WCCI 2010 IEEE World Congress on Computational Intelligence
July, 18-23, 2010 - CCIB, Barcelona, Spain FUZZ-IEEE

A Heterogeneous Evaluation Model for Assessing Sustainable Energy: A Belgian Case Study

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***Abstract*— Decision makers are increasingly involved in complex real decisions that require multiple viewpoints. A specific case of this fact is the evaluation of sustainable policies related to environment and energy sectors. In this evaluation process, different scenarios are evaluated according to multiple desired criteria that might have different nature. These evaluation processes aim to obtain an overall assessment for each scenario with a complete description of the different related criteria to compare the alternate scenarios for a ranking among them with the goal of identifying the best one. In such complex decision making problems a key problem is the modelling of experts' assessments for each criterion of the scenarios due to the vagueness, uncertainty and nature of such assessments. In this contribution, we propose an evaluation model applied to energy policy selection based on the decision analysis that can manage different types of information (numerical, interval-valued and linguistic) and eventually models linguistically the experts' information with the aim of facilitating the interpretation and keeping accurate results. We apply this model to a case study for evaluating Belgian long-term sustainable energy scenarios.**

I. Introduction

Time goes by and the energy consumption in general are increasing in our world, which implies energy resources are decreasing, resulting in a problem in the long-term energy scenario. In addition, extraction of energy resources generates other health and safety problems for the people and the environment.

It is thus common that international and national institutions are quite concerned about this problem and different proposals about sustainable energy policies arise. However, the main problem is that usually different policies are not compatible with each other or with current ones or unviable because of their costs. Hence, the evaluation of different policies is a key issue nowadays for many governments, producing an increase in the research on sustainable development and its evaluation.

Evaluation processes can be carried out by using different methods. The use of decision approaches has been successfully applied to solve evaluation problems in the literature [1], [2], [3], [4], [5], [6], [7]. From a simple resolution decision scheme (see Figure 1), the squared steps carry out an analysis process that allows to make decisions consistently, i.e., it helps to cope with difficult decisions. Such steps are called *decision analysis* that it is a suitable approach for evaluation processes because it helps to analyze the alternatives, criteria, indicators of the items under study that is the objective of an evaluation process.

In [8], the use of a fuzzy multi-criteria group decision support system (FMCGDSS) was a possible framework for the application of strategic choice for an intractable policy problem such as sustainable development. The development of fuzzy multicriteria decision making is an interesting option because decision makers can express their preferences about the set of criteria where some of them involve uncertainty or might have qualitative nature, the use of fuzzy linguistic approach [9] for managing such uncertainty has obtained good results in different disciplines, among them "information retrieval" [10], "marketing" [11], "recommender systems" [12], [13], "education" [14], and "sensory evaluation" [15].

In FMCGDSS, to observe the input data (provided by interviews, questionnaires, databases and direct entry) can be expressed in different domains (numerical, interval and/or linguistic) according to their nature and uncertainty. All of them are then transformed to fuzzy sets utilized in the computations for ranking the scenarios, such a ranking is based on a distance measure between the fuzzy collective evaluation of each scenario and a positive -and negative- ideal solution, obtaining a crisp value. The main disadvantage of FMCGDSS is its lack of interpretability of the collective evaluation of each scenario. Such values are suitable for ranking aims, but difficult to be interpreted. Taking into account that the final decision should be made by diverse persons (politicians, managers) and that they are not necessarily scientists, the facilitation of the understanding of the results is a key to make right decisions. Therefore, our aim consists of improving the comprehension of the results by a verbalization process that models, computes and produces linguistic information based on fuzzy linguistic approaches [9].

In this contribution, we propose an evaluation process for energy policies in long term scenarios based on decision analysis [16] defined in a heterogeneous framework where the input data can be expressed by numerical, interval-valued and linguistic information. In order to manage such data, we propose the use of the linguistic model presented in [17] that unifies the heterogeneous information in a linguistic domain by means of the linguistic 2-tuples representation [18] that

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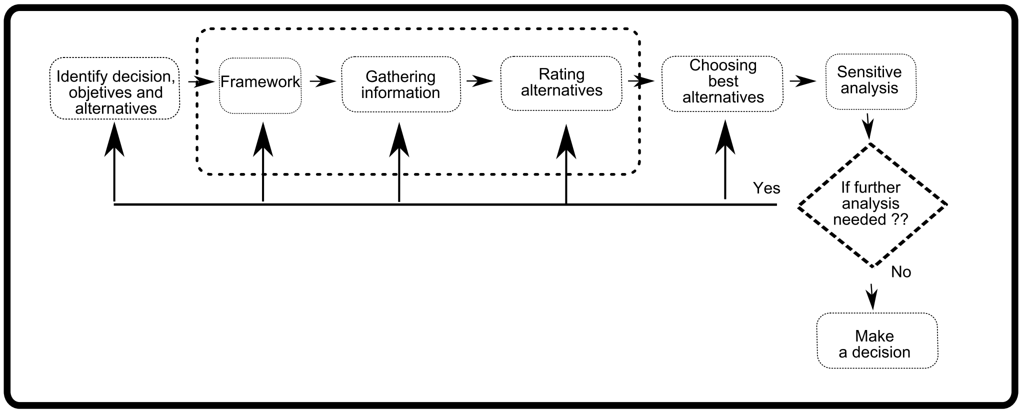

Fig. 1. Decision Analysis Scheme

allows to accomplish processes of computing with words in a symbolic and precise way, obtaining linguistic results.

To show such an evaluation model for the proposed problem of energy policy selection, we apply such a model to a Belgian case study. Because of the energy policy debate and increased research for sustainable development in Belgium, Laes [19] 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. The study [19] includes a set of criteria that characterize the sustainable development, using such an study we shall solve the evaluation problem and compare our results with the ones obtained in [8].

This contribution is structured as follows: Section 2 outlines a scheme of decision analysis and reviews in short a linguistic background necessary to understand the model to deal with heterogeneous information. Section 3 presents a heterogeneous evaluation model for sustainability policies. Section 4 shows a case study of the proposed model in Long-Term Scenarios for Belgium. Finally, Section 5 points out concluding remarks.

II. Preliminaries

In this section, we outline the scheme of the decision analysis in which our evaluation model will be based and we briefly review linguistic background that presents different concepts to understand the proposed evaluation model.

A. Decision Analysis

Decision Analysis is a discipline, which belongs to Decision Theory, whose purpose is to help decision makers to reach a consistent decision in a decision making problem. The evaluation process can be modeled as a type of decision making problems, in this contribution we model the evaluation process as a Multi-Expert Multi-Criteria Decision Making problem (MEMCDM). Decision makers express their opinions about a set of alternatives by means of an utility vector. A classical decision analysis scheme consists of the following phases (see Figure 1 [16]):

- *Identify decision, objectives and alternatives of the problem.*
- *Framework:* It defines the structure of the problem, in our case modelled as a MEMCDM [20], and the expression domains in which the preferences can be assessed.
- *Gathering information:* Decision makers provide their information.
- *Rating alternatives:* This phase obtains a collective value for each alternative.
- *Choosing best alternatives:* It selects the solution from the set of alternatives (applying a choice degree [21], [22] to the collective values computed in the before phase).
- *Sensitive analysis:* The solution obtained is analyzed in order to know if it is good enough to make a decision, otherwise, go back initial phases to improve the the quality of the results.
- *Make a decision.*

The application of the decision analysis to an evaluation process does not imply all phases. The essential phases regarding an evaluation problem that will be used in our proposal for the evaluation model are those dashed in a rectangle of Figure 1.

B. Linguistic Background

In this section, we are going to review some necessary concepts related to linguistic information in order to understand our proposal.

1) Fuzzy Linguistic Approach: Many aspects of different activities in the real world cannot be assessed in a quantitative form, but rather in a qualitative one, i.e., with vague or imprecise knowledge. In that case, a better approach may be to use linguistic assessments instead of numerical values. The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables [9].

In this approach, it is necessary to choose the appropriate linguistic descriptors for the term set and their semantics, there exist different possibilities (further description see [23]). One possibility of generating the linguistic term set consists of directly supplying the term set by considering all terms distributed on a linguistic term set on which a total order is defined [24]. For example, a seven-term set S, could be:

$$\begin{array}{ll} s_0 = None\ (N) & s_1 = Very\_Low\ (VL) \\ s_2 = Low\ (L) & s_3 = Medium\ (M) \\ s_4 = High\ (H) & s_5 = Very\_High\ (VH) \\ s_6 = Perfect\ (P) & \end{array}$$

Usually, in these cases, it is required that in the linguistic term set there exist:

1) A negation operator: $Neg(s_i) = s_j$ such that $j = g - i$ ($g + 1$ is the cardinality).
2) An order: $s_i \leq s_j \iff i \leq j$. Therefore, there exists a $\min$ and a $\max$ operator.

The semantics of the terms are given by fuzzy numbers defined in the [0,1] interval, which are usually described by membership functions.

2) 2-Tuple Linguistic Representation Model: This model presented in [18], [25] has different advantages of this representation to manage linguistic information over semantics and symbolic models. Furthermore, in [17], [26] the model was used to deal with heterogenous information. Due to these advantages and benefits, we shall use this linguistic representation model to accomplish our aim.

This model is based on symbolic methods and takes as the base of its representation the concept of Symbolic Translation.

Definition 1: The Symbolic Translation of a linguistic term $s_i \in S = \{s_0, ..., s_g\}$ is a numerical value assessed in $[-.5, .5)$ that supports the "difference of information" between an amount of information $\beta \in [0, g]$ and the closest value in $\{0, ..., g\}$ that indicates the index of the closest linguistic term $s_i \in S$, being [0,g] the interval of granularity of S.

From this concept the linguistic information is represented by means of 2-tuple (s_i, α_i), $s_i \in S$ and $\alpha_i \in [-.5, .5)$.

This model defines a set of functions between linguistic 2-tuples and numerical values.

Definition 2: Let $S = \{s_0, \ldots, s_g\}$ be a set of linguistic terms. The 2-tuple set associated with S *is defined as* $\langle S \rangle = S \times [-0.5, 0.5)$. *We define the function* $\Delta : [0, g] \longrightarrow \langle S \rangle$ *given by,*

$$\Delta(\beta) = (s_i, \alpha), \quad with \quad \begin{cases} i = \ round\,(\beta), \\ \alpha = \beta - i, \end{cases}$$

where "round" assigns to β the integer number $i \in \{0, 1, \ldots, g\}$ closest to β.

We note that Δ is bijective [18] and $\Delta^{-1} : \langle S \rangle \longrightarrow [0, g]$ is defined by $\Delta^{-1}(s_i, \alpha) = i + \alpha$. In this way, the 2-tuple of $\langle S \rangle$ will be identified with the numerical values in the interval $[0, g]$. This representation model has associated a computational model that was presented in [18].

3) Dealing with Heterogenous Information: In our proposal, we consider a heterogenous framework, in which the experts could use numerical, linguistic and/or interval-valued information. Therefore, we will have to accomplish computations with this type of information and we cannot operate directly with it because the information is expressed in different domains. In the literature, we find different approaches to manage this type of information [17], [27], [26], [28], [29].

In this section, we review in short the approach presented in [17] because results are expressed by linguistic 2 tuples, facilitating their comprehension and providing accuracy.

This approach consists in the following steps (graphically in Figure 2):

- Unification of the information into Fuzzy Sets into a term set (S_T).
- Transformation of the information into Linguistic 2 tuples into a term set (S_T).

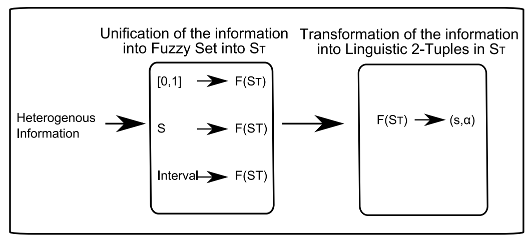

Fig. 2. Dealing with Heterogenous Information

1) **Unification of the information into Fuzzy Sets into S_T.** The non-homogeneous information will be unified into a specific linguistic domain, called *Basic Linguistic Terms Set*, S_T, that is selected with the aim of keeping as much knowledge as possible (see [17]). Each numerical, interval-valued and linguistic value is transformed into a fuzzy set on the S_T, $F(S_T)$, by using the following transformation functions:
   a) Transforming numerical values in $[0, 1]$ into $F(S_T)$.
   Definition 3: [17] *Let $v \in [0, 1]$ be a numerical value and $S = \{s_0, s_1, \ldots, s_g\}$ a linguistic term set. The numerical-linguistic transformation function $\tau_{NS_T} : [0, 1] \longrightarrow F(S_T)$ is defined by:*

   $$\tau_{NS_T}(v) = \{(s_0, \gamma_0), (s_1, \gamma_1), \ldots, (s_g, \gamma_g)\}$$

   with

   $$\gamma_i = \mu_{s_i}(v) = \begin{cases} 0, \ if\ x < a\ \ o\ \ v > d, \\ \frac{v-a}{b-a}, \ if\ a < v < b, \\ 1, \ if\ b \leq v \leq c, \\ \frac{d-v}{d-c}, \ if\ c < v < d \end{cases}$$

   where $\gamma_i \in [0, 1]$ and $F(S_T)$ is the set of fuzzy sets on S_T, and μ_{s_i} is the membership function of the linguistic label $s_i \in S_T$.
   b) Transforming interval-valued into $F(S_T)$.
   Definition 4: [17] *Let $I = [\underline{i}, \overline{i}]$, $\underline{i} \leq \overline{i}$ be an interval-value in $[0, 1]$ and $S = \{s_0, s_1, \ldots, s_g\}$ a linguistic term set. The*

interval-linguistic transformation function $\tau_{IS}: I \longrightarrow F(S_T)$ is defined by:

$$\tau_{IS}(I) = \{(s_0, \gamma_0), (s_1, \gamma_1), \ldots, (s_g, \gamma_g)\}$$

with

$$\gamma_i = \max_y \min \{\mu_I(y), \mu_{s_i}(y)\}, \; i = 0, 1, \ldots, g$$

where $F(S_T)$ is the set of fuzzy sets on S_T, and μ_I and μ_{s_i} are the membership functions of the interval-value I and the linguistic label $s_i \in S_T$, respectively.

c) Transforming linguistic terms into $F(S_T)$.

Definition 5: [17] *Let $S_T = \{s_0, s_1, \ldots, s_g\}$ and $S = \{s'_0, s'_1, \ldots, s'_h\}$ be two linguistic term sets, with $h \leq g$. The linguistic transformation function $\tau_{SS_T}: S \longrightarrow F(S_T)$ is defined by:*

$$\tau_{SS}(s'_j) = \{(s_0, \gamma_0), (s_1, \gamma_1), \ldots, (s_g, \gamma_g)\}$$

with

$$\gamma_i = \max_y \min \{\mu_{s'_j}(y), \mu_{s_i}(y)\}, \; i = 0, 1, \ldots, g$$

where $F(S_T)$ is the set of fuzzy sets on S_T, and $\mu_{s'_j}$ and μ_{s_i} are the membership functions of the linguistic labels $s'_j \in S$ and $s_i \in S_T$, respectively.

2) **Transformation of the Information into Linguistic 2-Tuple into S_T.**
The information has been unified into fuzzy sets in S_T to be manageable in the computing processes. However, different processes such as decision making or evaluation processes, the collective values should be easy to understand, to facilitate the interpretability of results, we shall transform the preference expressed by fuzzy sets into linguistic 2 tuples.
In [30], a function χ transforms a fuzzy set into a numerical value in the interval of granularity of S_T, $[0, g]$:
Definition 6: [30] *Given the linguistic term set $S_T = \{s_0, s_1, \ldots, s_g\}$, the function $\chi: F(S) \longrightarrow [0, g]$ is defined by*

$$\chi(F(S_T)) = \chi(\{(s_j, \gamma_j), \, j = 0, ..., g\}) =$$

$$\frac{\sum_{j=0}^{g} j\gamma_j}{\sum_{j=0}^{g} \gamma_j} = \beta,$$

where the fuzzy set, $F(S_T)$ could be obtained from τ_{NS_T}, τ_{SS_T} or τ_{IS_T}, respectively.
Therefore, applying the function Δ to β (see Definition 2), we obtain a collective preference relation whose values are expressed by means of linguistic 2 tuples:

$$\Delta(\chi(\tau(\vartheta))) = \Delta(\beta) = (s, \alpha)$$

III. An Energy Policy Evaluation Model Based on Linguistic 2 Tuples

Our aim is to propose an evaluation model for energy policies in long term scenarios based on a linguistic decision analysis scheme. Policies assessments will be verbalized with the aim of facilitating its interpretation and to establish a ranking among them with the purpose of identifying the best ones. The use of the linguistic 2-tuple model improves the accuracy of the results.

The decision analysis scheme for the evaluation model consists of the following phases (graphically, Figure 3) revised in Section II-A:

- Evaluation Framework.
- Gathering Information.
- Rating Scenarios:
  - Step 1: Unification of the Information.
  - Step 2: Aggregation of the Information.
  - Step 3: Ranking Scenarios.

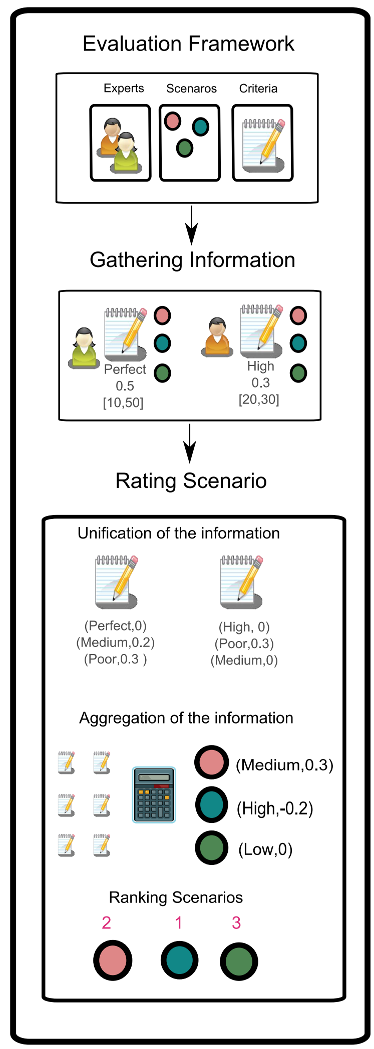

Fig. 3. Scheme of the Model

The following subsections present in detail phases of the above evaluation model.

A. Evaluation Framework

In this phase, the evaluation framework is defined to fix the problem structure. Hence, the evaluation framework will be as follows:

- Let $E = \{e_1, ..., e_n\}$ $(n \geq 2)$ be a set of experts.
- Let $S = \{S_1, S_2..., S_m\}$ $(m \geq 2)$ be a set of identified scenarios for evaluation by E.
- Let $C = \{c_1, c_2..., c_k\}$ $(k \geq 2)$ be a set of criteria that characterizes each scenario S_j.

Here, we consider a heterogeneous information framework. So, we assume that each expert can use different domains [17], [26] (numerical, interval-valued or linguistic information) to assess each criterion, attending to their knowledge about the criterion evaluated or its nature.

B. Gathering Information

Once the framework has been defined to evaluate the different scenarios, the knowledge must be obtained from the experts.

The experts will provide their preferences by using utility vectors. Each expert, e_i provides his/her preferences of the scenario S_j by means of a utility vector:

$$P_j^i = \{p_{j1}^i, p_{j2}^i, ..., p_{jh}^i\}$$

where p_{jk}^i is the preference provided to the criterion c_k of the scenario S_j by the expert e_i.

C. Rating Scenarios

The evaluation process aims to rank the scenarios. So this phase of the evaluation model computes a collective assessment for each scenario that will be used to obtain a ranking. As already mentioned, our aim is to verbalize the collective evaluations to facilitate their understanding, keeping the accuracy.

Our evaluation process is defined in a heterogeneous framework, therefore, first the information should be unified and transformed into linguistic 2 tuples. The information is then aggregated to obtain a collective 2-tuple assessment and finally, the ranking is computed. Therefore, this process is developed according to the following steps:

- Step 1: Unification of the information.
- Step 2: Aggregation of the information.
- Step 3: Ranking scenarios.

These steps are further presented in detail as follows:

1) Step 1: Unification of the Information: We define the domain where the collective values will be expressed and we unify the heterogeneous information obtained in the previous phase in this domain.

This step has the following stages:

- *Choice of the linguistic term set S_T.*

  Here must be fixed the final domain, i.e., the linguistic term set, $S_T = \{s_0, ..., s_g\}$, where the gathered information will be transformed and aggregated to obtain collective values in this domain.
- *Unification the information in fuzzy sets in S_T.*

  Once the selected S_T, the information obtained in the gathering information process will be expressed through fuzzy sets in S_T, using the functions τ_{NS_T}, τ_{IS_T} and τ_{SS_T} presented in Definitions 3, 4 and 5.

$$\tau_{NS_T} : [0, 1] \longrightarrow F(S_T),\ or$$
$$\tau_{IS_T} : I \longrightarrow F(S_T),\ or$$
$$\tau_{SS_T} : S_A^k \longrightarrow F(S_T).$$

  In this way, the information obtained in the evaluated process will be expressed into a unique linguistic term set, through fuzzy sets in S_T.

$$\vartheta_{jk}^i = \tau_{\_S_T}(p_{jk}^i) = \{(s_{T0}, \gamma_0), (s_{T1}, \gamma_1), \ldots, (s_{tg}, \gamma_g)\}_{jk}^i$$

- *Transforming into Linguistic 2 Tuples in S_T*

  To facilitate the accuracy in the aggregation process and the understandability of the results, we transform the fuzzy sets in S_T into linguistic 2-tuples using the functions Δ and χ presented in Definitions 2 and 6, respectively:

$$\Delta(\chi(\tau(\vartheta_{jk}^i))) = (u_{jk}^i, \alpha) \in S_T$$

  We note that all the information provided by the different experts has already unified into linguistic 2 tuples in the S_T.

2) Step 2: Aggregation of the Information: The evaluation model computes a collective evaluation for each scenario according to the information transformed into linguistic 2-tuples in S_T. Here, it is applied a two-step aggregation process to compute a global evaluation for each evaluated scenario:

- *Computing evaluations by scenario for each expert*: First, the rating process will compute a collective linguistic 2-tuple, (u_j^i, α), for each scenario, S_j, evaluated by the expert e_i, using an aggregation operator, $AGOP_1$, on the preferences of criterion c_k.

$$(u_j^i, \alpha) = AGOP_1((u_{j1}^i, \alpha_1), ..., (u_{jh}^n, \alpha_h)), (u_j^i, \alpha) \in S_T$$

- *Computing a collective evaluation for each scenario*: The final aim of the rating process is to obtain a global evaluation, (u_j, α), for each evaluated scenario, S_j, according to all the experts. To do so, this process will aggregate all the experts' collective assessment for each scenario by using an aggregation operator, $AGOP_2$:

$$(u_j, \alpha) = AGOP_2((u_j^1, \alpha_1), ..., (u_j^m, \alpha_m)), (u_j, \alpha) \in S_T$$

The aggregation operators, $AGOP_1$ and $AGOP_2$, could be the same or different ones depending on each evaluation, but the aggregation results will be linguistic 2-tuple into S_T.

3) Step 3: Ranking Scenarios: The final step in the evaluation process is to establish a ranking among scenarios with the purpose of identifying the best ones. The best scenario corresponds to the maximum collective evaluation $max\{(u_j, \alpha), = 1, 2, ..., m\}$.

IV. A Case Study in Long-term Scenarios for Belgian Energy Policy

In this section, we present a case study of the evaluation model presented previously in the problem of Long-term Scenarios for Belgian Energy Policy. Furthermore, we compare the results obtained with our model with the ones obtained in fuzzy multi-criteria group decision support system (FMCGDSS) [8].

A. Evaluation Framework

In this case study, the evaluation framework is composed by: 10 experts $E = \{e_1, e_2..., e_{10}\}$, who evaluate 8 scenarios $S = \{S_1, S_2..., S_8\} = \{MLCS, MPCS, MPLCS, MPLCSI, RLCS, RPCS, RPLCS, RPLCSI\}$, where each scenario are involved 44 criteria $C = \{c_1, c_2..., c_{44}\}$. For further detail about scenarios and criteria see [19].

In this case, the information is defined in the interval $[0, 1]$ because each expert gives two values to each criterion, worst and best values. In the interval, the value 0 represents the worst and the value 1 the best. Sometimes, experts could give the same values for the best and worst value, being the preference defined into a single numerical.

B. Gathering Information

In this phase, the information is gathered from the experts. Due to the great amount of information that we manage in this case study: (8 scenarios, 10 experts and 44 criteria), we show a reduced sample of the information gathered from the two experts, e_1 and e_2, about four criteria $\{c_1, c_2, c_3, c_4\}$ in two scenarios $\{MLCS, MPCS\}$ (see Table I).

TABLE I
An illustrative example of gathering information

	e_1		e_2	
	MLCS	MPCS	MLCS	MPCS
c_1	[.26, .30]	[.24, .29]	[.21, .25]	[.27, .30]
c_2	[.93, .96]	[.22, .51]	[.81, .86]	[.91, .94]
c_3	[.82, .84]	[.8, .53]	[.72, .78]	[.76, .82]
c_4	.12	.79	.79	.63

C. Rating Scenario

According to the evaluation model proposed in Section III, here, we show its application to our case study.

1) Step 1: Unification of the Information: The first step to unify the information is to choose the domain, S_T, where the information will be unified. This domain is a key in our model because the results will be verbalized in it.

In this case study, we have chosen the S_T represented in Figure 4.

$Perfect\ (s_6) = (.83, 1, 1)$ $VeryHigh\ (s_5) = (.67, .83, 1)$
$High\ (s_4) = (.5, .67, .83)$ $Medium\ (s_3) = (.33, .5, .67)$
$Low\ (s_2) = (.17, .33, .5)$ $VeryLow\ (s_1) = (0, .17, .33)$
$None\ (s_0) = (0, 0, .17)$.

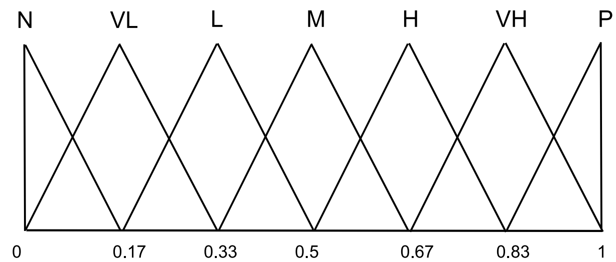

Fig. 4. Domain chosen to verbalize the results S_T

Once chosen the domain, we can transform all the information into the selected domain. To do so, we use different transformation functions and operators that allow to unify the heterogenous information and also to transform fuzzy sets over the S_T into linguistic 2-tuple.

To illustrate the case study, in Table II, we show the unified information into linguistic 2-tuple in S_T of Table I. Following, as example, we show the necessary transformations to unify the preference provided by the expert e_1 about the criterion c_1 of the scenario S_1 into linguistic 2-tuple.

TABLE II
An illustrative example of unified information of an expert

	e_1		e_2	
	MLCS	MPCS	MLCS	MPCS
c_1	$(L, -.32)$	$(L, -.5)$	$(VL, .38)$	$(L, -.29)$
c_2	$(P, -.33)$	$(L, .19)$	$(VH, -.45)$	$(P, -.33)$
c_3	$(VH, -.02)$	$(L, -.17)$	$(VH, -.50)$	$(VH, -.26)$
c_4	$(VL, -.28)$	$(VH, -.26)$	$(VH, -.26)$	$(H, -.22)$

$$\tau_{IS_T}([.26, .30]) = \{(s_0, 0), (s_1, .44), (s_2, .8), (s_3, 0), (s_4, 0), (s_5, 0), (s_6, 0)\}.$$

$$p_{11}^1 = \Delta(\chi(\tau([.26, .30]))) = \Delta(\frac{1 \cdot .44 + 2 \cdot .8}{.44 + .8}) = \Delta(1.64) = (s_2, -.32) = (Low, -.32).$$

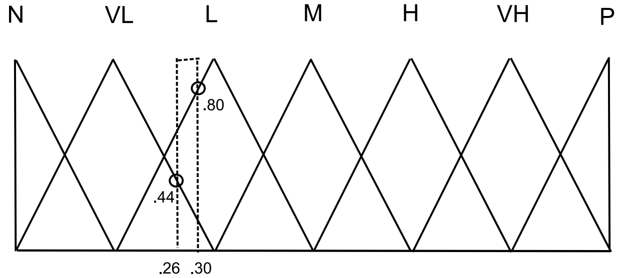

Fig. 5. Transforming an interval-value, $[0.26, 0.30]$, into a fuzzy set in S_T

2) Step 2: Aggregation of the Information: In this case study, it is applied a two-step aggregation process to compute a collective evaluation for evaluated scenarios, similar to [8]. In our problem, all the experts and criteria are equally important. Therefore, the arithmetic mean for linguistic 2-tuple are used to aggregate the information provided by the experts.

In this step, the process consists of two aggregation steps. As we have done in the previous steps, we show an example to illustrate this phase.

- *Computing evaluations by scenario for each expert*. For each scenario, S_j, evaluated by the expert e_i, using the aggregation operator arithmetic mean on the preferences of criterion c_k.

TABLE III
AN ILLUSTRATIVE EXAMPLE TO CALCULATE A COLLECTIVE VALUE OF EACH SCENARIO FOR AN EXPERT

	e_1		e_2	
	MLCS	MPCS	MLCS	MPCS
c_1	$(L, -.32)$	$(L, -.5)$	$(VL, .38)$	$(L, -.29)$
c_2	$(P, -.33)$	$(L, .19)$	$(VH, -.45)$	$(P, -.33)$
c_3	$(VH, -.02)$	$(L, -.17)$	$(VH, -.50)$	$(VH, -.26)$
c_4	$(VL, -.28)$	$(VH, -.26)$	$(VH, -.26)$	$(H, -.22)$
Collec. Values	$(M, .26)$	$(M, -.33)$	$(H, -.21)$	$(H, -.03)$

The collective value by the expert e_1 for the scenario S_1 is $(M, .26)$. It is obtained for the following way:

$$\Delta(\frac{\Delta^{-1}(s_2, -.32) + \Delta^{-1}(s_6, -.33) + \Delta^{-1}(s_5, -.02) + \Delta^{-1}(s_1, -.28)}{4})$$

$$\Delta(\frac{1.68 + 5.67 + 4.99 + 0.72}{4}) =$$

$$\Delta(3.26) = (s_3, .26) = (Medium, .26)$$

- *Computing a collective evaluation for each scenario*. The final aim of the rating process is to obtain a global evaluation, (u_j, α), for each evaluated scenario, S_j, according to all the experts. To do so, this process will aggregate the collective linguistic 2-tuple for each expert by using the arithmetic mean on the preferences of each scenario S_j.

As an illustrative example of how to obtain the collective evaluations for each scenario, below we compute such values with 2 out of 10 experts (the values with the 10 experts are showed in Table IV):

$$MLCS = \Delta(\frac{\Delta^{-1}(s_3, .26) + \Delta^{-1}(s_4, -.21)}{2}) =$$

$$MLCS = \Delta(\frac{3.26 + 3.79}{2}) =$$

$$\Delta(7.05) = (s_4, -.48) = (High, .48)$$

$$MPCS = \Delta(\frac{\Delta^{-1}(s_3, -.32) + \Delta^{-1}(s_4, -.02)}{2}) =$$

$$MPCS = \Delta(\frac{2.67 + 3.97}{2}) =$$

$$\Delta(3.32) = (s_3, -.32) = (Medium, .32)$$

In Table IV (third column), we show the collective results obtained in our case study where are involved 10 experts that evaluate 44 criteria for 8 scenarios.

3) Step 3: Ranking Scenarios: Finally, we put in order all collective evaluations and we establish a ranking among them with the purpose of identifying the best ones.

In the case study, $(Low, .179)$ is the highest collective value and it corresponds to the scenario S_7. Therefore, the best scenario is RPLCS.

The ranking of all scenarios is shown in Table IV.

D. Analyzing Results

The ranking obtained in our case study is equal to that obtained using the algorithm FMCGDSS [8] with the same data (see Table IV). This fact shows that our proposal is consistent.

TABLE IV
COMPARATIVE TABLE OF COLLECTIVE VALUES USING BOTH MODELS

	Our Model			FMCGDSS	
1	(S_7)	$(Low, .179)$	1	(S_7)	0.502452
2	(S_8)	$(Low, .135)$	2	(S_8)	0.492995
3	(S_5)	$(Low, -.079)$	3	(S_6)	0.447134
4	(S_6)	$(Low, -.180)$	4	(S_5)	0.445296
5	(S_4)	$(Low, -.285)$	5	(S_4)	0.428454
6	(S_3)	$(Low, -.325)$	6	(S_3)	0.416317
7	(S_1)	$(Low, -.384)$	7	(S_2)	0.391864
8	(S_2)	$(Low, -.482)$	8	(S_1)	0.390356

The collective evaluation obtained for the best scenario, S_7, in our model is $(Low, .179)$ and with the algorithm FMCGDSS is $.502452$. As we see, our collective evaluation facilitates the comprehension results because they are verbalized.

This analysis shows some of the improvements and advantages of the proposed model applied to the energy policies. The main achievement is that results are verbalized, facilitating their comprehension without loss of accuracy.

V. Conclusions

In this contribution, we have proposed an evaluation model applied to the energy policy selection based on the decision analysis that can manage different types of information (numerical, interval-valued and linguistic) with the aim to verbalize the results without loss of information. We have applied this model to a case study for evaluating long-term sustainable energy scenarios for Belgium and our model obtains similar results that other approaches using the same data, but in our case the results are verbalized, facilitating their understanding.

Acknowledgments

This contribution has been partially supported by the research projects TIN2009-08286 and P08-TIC-3548 (Spain) and BELSPO SD/EN/7A (Belgium).

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