate evaluation results of all experts and obtain an overall result. Figure 5 indicates the overall result on all criteria. In this case the seventh scenario (i.e., RPLCS) is the preferred one, which is in accordance with our early result in [Ruan et al, 2007].

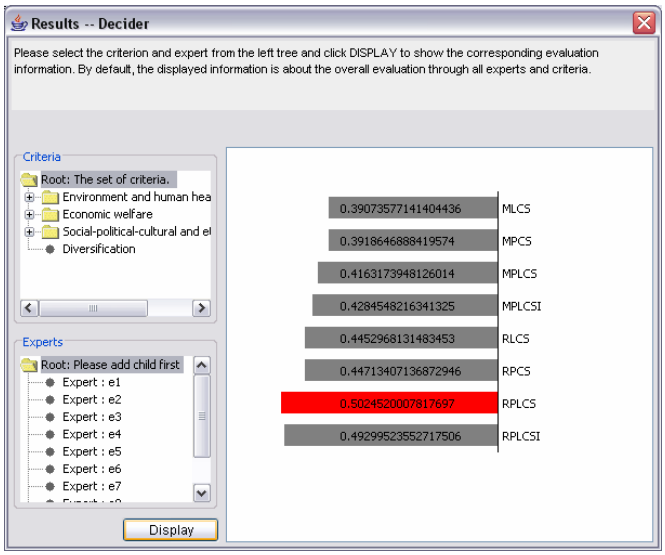

Figure 5: Overall results on all criteria.

For this case study, we summarize the detailed steps of the working flowchart of the FMCGDM algorithm in Figure 6.

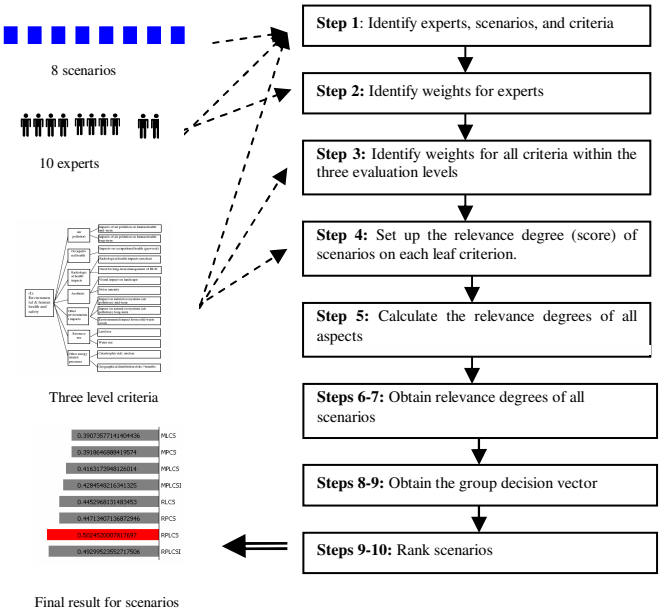

Figure 6: The flowchart of evaluation process with the FMCGDM method

5 Discussions and Comparisons between FMCDM and MCDM for the Validation of the Results

The MCDM approach implemented in [Laes, 2006] assigns to each criterion a non-monetary subjective utility, which is then aggregated with a simple multiplicative and additive function in order to obtain an overall utility index for the assessed alternative. In [Laes, 2006], it is argued that this approach provides an interesting alternative to traditional cost-benefit analysis, which has already been used with some success in the more short-term sustainability impact assessment of energy policy measures. However, the MCDM approach discussed in [Laes, 2006] also has its drawbacks: the choice of the partial utility functions and values as well as the selection of weights – already a difficult task in a single decision-maker case – becomes almost impossible in a group decision-making context.

Another important desirable property in the context of sustainability assessment is the possibility of dealing with mixed criterion scores. The presence of qualitative information in evaluation problems concerning socio-economic and physical planning is a rule, rather than an exception. This implies that there is a clear need for methods

that are able to take into account information of a "mixed" type (both qualitative and quantitative criterion scores). Moreover, ideally, this information should be precise, certain, exhaustive and unequivocal. But in reality, it is often necessary to use information that does not have those characteristics so that one has to face the uncertainty of a stochastic and/or fuzzy nature present in the data. If it is impossible to establish exactly the future state of the system studied, a stochastic uncertainty exists, this type of uncertainty is well known in decision theory and economics, where it is called "decisions under risk." "Fuzzy uncertainty" on the other hand focuses on the ambiguity of information in the sense that the uncertainty does not concern the occurrence of an event but the event itself, which cannot be described unambiguously. This situation is very common in human systems. These systems are complex systems characterized by subjectivity, incompleteness and imprecision. As the complexity of a system increases, our ability to make a precise and yet significant statement about its behavior diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics (incompatibility principle). In conclusion, multi-criteria methods are able to tackle consistently the widest types of mixed information and different sources of uncertainty – such as the FMCDM discussed in this paper – should be considered as desirable ones in the context of complex societal questions such as deciding on a sustainable energy strategy for the long-term future.

Finally, in a policy framework for sustainability, to have a ranking of all the different courses of actions is better than to select just one alternative. This is mainly because in this way social compromises are easier (the second or the third alternative in the ranking may minimize opposition much more than the first one). Technically speaking this implies that multi-criteria methods dealing with the decision problem formulation have to be preferred and that dominated alternatives cannot be excluded a priori.

6 Conclusions

In this paper, we successfully applied the proposed FMCGDM algorithm and its developed software tool to support the analysis long-term scenarios of Belgian energy policy. The illustrated software tool provides a helpful means to accept input data as linguistic variables for fuzziness related uncertainties. Moreover, the proposed algorithm can easily deal with large data sets ranging from numerical, linguistic, or missing values from a group of experts whose views may not agree with each other. From the input data, the FMCGDM tool 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, scenarios, and experts, the FMCGDM tool can automatically deal with all conflict situations for the final rank of the given scenarios by multi-criteria group decision-making techniques. From the case study of long-terms scenarios of Belgian energy policy, we strongly believe the FMCGDM tool helps to provide more insight into the nature of these conflicts by providing systematic information for the social-economic analysis of nuclear systems in particular and for any complex evaluation systems in general.

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