Multi-criteria decision making with linguistic labels: A comparison of two methodologies applied to energy planning

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Abstract

This paper compares two multi-criteria decision making (MCDM) approaches based on linguistic label assessment. The first approach consists of a modified fuzzy TOPSIS methodology introduced by Kaya and Kahraman in 2011. The second approach, introduced by Agell et al. in 2012, is based on qualitative reasoning techniques for ranking multi-attribute alternatives in group decision-making with linguistic labels. Both approaches are applied to a case of assessment and selection of the most suitable types of energy in a geographical area.

Keywords: Fuzzy reasoning, Group decision making, Multi-criteria decision-making, Qualitative reasoning, Energy planning.

1 INTRODUCTION

Multi-criteria decision making under uncertainty and fuzzy systems are proved to be very suitable techniques in problems involving conflicting in particular in sustainable energy analysis and planning [1][2][3][4][5]. Fuzzy and qualitative reasoning techniques are applied to overcome uncertainty in human judgments that involve vague information. In these cases, it is often difficult to obtain exact numerical values for criteria and indicators [6] and fuzzy and qualitative reasoning are capable of representing uncertainty, emulating skilled humans, and handling vague situations. Frequently, this uncertainty is captured by using linguistic terms or fuzzy numbers to evaluate the set of criteria or indicators [7]. In addition, considering that in general not all the criteria have the same importance, setting up of weights is necessary. In a decisional process, assessment and selection of alternatives derive from complex hierarchical comparisons among them, which are often based on conflict criteria [8].

Recently, fuzzy systems are used as systematic tools for sustainability assessment. Different studies on energy planning have been developed to help energy planners and policy makers to design strategies for energy system models. The aim of this paper is to analyze and compare some MCDM approaches based on fuzzy and qualitative reasoning techniques for energy planning [9]. In particular, we compare two MCDM approaches based on linguistic label assessment. The first approach, introduced by Kaya and Kahraman in 2011,isbased on fuzzy TOPSIS methodology [10]. The second approach, introduced by Agell et al. in 2012, is based on qualitative reasoning techniques for ranking multi-attribute alternatives in group decision-making with linguistic labels [11].The main contribution of this paper is the comparison of both approaches in an example based on data provided in a paper by Kaya and Kahraman in 2011 [10],which is used to illustrate the mechanisms employed in both approaches and analyzes their similarities and differences.

The paper is organized as follows. Section 2 describes some relevant fuzzy MCDM methods applied to ranking and selection of alternatives. Section 3 introduces and compares two specific MCDM methods where fuzzy and qualitative alternatives' descriptions are considered. In Section 4 a case example based on renewable energies assessment is presented and a comparison of the results obtained by both methods is conducted. Finally, the last section highlights some conclusions and future research directions.

2 LITERATURE REVIEW

MCDM is a powerful tool used for evaluating problems and deal with the process of making decisions with multiple objectives, introduced in the early 1970s. It has two main purposes, the first one is describing trade-offs among different objectives and the other one is structuring decision process, defining and selecting alternatives, determining criteria formulations and weights, applying value judgments and finally evaluating the results to make

decisions. Most of MCDM approaches which can handle both quantitative and qualitative criteria, share the common characteristics of conflict among criteria and difficulties in design/selection of alternatives [1][3].

MCDM usually deals with three kinds of problems: choice problems, ranking problems and sorting problems. The goal of the decision maker in each type of problem is different: in choice problems the aim is to find the best alternative, in ranking problems we want to know the goodness of all alternatives, which is usually presented as a ranking from the best to the worst, and in sorting problems we want to know which alternatives belong to each class of a predefined set of ordered classes [12].

Reference point methods are a group of MCDM methodologies widely used for ranking problems. Among them we can highlight TOPSIS method, which was developed by Huang and Yong as an alternative to ELECTRE. TOPSIS is based on an aggregating function of the evaluation scores of the experts and determines the best alternative by calculating the distances from the positive and negative ideal solutions [13].

The question of how can the experts express their preferences to make a decision is a major issue to be faced. Therefore, most of the selection parameters cannot be given precisely and the evaluation data of the alternatives' suitability for various subjective criteria and the weights of the criteria are usually expressed in linguistic terms by the decision-makers [3].There exist many different representation formats that can be used in each model, i.e., preference orderings, utility values, multiplicative preference relations, fuzzy preference relations and so on. Every representation format has its own advantages and disadvantages, like precision or easiness of use and understanding. The use of Fuzzy Sets Theory, proposed by Zadeh in 1965 has given very good results for modeling qualitative information. It can be treated as a mechanism that mimics the human inference process with fuzzy information. It is a tool with the ability to compute with words to model qualitative human thought process in the analysis of complex systems and decisions. Therefore, fuzzy logic is appropriate for unstructured decision making [14].

On the other hand, Qualitative Reasoning (QR) is another subarea of Artificial Intelligence that tries to understand and explain human beings' ability to reason without having exact information. The main objective of QR is to develop systems that permit operating in conditions of insufficient or no numerical data [15]. Qualitative Reasoning also deals with problems in such a way that the principle of relevance is preserved, that is, each variable is valued with the level of precision required. In group decision evaluation processes, it is not unusual for a situation to arise in which different levels of precision have to be worked with simultaneously depending on the information available to each expert. QR tackles the problem of integrating the representation of existing uncertainty within the group [11].

As the importance of renewable energies since the 1990's has increased, a decision for governments and businesses to establish renewable energy systems in a suitable place and to decide which renewable energy source or combination of sources is the best choice to investment become an important issue [1][16][17]. It is necessary to change the energy structure, integrating new sources and modifying the way we use fossil fuel because of its damage to environment. The Kyoto Protocol of 1997 and after that the strategy of Europe 2020 can be mentioned as recent incentives in the European Union [18].

Energy planning problems are complex problems usually involving multiple decision makers (DMs) and multiple criteria. These problems are quite suited to the use of MCDM as a way of evaluating environmental sustainability [4][6][19]. Each country must prepare its own energies policies based on geographical and environmental factors due to their differences. For this reason, several strategies planning and researches have been done in different countries. A group of studies refers to applying MCDM methods as a strong tool in energy planning with their own categorization and introduced different methods [4][5][6][20][21].

3 TWO MULTI-CRITERIA DECISION MAKING APPROACHES

In general, in decision problems where the information is imprecise and involves uncertainty, alternatives cannot be assessed by means of precise numerical values. This fact is even more important when alternatives bear on uncertainty due to qualitative aspects of the involved variables. This uncertainty is usually framed in terms of preferences with interval or fuzzy values through a linguistic approach [11][22].

3.1. MODIFIED FUZZY TOPSIS

TOPSIS is a widely accepted multi-attribute decision-making technique due to its simultaneous consideration of the ideal and the anti-ideal solutions, and its easily programmable computation procedure [20]. In fuzzy TOPSIS, linguistic preferences are converted to fuzzy numbers. In Kaya and Kahraman study in 2011 [10] a modified fuzzy TOPSIS methodology is proposed to make a multi-criteria selection among energy alternatives.

The Kaya and Kahraman study uses triangle fuzzy numbers a linguistic term, that each triplet vector (τ_1,τ_2,τ_3) correspond to a linguistic term by using fuzzy membership functions as in Eq. 1.

$$\mu_{\tilde{\tau}}(x) = \begin{cases} 0, & x_{1\leq}\tau_1, \\ \frac{x-\tau_1}{\tau_2-\tau_1}, & \tau_1 \leq x \leq \tau_2, \\ \frac{x-\tau_3}{\tau_2-\tau_3}, & \tau_2 \leq x \leq \tau_3, \\ 0, & x \geq \tau_3, \end{cases} \quad (1)$$

Alternatives are assessed by means of the above fuzzy numbers by a group of DMs. Then, using a convenient set of weights, the corresponding fuzzy numbers are aggregated for each alternative. Then FPIS (fuzzy positive ideal solution) A^* and FNIS (fuzzy negative ideal solution) A^- are computed and the distance of each alternative from FPIS and FNIS is calculated by means of (Eq. 2):

$$d(\tilde{\rho},\tilde{\tau}) = \sqrt{\frac{1}{3}[(\rho_1-\tau_1)^2 + (\rho_2-\tau_2)^2 + (\rho_3-\tau_3)^2]} \quad (2)$$

Finally the closeness coefficient of each alternative is obtained by Eq. 3 and the alternatives ranked according to the maximum CC_i values.

$$CC_i = \frac{d_i^-}{d_i^*+d_i^-}, \quad i = 1,2 \dots, m. \quad (3)$$

3.2. A QUALITATIVE APPROACH

Agell et al. introduced in 2012 a qualitative approach for ranking alternatives described qualitatively inspired by the Reference Point Method which ranks the alternatives by using a distance function (previously defined on the absolute order-of-magnitude qualitative space) [11]. This technique uses qualitative assessments of alternatives and minimizes the distance between them and a certain target point that models the best performance for each criterion considered. It deals with the problem in such a way that the principle of relevance is preserved, i.e., each variable is valued with the level of precision required.

This approach uses a set of qualitative labels with different levels of precision. The basic labels, corresponding to linguistic terms, are defined by a discretization given by a set $\{a_1, \dots, a_{n+1}\}$ of real numbers as landmarks, $B_i = [a_i, a_{i+1}]$ $i = 1, \dots, n$. The non-basic labels describing different levels of precision, are defined as$[B_i, B_j] = [a_i, a_{j+1}]$ $i,j = 1, \dots, n$.
Then a location function is defined by the addition of measures of basic label to its right and to its left (Eq. 4).

$$I\left([B_i, B_j]\right) = (-(i-1), n-j) \quad (4)$$

This function codifies each alternative via a 2-m dimensional vector of integer numbers (being m the product of the number of experts by the number of criteria) and the vector $(B_n, \dots, B_n)$ is considered as a reference label to compute distances. Finally, alternatives are ranked according to their minimum distance to the reference label.

3.3. COMPARING BOTH METHODOLOGIES

Although both above presented MCDM approaches process uncertainty in different ways, they can deal with the same kind of linguistic information. Table 1 shows differences and similarities of these two methods (See Table 1).

Table 1: Differences and similarities of two methods

		Agell et al.	Kaya and Kahraman
Differences	Scale	Qualitative intervals	Fuzzy numbers
	Aggregation step	Distance to the maximum	Aggregation + distances to the positive and negative ideal solutions
	Normalization	Without prior normalization	With normalization
Similarities		Using linguistic labels	
		Using distance functions	

In order to demonstrate the potential of these methodologies, an application in the energy planning area will be presented.

4 A CASE EXAMPLE: RENEWABLE ENERGIES ASSESSMENT

Energy is a significant factor for economic development of countries. As economy advances and human society requires more energy, the lack of fossil energy and its pollution on the environment has given rise to a serious contradiction among energy providing, environment protection and economic development [4]. Therefore, renewable energy such as solar, wind, hydropower, biomass and geothermal are potential sources to supply global energy requirements in a sustainable way. The great advantages of these energy sources are primary, domestic, and clean and also considerable feature is inexhaustible energy sources [1]. The assessment and selection of the most suitable types of energy in a geographical area is a complex problem, involving technical, economic, environmental, political, and social criteria.

An example, based on data provided in a paper by Kaya and Kahraman in 2011, is used to illustrate the mechanisms employed in the approaches introduced in the above section. Then we analyze their similarities and differences [10].

4.1. ALTERNATIVES, CRITERIA AND INDICATORS FOR SUSTAINABILITY ASSESSMENT

We consider seven energy alternatives solar, wind, nuclear, biomass, hydraulic, combined heat and power and conventional.

Although some articles define different quantitative and qualitative indicators to assess energy planning, four main criteria are accepted by most of the researchers: technological, environmental, economic and social [5][8][19].

Next, both MCDM methods introduced in Section 3 are performed on the basis of nine indicators (See Table 2) - as conveniently weighted by a group of three experts using AHP [10].

Table 2: Criteria and Indicators

Technical	Economical	Environmental	Social
Efficiency	Investment cost	NO_X emission	Social acceptability
Exergy (rational) efficiency	Operation and maintenance cost	CO_2 emission	Job creation
		Land use	

4.2. RESULTS

Once determined the evaluation criteria, indicators, weights and the alternatives set, the steps of the modified fuzzy TOPSIS algorithm and qualitative reasoning are executed.

4.2.1. Modified Fuzzy TOPSIS

To determine the best energy alternative with the proposed fuzzy TOPSIS procedure, three experts evaluated the energy alternatives with respect to each indicator using Table 3.

Table 3: Fuzzy evaluation scores for the alternatives (Kaya and Kahraman)

Linguistic terms	Fuzzy numbers
Very Poor(VP)	(0,0,1)
Poor(p)	(0,1,3)
Medium Poor(MP)	(1,3,5)
Fair(F)	(3,5,7)
Medium Good(MG)	(5,7,9)
Good(G)	(7,9,10)
Very Good(VG)	(9,10,10)

Then experts' linguistic evaluations are normalized and aggregated to get a mean value for each pair-wise comparison and weighted normalized fuzzy decision matrix is constructed.

The procedure detailed in Subsection 3.1 was applied and according to the CC_i values, the best alternative is A4 (wind energy). The order of the rest of alternatives is Biomass, solar, CHP, hydraulic, nuclear, and conventional energy.

4.2.2. Qualitative Approach

The Agell et al. approach also uses in this example 7 basic qualitative labels (See Table 4).

Table 4: Qualitative evaluation scores for the alternatives (Agell et al.)

Linguistic terms	Qualitative labels	locations
Very Poor(VP)	B_1	(0,6)
Poor(p)	B_2	(-1,5)
Medium Poor(MP)	B_3	(-2,4)
Fair(F)	B_4	(-3,3)
Medium Good(MG)	B_5	(-4,2)
Good(G)	B_6	(-5,1)
Very Good(VG)	B_7	(-6,0)

Via the location function, each alternative is represented by a 54-dimensional vector of integer numbers (Eq. 5, Eq. 6), and the vector $(B_7, \dots, B_7)$ is considered as the reference label to compute distances.

$$A \leftrightarrow (\overbrace{L_{11}, \dots, L_{19}}^{Expert\ 1}, \overbrace{L_{21}, \dots, L_{29}}^{Expert\ 2}, \overbrace{L_{31}, \dots, L_{39}}^{Expert\ 3}) \quad (5)$$

$$A \leftrightarrow (X_{11}, \dots, X_{1,18}, X_{21}, \dots, X_{2,18}, X_{31}, \dots, X_{3,18}) \quad (6)$$

Then, the Euclidean weighted distance of each alternative to the reference vector is computed (Eq.7)

$$d(A, \tilde{A}) = \sqrt{\sum_{n=1}^{9} w_i (\sum_{k=1}^{6} (X_{ki} - \widetilde{X_{ki}})^2)} \quad (7)$$

Where w_i is the weight corresponding to each indicator. Then the alternatives are ranked according to the minimum distance.

4.2.3. Comparing Results

In the example, the proposed algorithms were implemented and wind energy is found to be the best alternative among other energy technologies in both studies for a particular scenario (considering w_1=0.09; w_2=0.1; w_3=0.1; w_4=0.11; w_5=0.13; w_6=0.15; w_7=0.11; w_8=0.09; w_7=0.12). Applying both, Kaya and Kahraman and Agell et al. methodologies, the final ranking obtained is:

wind > biomass > solar > CHP > hydraulic > nuclear > conventional energy.

So, although both MCDM linguistic approaches process uncertainty in different ways, their results produce the same ranking in this first scenario.
In addition, 4 scenarios (changing the weights for each criterion) have been considered to analyze the sensitivity of the results obtained by both methods. The results corresponding to these four scenarios, along with the first scenario's results, are summarized in Table 5. Differences between both rankings were found just in the shadowed

cells. In each shadowed cell the first energy source corresponds to Kaya and Kahraman methodology [10] and the second one to Agell et al. approach.

Table 5: Sensitivity Analysis

Scenario1	Scenario2	Scenario3	Scenario4	Scenario5
Wind	Biomass	Biomass	Wind	Biomass
Biomass	Wind	Wind	Solar/ Biomass	Solar
Solar	Solar	Solar	Biomass/ Solar	Wind/CHP
CHP	CHP	Nuclear/CHP	CHP	Nuclear/Wind
Hydra.	Nuclear/ Hydra.	CHP/Hydra.	Hydra.	CHP/Hydra.
Nuclear	Hydra./ Nuclear	Hydra./ Nuclear	Nuclear	Convent./ Nuclear
Convent.	Convent.	Convent.	Convent.	Hydra./ Convent.

As it can be seen in the table, the results obtained from both methodologies always coincide in the first option and in general they produce compatible rankings of alternatives. Higher differences were found in the last scenario. A plausible reason for these differences is that, in this case, the greater weights correspond to those indicators in which there was a greater disagreement among experts' scores [10], producing higher uncertainty.

4.3. CONCLUSION AND FUTURE WORK

Since qualitative criteria make the evaluation process hard and vague, it is suitable to express the judgments of experts in linguistic variables such as fuzzy numbers or qualitative intervals. In this paper two MCDM approaches based on linguistic label assessment have been compared and applied in an example in the energy sector. The modified fuzzy TOPSIS methodology proposed by Kaya and Kahraman utilizes fuzzy linguistic variables in the evaluation processes of both criteria and alternatives and in Agell et al.a group decision method is given for ranking the alternatives by comparing distances to a reference k-dimensional vector of qualitative labels.

For further research a new hybrid fuzzy-qualitative-based multi-criteria decision-making procedure in order to determine the most appropriate renewable energy alternative in a specific area can be developed. Moreover, the results of this study may be compared with the results of other fuzzy MCDM methods like ELECTRE, PROMETHEE, or VIKOR. Finally the theoretical framework including more indicators, such as waste management, public health risk, possible accidents impact or others can be extended.

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