Absolute order-of-magnitude reasoning applied to a social multi-criteria evaluation framework

A. Afsordegan[a], M. Sánchez[a], N. Agell[b1], J. C. Aguado[a] and G. Gamboa[c]

[a]Universitat Politècnica de Catalunya, Barcelona, Spain
[b]ESADE Business School, Universitat Ramon Llull, Barcelona, Spain
[c]Universitat Autònoma de Barcelona, Spain

A social multi-criteria evaluation framework for solving a real-case problem of selecting a wind farm location in the regions of *Urgell* and *La Conca de Barberà* in Catalonia (northeast of Spain) is studied. This paper applies a qualitative MCDA approach based on linguistic labels assessment able to address uncertainty and deal with different levels of precision. This method is based on qualitative reasoning as an artificial intelligence technique for assessing and ranking multi-attribute alternatives with linguistic labels in order to handle uncertainty. This method is suitable for problems in the social framework such as energy planning which require the construction of a dialogue process among many social actors with high level of complexity and uncertainty. The method is compared with an existing approach, which has been applied previously in the wind farm location problem. This approach, consisting of an outranking method, is based on Condorcet original method. The results obtained by both approaches are analyzed and their performance in the selection of the wind farm location is compared in aggregation procedures. Although results show that both methods conduct to similar alternatives rankings, the study highlights both their advantages and drawbacks.

Keywords. Absolute order-of-magnitude, Multi-criteria decision analysis, linguistic labels, qualitative reasoning, TOPSIS, energy planning.

1. Introduction

Multi-Criteria Decision Analysis (MCDA) includes various collections of mathematical techniques related to decision support systems for non-deterministic environments to support decision makers in a large range of applications such as energy planning. Since the 1960s and 1970s, MCDA has been known as one of the comprehensive tools to study the solution for different kinds of problems in which several alternatives are described with respect to a set of variables (Figueira, Greco, & Ehrgott, 2005). Recently a large number of challenges related to environmental issues, especially sustainable energy strategies using multi-criteria evaluation methods are being considered (Liu, 2007; Pohekar & Ramachandran, 2004; Wang, Jing, Zhang, & Zhao, 2009). Energy problems are addressing conflicting economic, technological, social and environmental aspects to provide an appropriate equilibrium of energy production and consumption

[1] Corresponding author. E-mail : nuria.agell@esade.edu

with minimum negative impact on environment. These aspects include several qualitative variables that are difficult to analyze and quantify; the information needed for their evaluation is imprecise and involves uncertainty. Some of the currently used MCDA methods support decision makers in all stages of the decision-making process by providing useful data to assess criteria with imprecise and uncertain value.

The structure of multi-criteria methods involves a set of alternatives, the corresponding criteria and the weights allocated to each criterion. The selection of the method depends on the specific type of problem, criteria features and context of use. For example, the problems in the social framework such as energy planning require the construction of a dialogue process among many social actors under uncertainty (Munda, 2004). Some of the most common methods used to support energy policy systems and energy planning towards sustainability are Analytical Hierarchy Process, ELECTRE, PROMETHEE and TOPSIS methods (Pohekar & Ramachandran, 2004). There exist many different representation preferences formats that can be used in each model, such as preference orderings, utility values, multiplicative preference relations, fuzzy and qualitative preference relations. Generally, the variables which are defined by words or sentences rather than numbers in a natural or artificial language are called linguistic variables (Zadeh, 1975). These variables can be used to assess alternatives under uncertainty. Each linguistic value is characterized by a label and a meaning as syntactic and semantic values, respectively. These preferences can be defined by using a linguistic approach involving qualitative labels (computing with words), to handle the high level of complexity and uncertainty (Catalina, Virgone, & Blanco, 2011; Doukas, Karakosta, & Psarras, 2010).

In this way, one of the systematic tools for assessment in social frameworks is Qualitative Reasoning (QR), which is a subfield of research in Artificial Intelligence (AI). This technique attempts to understand and explain the skill of human beings to reason without having precise knowledge. QR techniques are able to reason at a qualitative or symbolic level directly in terms of orders of magnitude. Qualitative absolute order-of-magnitude models were introduced by Dubois and Prade (1980), use QR models by means of a linguistic approach in terms of an interval algebra. It can be defined via intuitive landmark values, and it capable of working at different levels of precision (Forbus, 1984; Tapia García, del Moral, Martínez, & Herrera-Viedma, 2012). This technique can be integrated with multi-criteria decision making methods, such as TOPSIS, to evaluate alternatives with respect to different criteria for ranking problems.

Linguistic approaches have been widely used in MCDA methods in several fields such as power generation for tri-generation systems (Jing, Bai, & Wang, 2012; Nieto-Morote, Ruz-vila, & Canovas-rodriguez, 2010; Wang, Jing, Zhang, Shi, & Zhang, 2008), urban planning (Chang, Parvathinathan, & Breeden, 2008; Hsieh, Lu, & Tzeng, 2004; Mosadeghi, Warnken, Tomlinson, & Mirfenderesk, 2015), Life Cycle Impact Assessment (Cherubini & Strømman, 2011) and many others. In energy planning, different aspects of environmental assessments have been considered in various studies, for example developing the local energy sources to rank energy alternatives (Goumas & Lygerou, 2000), evaluating water resources (Dai, Qi, Chi, Chen, & Yang, 2010), assessing renewable energy alternatives (Doukas et al., 2010; Kahraman, Cebi, & Kaya, 2010; San Cristóbal, 2011) and finding optimal locations for energy projects (Aras, Erdoğmuş, & Koç, 2004; San Cristóbal, 2012; Yeh & Huang, 2014). Furthermore, different applications of fuzzy multi-criteria decision-making methods in energy planning can be found in Kahraman (2008).

The two main aims of this paper are the application to a wind farm location problem of qualitative TOPSIS methodology by using linguistic labels in a social framework, and the comparison of its results with C-K-Y-L (Condorcet-Kemeny-Young-Leveng) methodology, which was previously used in this specific case (Gamboa & Munda, 2007). This comparison between two models highlights their advantages and disadvantages and represents a first step in considering a possible integration of both methods in future studies.

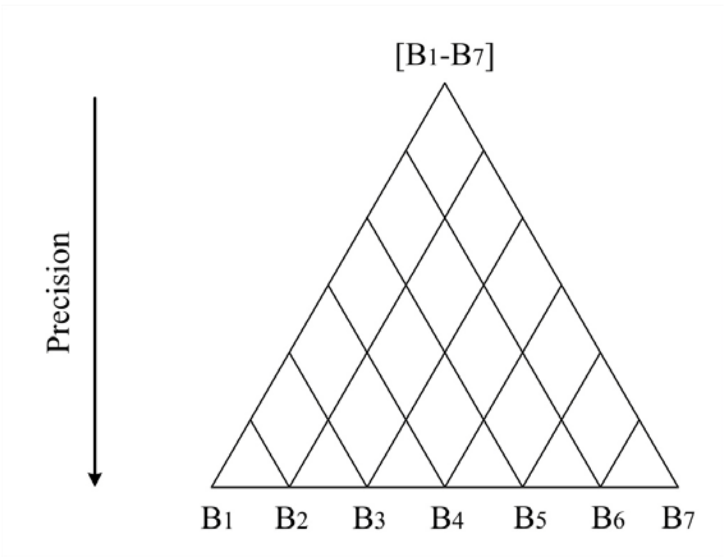
This article first describes the qualitative reasoning techniques and absolute order-of-magnitude theoretical framework. Next, it introduces qualitative TOPSIS methodology and the description of the algorithm which is applied to the wind farm location problem. Then, this method compares with the aggregation procedures of method based on Condorcet approach, and the results obtained in this application. Finally, it summarizes the main findings of the paper and some conclusions that maybe reached in future studies.

2. Theoretical framework

Qualitative reasoning techniques are an active subfield of research in AI applied to physical systems, where some magnitudes are not easy to quantify. Such techniques make it possible to reason at a qualitative or symbolic level, for example reasoning directly with respect to orders of magnitude. With such techniques, data can be managed in terms of absolute or relative orders-of-magnitude. Absolute orders-of-magnitude models usually consider a discretization of the real line in intervals corresponding to different qualitative labels.

The absolute order-of-magnitude (AOM) models are constructed via a partition of $\mathbb{R}$ which defines the quantity space S. The partition is defined by a set of real landmarks. Each element of the partition stands for a basic qualitative label; the set of basic labels is represented by $\mathbb{S}_* = \{B_1, \dots, B_n\}$. A general algebraic structure, called Qualitative Algebra, providing a mathematical structure which combines sign algebra and interval algebra is defined. This structure has been extensively studied by Travé-Massuyès et al. (2005). Figure 1 shows the linguistic hierarchy of qualitative labels corresponding to the absolute order-of-magnitude space $\mathbb{S}_7$.

Figure 1. The linguistic hierarchy corresponding to $\mathbb{S}_7$



For example, the seven classes can correspond to the following seven labels: Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (0), Positive

Small (PS), Positive Medium (PM) and Positive Large (PL). In absolute order-of-magnitude qualitative space, structures and the space of k-dimensional vectors of labels allow the representation of alternatives from linguistic evaluations of experts by basic label (e.g. $[\mathrm{B}_1]$ = Negative Large) or non-basic labels ($[\mathrm{B}_1 - \mathrm{B}_7]$ = Negative Large to Positive Large) which means that the expert doesn't have any specific knowledge in this case. The level of precision from top to down is increased by the expert`s knowledge.Techniques based on order-of-magnitude reasoning have provided theoretical models that can obtain results from non-numeric variables. The main advantage of this method is the capability of dealing 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. Another advantage is that it addresses the problem of integrating the representation of existing uncertainty within group decision-making problems (Forbus 1984).

With respect to the above, assessing alternatives via linguistic information in the form of qualitative labels is performed easily and decision-making problems can be solved by means of these three main actions: the choice of the linguistic term set with its semantic value, the choice of the aggregation operator to deal with linguistic information and, finally, the choice or ranking of the best alternatives according to the aggregation phase (Herrera & Herrera-Viedma, 2000).

Agell et al. (2012) present a new approach based upon QR techniques for representing and synthesizing the information given by a group of evaluators. A mathematical formulation is developed that contributes to decision analysis in the context of multi-criteria and group decision-making for ranking problems. The method used for ranking alternatives is based on comparing distances against a single optimal reference point which is modified in our proposed methodology, to capture the idea of TOPSIS methodology according to best and worst reference points. To do so, the proposed qualitative TOPSIS methodology and different steps of algorithm description are presented in the following section.

3. Proposed qualitative TOPSIS methodology

In this section the extension of the QR approach introduced in Agell et al. (2012) is considered together with TOPSIS decision-making methodology. TOPSIS, developed by Hwang and Yoon in 1981, is one of the MCDA techniques used to rank alternatives. The basic idea in TOPSIS that is used in this paper is that the compromise solution has the shortest distance to the positive "ideal" and the farthest distance from "negative ideal" solution (Hwang & Yoon, 1981). It is particularly useful for those problems in which the valuations of the alternatives on the basis of the criteria are not represented in the same units (Cables, García-Cascales, & Lamata, 2012).

Regarding Section 1, QR techniques manage data in terms of absolute order-of-magnitude qualitative labels corresponding to different intervals. When considering linguistic rather than numerical valuations, a qualitative operation is needed to rank alternatives. Our proposed methodology is presented the linguistic extension of TOPSIS multi-criteria method to with qualitative labels. The proposed qualitative TOPSIS algorithm description for linguistic variables is detailed in the following steps:

(1) Let us consider a set of possible alternatives $A = \{A_1, \dots, A_s\}$ and a set of criteria $C = \{C_1, \dots, C_m\}$ together with their weights defined by w_j such that $\sum_{j=1}^{m} \mathrm{w_j} = 1$. The assessment of alternatives with respect to criteria provides the decision matrix.

(2) Each alternative is represented by a k-dimensional vector of qualitative labels, being $k = r{\cdot}m$, where r and m are the number of experts and the number of criteria, respectively.
The expert's evaluations are given through a set of qualitative labels belonging to certain absolute order-of-magnitude spaces. The basic qualitative labels, corresponding to linguistic terms, are usually defined via a discretization given by a set $\{a_1, \dots, a_{n+1}\}$ of real numbers $a_1 < \cdots < a_{n+1}$, $B_i = [a_i, a_{i+1}]$ $i = 1, \dots, n$. The non-basic qualitative labels, describing different levels of precision, are defined by $[B_i,\ B_j] = [a_i,\ a_{j+1}]$, $i, j = 1, \dots, n,$ with $i < j$, considering $[B_i,\ B_i] = \ B_i$.

(3) A measure μ is defined over the set of basic labels. Then, the location function value of each qualitative label $[B_i,\ B_j]$ is introduced as an element in $\mathbb{R}^2$ whose first component is the opposite of the addition of the measures of the basic labels to the left of $[B_i, B_j]$ and whose second component is the addition of the measures of the basic labels to its right (Eq. 1):

$$\mathrm{l}\left(\left[B_i, B_j\right]\right) = \left(-\sum_{s=1}^{i-1} \mu(B_s)\,, \sum_{s=j+1}^{n} \mu(B_s)\right) \qquad (1)$$

(4) The location function is applied to each component of the k-dimensional vector of labels representing an alternative. Therefore, each alternative is codified via a vector in $\mathbb{R}^{2k}$. The reference labels to compute distances are, respectively, the minimum reference label, which is the vector $A^{-} = (B_1, \dots, B_1) \in \mathbb{R}^2$, and the maximum reference label, which is the vector $A^{*} = (B_n, \dots, B_n) \in \mathbb{R}^2$. Their location function values are as follows (Eq. 2 and Eq. 3):

$$L(A^{-}) \ = (0\,, \sum_{s=2}^{n} \mu(B_s)\,, \dots, 0\,, \sum_{s=2}^{n} \mu(B_s)) \qquad (2)$$

$$L(A^{*}) \ = (-\sum_{s=1}^{n-1} \mu(B_s)\,, 0, \dots, -\sum_{s=1}^{n-1} \mu(B_s)\,, 0) \qquad (3)$$

(5) Then it can be integrated with TOPSIS to compute the weighted Euclidean distances of each alternative location to A^{*} and A^{-} locations (Eq. 4).

$$d(X, Y) = \sqrt{\sum_{j=1}^{m} w_j \left(\sum_{k=1}^{2r} \left(X_{kj} - Y_{kj}\right)^2\right)} \qquad (4)$$

(6) The qualitative closeness coefficient (QCC_i) of each alternative is obtained by Eq. 5

$$QCC_i = \frac{d_i^{-}}{d_i^{*} + d_i^{-}}, \quad i = 1,2 \dots, m. \qquad (5)$$

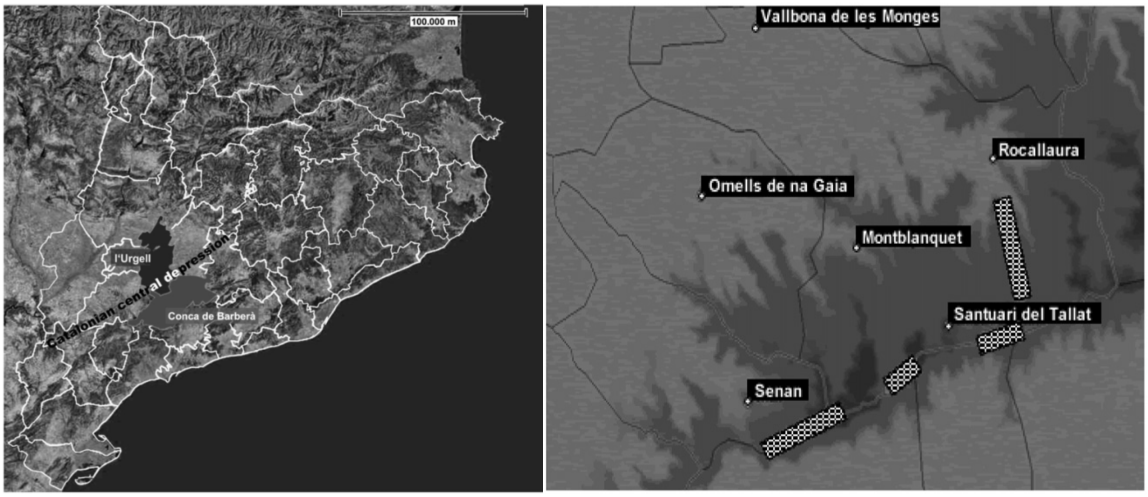
where d_i^{*} is the distance between $L(A_i)$ and $L(A^{*})$ location functions, meanwhile d_i^{-} is the distance between $L(A_i)$ and $L(A^{-})$ location functions. Finally, the alternatives are ranked by the decreasing order of QCC_i values.

Note that in qualitative TOPSIS algorithm, when utilizing linguistic terms the previous normalization of the weighted matrix is not necessary.

3.1. An application to the wind farm location problem in Catalonia

A case of wind farm location problem in Catalonia (northeast of Spain) (Gamboa & Munda, 2007), in a region between the counties of *Urgell* and *Conca de Barberà*, is used to illustrate the potential of the proposed method in Section 3 (see Figure 2).

Figure. 2. *Urgell* and *Conca de Barberà* counties and technical feasibility zones



The rapid development in wind energy technology has led to it being considered promising alternative to conventional energy systems. It is argued that wind energy, being a powerful source of renewable energy with rapid and simple installation, lack of emissions and low water consumption, is one of the most promising tools for confronting global warming (Aras et al., 2004). Nevertheless, wind farm location is a problem that involves multiple and conflicting factors related to public opinion and public interest. To find the best wind farm location, the relevant economic, social, technical and environmental perspectives must be taken into account, as well as the decision-making process to reach a decision. Some studies have examined these key factors (Lee, Chen, & Kang, 2009; Wolsink, 2010; Yeh & Huang, 2014).

Considering the two preliminary alternatives corresponding to *Coma Bertran* and *Serra del Tallat* projects, other alternatives were generated based on the technological and economic feasibility, and acceptance of some social actors involving in this project (considering the worry of some people about the visual impact of the wind farms). Table 1 indicates the different alternatives that were finally proposed for the location of the desired wind farms. Two modified projects L and R consider the reduction of visual impact of the original proposals.

Table 1. Alternatives for the location of wind farm

Alternatives
CB-Pre: Coma Bertran Preliminary project.
CB: Coma Bertran project.
ST: Serra del Tallat project.
CBST: Combination of CB and ST projects.
L: Based on CB and ST projects, this alternative considers the windmills located at least 1.5 km from population centers and potential tourist attractions (Santuari del Tallat).
R: This option attempts to move the windmills away from population centers presenting higher resistance to the wind farms (Senan and Montblanc)
NP: the possibility of constructing no project at all.

These alternatives are evaluated on the basis of nine indicators which are defined by combining information from participatory processes, interviews and a review of the projects performed by the research group (see Table 2). Note that in this study, equal weights for indicators are considered.

Table 2. Evaluation Criteria

Criteria	Indicators	Direction
Economic	Land owner`s income	+
	Economic activity tax	+
	Construction tax	+
Social	Number of jobs	+
	Visual impact	-
Ecological	Deforestation	-
	Avoided CO2 emissions	+
	Noise	-
Technical	Installed capacity	+

3.2. Results

The criteria scores were computed to construct the multi-criteria impact matrix. Table 3 presents the impact matrix of the problem we are dealing with. The criteria scores are obtained from the study of Gamboa & Munda (2007). These scores must be aggregated by means of the proposed algorithm to achieve the final ranking of the alternatives.

Table 3. Multi-criteria impact matrix

Criteria	CB-Pre	CB	ST	CBST	L	R	NP
Land owner`s income (€/year)	48000	33000	99000	132000	78000	72000	-
Economic activity tax (€/year)	12750	15470	46410	61880	36570	33750	-
Construction tax (€)	61990	55730	96520	15250	81890	67650	-
Number of jobs (Jobs)	2	1	4	5	3	3	-
Visual impact (km^2)	76057	71.465	276.55	348.015	220.4	163.29	-
Deforestation (ha)	804	8.1	6.6	14.7	3.9	2.6	-
Avoided CO_2 emissions (ton CO_2 /year)	4680	6010	19740	25750	14740	13760	-
Noise (dB(A))	14.64	23.86	18.6	23.84	20.88	14.66	-
Installed capacity (MW)	13.6	16.5	49.5	66	39	36	-

To this end, the steps of the qualitative TOPSIS algorithm, detailed in Section 3, are executed. The highest and lowest scores of each criterion are respectively considered, in this case, as the maximum and minimum elements of the qualitative space, and therefore as reference labels. The first step of this algorithm is assigning qualitative labels to the quantitative scores to simplify the computation in the process of ranking. Table 4 shows these qualitative labels together with their locations, obtained directly from Eq. 1 where the considered measure μ over the set of basic labels is $\mu(B_i) = 1$, for all i= 1,…,7. The qualitative TOPSIS approach considered in this example uses seven basic qualitative labels for each criterion. The basic qualitative labels correspond to seven intervals defined from minimum and the maximum values of the corresponding raw scores in Table 3 and their lengths, which are one seventh of the distance between these two values. For instance, land owner`s income indicator has the same label (B_4) in projects L and R, because both of them stand on the same interval B_4. In the same way, the rest of labels are provided to construct the qualitative impact matrix (Table 5).

Table 4. Different levels of qualitative labels

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)

Table 5. Qualitative impact matrix

Criteria	**CB-Pre**	**CB**	**ST**	**CBST**	**L**	**R**	**NP**
Land owner`s income	B3	B2	B5	B7	B4	B4	B1
Economic activity tax	B2	B2	B5	B7	B4	B4	B1
Construction tax	B3	B3	B5	B7	B6	B3	B1
Number of jobs	B3	B2	B6	B7	B5	B5	B1
Visual impact	B6	B6	B3	B1	B4	B5	B7
Deforestation	B3	B3	B4	B1	B6	B6	B7
Avoided CO2 emissions	B2	B2	B6	B7	B5	B4	B1
Noise	B3	B1	B2	B1	B1	B3	B7
Installed capacity	B2	B2	B5	B7	B4	B4	B1

Each alternative (A) is represented by a 9-dimensional vector of qualitative labels $\mathrm{A} = (\mathrm{C}_1, \dots, \mathrm{C}_9)$, obtained from assessment of indicators (C).
As mentioned in Section 3, each label is represented via a vector in $\mathbb{R}^{2\mathrm{k}}$. Therefore, the location function L(A) codifies each alternative by an 18-dimensional vector of real numbers representing the position of the vector A, $\mathrm{L(A)} = (\mathrm{X}_1, \dots, \mathrm{X}_{18})$.

Table 6 shows the alternative evaluation matrices via the locations of the nine indicators. The two vectors $\mathrm{L(A^-)} = \mathrm{L(B_1, \dots, B_1)} = (0,6, \dots ,0,6)$ and $\mathrm{L(A^*)} = \mathrm{L(B_7, \dots, B_7)} = (-6,0, \dots, -6,0)$ are considered as reference labels to compute distances (worst and best options).

Table 6. Location impact matrix

Criteria	**CB-Pre**	**CB**	**ST**	**CBST**	**L**	**R**	**NP**
Land owner`s income	(-2,4)	(-1,5)	(-4,2)	(-6,0)	(-3,3)	(-3,3)	(0,6)
Economic activity tax	(-1,5)	(-1,5)	(-4,2)	(-6,0)	(-3,3)	(-3,3)	(0,6)
Construction tax	(-2,4)	(-2,4)	(-4,2)	(-6,0)	(-5,1)	(-2,4)	(0,6)
Number of jobs	(-2,4)	(-1,5)	(-5,1)	(-6,0)	(-4,2)	(-4,2)	(0,6)
Visual impact	(-5,1)	(-5,1)	(-2,4)	(0,6)	(-3,3)	(-4,2)	(-6,0)
Deforestation	(-2,4)	(-2,4)	(-3,3)	(0,6)	(-5,1)	(-5,1)	(-6,0)
Avoided CO2 emissions	(-1,5)	(-1,5)	(-5,1)	(-6,0)	(-4,2)	(-3,3)	(0,6)
Noise	(-2,4)	(0,6)	(-1,5)	(0,6)	(0,6)	(-2,4)	(-6,0)
Installed capacity	(-1,5)	(-1,5)	(-4,2)	(-6,0)	(-3,3)	(-3,3)	(0,6)

Then, the weighted Euclidean distance of each alternative from the two reference labels is calculated by means of Eq. 6.

$$d(A, \tilde{A}) = \sqrt{\sum_{j=1}^{9} w_i (X_j - \widetilde{X}_j)^2)} \qquad (6)$$

The considered weights in this case are equal and the procedure detailed in Section 3 was applied. Table 7 shows the values of the distances to the reference labels of each alternative together with the values of the $\mathrm{QCC_i}$.

Table 7. Closeness coefficient factors

	d_i^-	d_i^*	QCC_i
CB-Pre	3.26	5.88	0.35
CB	2.90	6.56	0.30
ST	5.33	3.88	0.57
CBST	6.92	4.89	0.58
L	5.12	4.26	0.54
R	4.73	4.13	0.53
NP	4.89	6.92	0.41

According to the maximum $\mathrm{QCC_i}$ values, the best alternative is CBST and the order of the remaining of alternatives is ST > L > R > NP > CB-Pre > CB.

4. Comparison of the qualitative TOPSIS and a Condorcet based method

There are many multi-criteria models that can be used to obtain a ranking of the available alternatives (Polatidis, Haralambopoulos, Munda, & Vreeker, 2006; Roy & Słowiński, 2013). Each of them has its own advantages and disadvantages. The reason for selecting the C-K-Y-L method for this comparison is its simple adaptation for social choice and sustainability issues. In addition, in this method a weakness of criteria is not compensated by strength of other desirable criteria, and using non-compensatory models in a social framework helps preserve all social actors' opinions. We assume this method can be further enhanced via combining it with QR methods. Let us first introduce the C-K-Y-L method briefly in the following subsection and then compare both the advantages and drawbacks of two methods applied to the wind farm location problem.

4.1. C-K-Y-L outranking method

The C-K-Y-L method was presented as a combination of the original Condorcet approach and the future attempts of Kemeny, Young and Levenglick (Young & Levenglick, 1978) in the study of social framework by Munda (2005). This model integrates social, economic and technical factors inside a coherent framework and is a powerful model for energy policy analysis. The underlying idea for the development of this method was to enrich the dominance relation by some elements based on preference aggregation. In the C-K-Y-L method, the decision maker compares two alternatives according to preferences and indifferences between them (expressed by indifference and preference thresholds defined for each criterion) (Eq. 7).

$$a_j P a_k \Leftrightarrow g_m(a_j) > \ g_m(a_k) + q \qquad (7)$$

$$a_j I a_k \Leftrightarrow \left| g_m(a_j) - \ g_m(a_k) \right| q$$

where P and I indicate a "preference" and an "indifference" relation, respectively and q is the positive indifference threshold. It means a higher value of criterion score is preferred to lower one (when criterion is for maximizing) and the same scores indicate an indifference relation when the difference between criteria is no more than the threshold. The maximum likelihood ranking of N alternatives is the ranking supported by the maximum number of criteria for each pair-wise comparison, summed over all pairs of alternatives considered. The outranking matrix composed by N (N-1) pair-wise comparisons between alternatives. By means of a pair-wise comparison between alternative j and k, an outranking matrix with elements e_{jk} is constructed using Eq. 8:

$$e_{jk} = \sum_{m=1}^{M} \left(w_m(P_{jk}) + \frac{1}{2} w_m(I_{jk}) \right) \tag{8}$$

where w_m indicates the weight of each criterion. Considering that there are N! possible complete rankings of alternatives, the corresponding score φ_s is computed for each one of them and the final ranking is the one that maximizes φ_s (Eq. 9).

$$\varphi_s = \sum e_{jk} \qquad j \neq k, s = 1,2, \ldots N! \text{ and } e_{jk} \in e_s \tag{9}$$

4.2. Results Comparison

In this section, qualitative TOPSIS is compared with C-K-Y-L methodology, not only comparing the results obtained by both methodologies but also comparing their main theoretical features.

The results provided by the C-K-Y-L method in Gamboa & Munda (2007) present the five best rankings with the maximum score among all 5040 possible rankings according to the seven alternatives (see Table 8).

Table 8. Best rankings

C-K-Y-L	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Ranking 1	CBST	ST	L	R	CB	CB-Pre	NP
Ranking 2	CBST	ST	L	R	CB-Pre	CB	NP
Ranking 3	CBST	L	ST	R	CB	CB-Pre	NP
Ranking 4	CBST	ST	R	L	CB	CB-Pre	NP
Ranking 5	CBST	ST	L	R	CB	NP	CB-Pre

To sum up, Table 9 shows the final ranking produced by qualitative TOPSIS together with the first ranking obtained by applying the C-K-Y-L method.

Table 9. Ranking results

Ranking	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Qualitative TOPSIS	CBST	ST	L	R	NP	CB-Pre	CB
C-K-Y-L	CBST	ST	L	R	CB	CB-Pre	NP

As shown in Table 9, the differences of rankings occurred in the case of the NP option. In the proposed qualitative TOPSIS method, the option of No Project is not considered as a worst option because it depends on the distance of this alternative from the best and worst scores. So, the intensity of preferences is considered. In contrast, C-K-Y-L method does not consider this intensity and this alternative always loses in the pair-wise comparison against all the others. Also, the qualitative TOPSIS constructs only one ranking, whereas C-K-Y-L explores all N! possible Rankings, which represent different social actors' preferences.

Although these two methods have produced similar rankings, they have different characteristics in the structure of aggregation procedures. The qualitative TOPSIS method does not require the handling of the previous discretization or definition of landmarks to define initial qualitative terms because the calculations are performed directly with the labels; the computations are very fast and easy. This method considers the intensity of preferences. In contrast, the C-K-Y-L method uses a maximum likelihood approach as an aggregation function, which makes it more difficult to compute; in fact, and it becomes unmanageable as the number of alternatives rises.

Additionally, the qualitative TOPSIS method can address different levels of precision, from the basic labels representing the most precise ones to the least precise label which can be used to represent unknown values. This strength of the proposed method has not been used in this real example with given evaluation scores. On the other hand, C-K-Y-L avoids compensation and trade-offs by representing the weights as the importance coefficients. Therefore, low scores on one criterion cannot be compensated by high scores on another. Table 10 shows the main characteristics of both methodologies.

Table 10. Comparison of both ranking methodologies

	Qualitative TOPSIS	**C-K-Y-L**
Scale	Qualitative labels	Ordinal/interval/ratio scales
Compensatory	Compensatory Model	Non-Compensatory Model
Weights	Trade-off	Importance coefficients
Aggregation step	Based on distance function	Outranking and pair-wise comparison
Aggregation function	Distance to the maximum and minimum	Maximum likelihood approach

These differences suggest that both methods could be used together synergistically. For instance the qualitative TOPSIS can more efficiently to process data when it is qualitative from the beginning; meanwhile C-K-Y-L can enforce the absence of compensation.

5. Conclusion

Generally, the variables which are defined by words or sentences rather than numbers in a natural or artificial language are called linguistic variables. These variables can be used to assess alternatives under uncertainty. Techniques based on order-of-magnitude QR have provided theoretical models that can obtain results from non-numeric variables.

This paper introduces a MCDA application to wind farm location selection based on a qualitative TOPSIS methodology. This method takes into account intensity of preferences and gives experts the ability to assess alternatives under uncertainty. In addition, in the case of providing data from expert's preferences, it enables them to express their preferences with an appropriate degree of precision (from the absolute to unknown opinions). This is a desirable feature in order to consider transparent decision processes. The results are compared with C-K-Y-L methodology based on outranking. This approach is strongly recognized from a sustainability point of view as a non-compensatory method. This method does not take the intensity of preferences into account; however, one of its advantages is that it pays attention to the important issue that a social or environmental disaster cannot be compensated with another criterion such as economic success.

In future research the integration of both methods will be considered. On the one hand, the use of non-compensatory methods is considered very useful in sustainability problems as mentioned above. On the other hand, the use of qualitative labels determined by a partition of the real line, introduced in QR, is considered to provide an appropriate evaluation framework for group decision-making under uncertainty. In future research new real cases will be considered to apply the proposed method using different levels of precision in alternative assessments.

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