Int. J. Environ. Sci. Technol. (2016) 13:1419–1432
DOI 10.1007/s13762-016-0982-7

ORIGINAL PAPER

Decision making under uncertainty using a qualitative TOPSIS method for selecting sustainable energy alternatives

A. Afsordegan[1] · M. Sánchez[2] · N. Agell[1] · S. Zahedi[3] · L. V. Cremades[4]

Received: 11 March 2015 / Revised: 11 March 2016 / Accepted: 15 March 2016 / Published online: 12 April 2016

Abstract Multi-criteria decision-making methods support decision makers in all stages of the decision-making process by providing useful data. However, criteria are not always certain as uncertainty is a feature of the real world. MCDM methods under uncertainty and fuzzy systems are accepted as suitable techniques in conflicting problems that cannot be represented by numerical values, in particular in energy analysis and planning. In this paper, a modified TOPSIS method for multi-criteria group decision-making with qualitative linguistic labels is proposed. This method addresses uncertainty considering different levels of precision. Each decision maker's judgment on the performance of alternatives with respect to each criterion is expressed by qualitative linguistic labels. The new method takes into account linguistic data provided by the decision makers without any previous aggregation. Decision maker judgments are incorporated into the proposed method to generate a complete ranking of alternatives. An application in energy planning is presented as an illustrative case example in which energy policy alternatives are ranked. Seven energy alternatives under nine criteria were evaluated according to the opinion of three environmental and energy experts. The weights of the criteria are determined by fuzzy AHP, and the alternatives are ranked using qualitative TOPSIS. The proposed approach is compared with a modified fuzzy TOPSIS method, showing the advantages of the proposed approach when dealing with linguistic assessments to model uncertainty and imprecision. Although the new approach requires less cognitive effort to decision makers, it yields similar results.

Keywords Multi-criteria decision making · Linguistic labels · TOPSIS · Qualitative reasoning · Energy planning

Introduction

Since social and economic development is affected by the appropriate energy planning, evaluating sustainable energy alternatives when determining valid energy policies is essential. However, assessing and selecting the most suitable and sustainable types of energy in a geographical area is a complex problem. For governments and businesses, important decisions include whether to establish energy systems in a given place and deciding which energy source, or combination of sources, is the best option when considering potentially conflicting criteria including environmental, technical and economic aspects (Baños et al. 2011; Karimi et al. 2011). These criteria in energy problems involve different qualitative and quantitative variables and require specific techniques to aggregate and summarize assessments made in such complex situations.

Multi-Criteria Decision-Making (MCDM) approaches, introduced in the early 1970s, are powerful tools used for

✉ N. Agell
nuria.agell@esade.edu

[1] ESADE Business School, Ramon Llull University, Av. Pedralbes, 60, 08034 Barcelona, Spain

[2] Department of Mathematics, Universitat Politècnica de Catalunya, UPC-BarcelonaTech, Edifici Omega, C/Jordi Girona Salgado,1-3, 08034 Barcelona, Spain

[3] Department of Business Administration, Universitat Politècnica de Catalunya, UPC-BarcelonaTech, Av. Diagonal, 647, 08028 Barcelona, Spain

[4] Department of Engineering Projects, Universitat Politècnica de Catalunya, UPC-BarcelonaTech, Av. Diagonal, 647, 08028 Barcelona, Spain

evaluating problems and addressing the process of making decisions with multiple criteria. MCDM involves structuring decision processes, defining and selecting alternatives, determining criteria formulations and weights, applying value judgments and evaluating the results to make decisions in design, or selecting alternatives with respect to multiple conflicting criteria (Carlsson and Fuller 1996; Yilmaz and Dadeviren 2011). Moreover, MCDM techniques have a strong decision support focus and interact with other disciplines such as intelligent systems dealing with uncertainty. Some of the currently used MCDM methods, in which the present study can be included, support decision makers in all stages of the decision-making process by providing useful data to assess criteria with uncertain values (Kara and Onut 2010).

The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981), is one of the most well-known distance-based approaches for such decision making. TOPSIS ranks the alternatives with respect to their geometric distance from the positive and negative ideal solutions. This approach is categorized as one of the MCDM methods in which value judgments of criteria are expressed through crisp values. However, in real situations when analyzing and quantifying different types of variables from different spheres, it is generally found that the information is imprecise and lacks crispness due to inaccurate estimates of values from decision maker judgments (Herrera et al. 2008; Parreiras et al. 2010). Thus, in real situations, where the information is imprecise, the alternatives can be better assessed by means of fuzzy sets or linguistic variables (Herrera et al. 2008; Ashtiani et al. 2009). In particular, in the case of MCDM under uncertainty, fuzzy systems have been proven to provide very suitable techniques for a remarkable range of real-world problems and, in particular, in energy planning. This is because these processes have many sources of uncertainty, long time frames, intensive investments, multiple decision makers and many conflicting criteria (Liu 2007; Tuzkaya et al. 2009).

When artificial intelligence (AI) techniques are used in the development or assessment of alternatives, the resulting systems are referred to as intelligent decision support systems. These techniques attempt to understand and explain the skill of human beings in reasoning without precise knowledge (Doumpos and Grigoroudis 2013). Qualitative reasoning (QR) techniques and fuzzy systems, which are considered subfields of research in AI, offer systematic tools for criteria assessment. Frequently, this uncertainty is captured by using linguistic terms or fuzzy numbers to evaluate the set of criteria or indicators. In different studies, fuzzy MCDM approaches have been developed to help energy planners and policy makers. In fact, fuzzy and QR techniques are capable of representing uncertainty, emulating skilled humans, and handling vague situations (Dubois and Prade 1980; Tuzkaya et al. 2009). Application of the fuzzy set theory, established by Zadeh (1965), plays an important role in overcoming uncertainties. Qualitative absolute order-of-magnitude models were introduced into the QR field with the aim of using a linguistic approach to work with different levels of precision (Travé-Massuyès et al. 2005).

This paper contributes to the MCDM literature, and especially to the models able to support uncertainty in decision making, by developing a new methodology to support decision making in complex areas like energy problems. The method offers decision makers the possibility to work with qualitative scales in their assessments. Moreover, different levels of precision for different experts based on their certain or uncertain knowledge helps to keep all the information of their assessments instead of allowing some information to be ignored. For example, if decision makers do not have enough knowledge about one criterion, they can indicate a range between "Very poor-Medium" instead of an exact assessment. Even if decision makers don't have any idea of the value for a specific attribute, they can use the label "I don't know," modeled by "Very poor-Very good." In this direction, the main contribution of this paper is a qualitative modified TOPSIS method, which is introduced and applied for selecting sustainable energy alternatives in a case example. This new method handles uncertainty and imprecision by means of such linguistic labels. Its main advantage is that, on the one hand, experts can make mistakes if they are forced to make more precise judgments than the available information allows. On the other hand, a substantial loss of information may happen if the experts are forced to make less precise judgments. By allowing flexibility as to precision, this method is able to capture the inherent ambiguity existing in human reasoning.

The proposed method is based on QR techniques for ranking multi-criteria alternatives in group decision making with linguistic labels with different levels of precision. It is inspired by a previous ranking method introduced by Agell et al. (2012). The presented method is compared with another MCDM approach based on a modified fuzzy TOPSIS method developed by Chen (2000). This comparison is performed using an example based on data provided by Kaya and Kahraman (2011).

Related work

Energy is a crucial factor for the economic development of nations. As economies and human society advances, more energy is required. The increasing scarcity of fossil fuel energy and its pollution of the environment have given rise to serious contradictions among the competing priorities of energy provision, environmental protection, and economic development. Since the importance of renewable energies has increased, a crucial decision for governments and businesses is deciding the best choice of energy source policies for investment (Polatidis et al. 2006).

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. In addition, energy planning problems usually involve multiple decision makers. These problems require the use of MCDM to evaluate environmental sustainability. Because of their differences, each country must prepare its own energy policies based on geographical and environmental factors to address sustainability issues. It is necessary to change the energy structure, integrating new sources and modifying the way we use fossil fuel, because of its damage to the environment. For this reason, several planning strategies have been utilized in different countries.

Many studies have applied MCDM methods as a useful tool in energy planning (Tzeng et al. 1992; Georgopoulou et al. 1998; Pohekar and Ramachandran 2004; Loken 2007; Tsoutsos et al. 2009; Kahraman et al. 2010; Moghaddam et al. 2011; Yeh and Huang 2014). For instance, in a study by Tsoutsos et al. (2009), a set of energy alternatives were determined for different sources of energy on the island of Crete in Greece. The study constitutes an exploratory analysis for regional energy planning in creating classifications of sustainable energy alternatives. Pohekar and Ramachandran (2004) reviewed different published papers on MCDM and considered their applications in the renewable energy area. Another review of the various types of renewable energy models such as solar, wind, biomass and bio-energy is conducted by Jebaraj and Iniyan (2006). Wang et al. (2009) conducted a literature review on MCDM methods used for the selection of energy and their applications to energy issues. The review identifies four main criteria categories for the evaluation of energy sources and site selection problems: technical, economic, environmental and social.

Table 1 shows the most important MCDM methods used for assessing energy policy and management: AHP; PROMETHEE; ELECTRE; and TOPSIS (Pohekar and Ramachandran 2004). Beccali et al. (1998) introduced a methodological tool able to organize the large set of variables of several specific assessments that help the decision maker in a complex problem. The authors used the ELECTRE methods to decide upon involving the use or non-use of fuzzy set concepts on the Italian island of Sardinia for renewable energy diffusion strategy planning. The case study explored the advantages and drawbacks of each ELECTRE methodology. In 2003, Beccali et al. used ELECTRE III to select the most suitable innovative technologies in the energy sector. Three decision scenarios were posited, each representing a coherent set of actions, and different fuzzification strategies were analyzed. In the study of Boran et al. (2012), intuitionistic fuzzy TOPSIS was introduced to evaluate renewable energy technologies for electricity generation in Turkey.

The use of criteria and indicators is a common way to describe and monitor complex systems and provide information for decision makers. Four main criteria from a sustainability point of view are accepted by experts in the literature review on the application of the MCDM techniques in energy planning: technological, environmental, economic, and social (Begic and Afgan 2007; Doukas et al. 2007; Wang et al. 2008, 2009). Table 2 shows the most important "criteria" and "indicators" used in recent MCDM studies conducted on energy issues. Each indicator is assigned to a specific criterion, and the corresponding study citations are included.

In this study, from among the indicators in Table 2 the most frequently used indicators in the literature have been considered: efficiency; exergy (rational efficiency); investment cost; operation and maintenance cost; NO_X emission; CO_2 emission; land use; social acceptability; and job creation.

To evaluate different sources of energy with respect to these indicators, TOPSIS is one of the best known reference level models in the energy area. TOPSIS was developed by Hwang and Yoon (1981) and is based on an aggregating function of the evaluation scores of experts; it determines the best alternative by calculating the distances from the positive and negative ideal solutions. The basic idea is that the preferred alternative should have the shortest distance from the ideal solution and the farthest distance from the negative ideal solution (Opricovic and Tzeng 2004; Hwang and Yoon 2005). Behzadian et al. (2012) studied various literature reviews in sustainable energy policy, energy planning, and suitable indicators for assessing energy using the TOPSIS methodology.

Using linguistic variables and TOPSIS approach, which takes values from a set of linguistic terms, was reported in some studies for the evaluation of energy policy options (Doukas et al. 2010; Kahraman et al. 2010). Doukas et al. (2010) presented an extension of a numerical multi-criteria TOPSIS method for processing linguistic information in the form of 2-tuple fuzzy numbers. He shows how energy policy objectives for sustainable development and renewable energy sources options are assessed using linguistic variables. Kaya and Kahraman (2011) applied the modified fuzzy TOPSIS, which takes an evaluated fuzzy decision matrix as input to the selection of the best energy alternative.

Linguistic variables enable experts to express their preferences as a major issue to be faced for making a

Table 1 Review of MCDM applied to energy issues

Method	Focus	Author(s)
AHP	Ranking energy alternatives	Akash et al. (1999), Kablan (2004) and Nigim et al. (2004)
MAUT	Examining energy policy	Buehring et al. (1978)
	Strategic energy planning	Pan and Rahman (1998)
Goal Programming	Energy resource planning	Meier and Hobbs (1994)
	Renewable energy planning	San Cristóbal (2012)
TOPSIS	Evaluating renewable energy	Cavallaro (2010b) and Boran et al. (2012)
	Assessing energy policy objectives	Doukas et al. (2010)
	Selecting the best energy alternative	Kaya and Kahraman (2011); Proposed method
PROMETHEE II	Ranking energy alternatives	Georgopoulou et al. (1998) and Goumas and Lygerou (2000)
PROMETHEE I and II	Assessing renewable energies	Topcu and Ulengin (2004)
	Sustainable energy planning	Tsoutsos et al. (2009)
	Assessing energy technologies	Tzeng et al. (1992) and Oberschmidt et al. (2010)
ELECTRE III	Energy planning	Beccali et al. (2003) and Cavallaro (2010a)

Table 2 The most important criteria and indicators used in MCDM studies on energy issues

Criteria	Indicators	Author(s)
Technical	Efficiency	Begic and Afgan (2007) and Evans et al. (2009)
	Exergy (rational efficiency)	Kaya and Kahraman (2011)
	Reliability	Jing et al. (2012) and Kahraman et al. (2010)
	Technical risk	Nigim et al. (2004)
	Energy payback time	Stamford and Azapagic (2011)
	Capacity	Varun et al. (2009)
Economic	Investment cost	Evans et al. (2009), Wang et al. (2009) and Streimikiene et al. (2012)
	Operation and maintenance cost	Evans et al. (2009) and Jing et al. (2012)
	Internal rate of return (IRR)	Wang et al. (2009)
	Payback period (PBP)	Rovere et al. (2010) and Jing et al. (2012)
	Net present value	Rovere et al. (2010)
	Availability of funds	Stamford and Azapagic (2011)
Environmental	NO_X emission	Kaya and Kahraman (2011) and Rovere et al. (2010)
	CO_2 emission	Kaya and Kahraman (2011) and Rovere et al. (2010)
	CO emission	Kaya and Kahraman (2011) and Rovere et al. (2010)
	Suspended particulate matter emission (SPM)	Begic and Afgan (2007) and Wang et al. (2009)
	Land use	Beccali et al. (2003)
	Noise	Streimikiene et al. (2012)
	Environmental risk	Rovere et al. (2010)
Social	Social acceptability	Kaya and Kahraman (2011)
	Job creation	Begic and Afgan (2007) and Rovere et al. (2010)
	Health risk	Wang et al. (2009)
	Fatal accidents	Stamford and Azapagic (2011)

decision. Most of the selection parameters cannot be given precisely, and decision makers usually express the evaluation data of the suitability of the alternatives for various subjective criteria, and the weights of the criteria, in linguistic terms (Belton and Stewart 2002; Wang et al. 2009). There are many different representation formats that can be used in each model, such as preference orderings, utility values, multiplicative preference relations, fuzzy preference relations and so on. Every representation format has its own advantages and disadvantages, such as precision or ease of use and understanding. The use of fuzzy sets theory has achieved very good results for modeling qualitative information. Such modeling 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 the qualitative human thought process in the analysis of complex systems and decisions. Therefore, fuzzy logic is appropriate for unstructured decision making (Zadeh 1975).

QR is another sub-area of AI that attempts to understand and explain the ability to reason without having exact information. The main objective of QR is to develop systems that enable operation in conditions of insufficient or no numerical data (Forbus 1984; Travé-Massuyès et al. 2005). QR also addresses 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 used simultaneously depending on the information available to each expert. QR tackles the problem of integrating the representation of existing uncertainty within the group (Agell et al. 2012).

Linguistic approaches have been widely used in MCDM methods in several fields such as power generation for trigeneration systems (Nieto-Morote et al. 2010; Wang et al. 2008; Chang et al. 2008), life cycle impact assessment (Kara and Onut 2010; Cherubini and Strømman 2011), and urban planning (Chang et al. 2008; Kowkabi et al. 2013; Mosadeghi et al. 2015), among others. In energy planning, different aspects of environmental assessments have been considered in various studies, and examples include: developing local energy sources to rank energy alternatives (Goumas and Lygerou 2000), evaluating water resources (Dai et al. 2010), assessing renewable energy alternatives (Doukas et al. 2007; Kahraman et al. 2010) and finding optimal locations for energy projects (Aras et al. 2004; San Cristóbal 2012; Yeh and Huang 2014; Afsordegan et al. 2016). Doukas et al. (2007) present a MCDM approach with linguistic variables to assist policy makers in formulating sustainable technologies in a Greek energy system. Furthermore, different applications of fuzzy MCDM methods in energy planning can be found in Kahraman (2008).

Materials and methods

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 in the study of Agell et al. for ranking alternatives, based on comparing distances against a single optimal reference point, has been modified in the method proposed in this paper to capture the idea of the TOPSIS approach according to the best and worst reference points. To do so, the proposed method of TOPSIS, namely "Qualitative TOPSIS" (Q-TOPSIS) is defined after some preliminaries are introduced.

Preliminaries

Absolute qualitative order-of-magnitude models

The absolute order-of-magnitude (AOM) models are constructed via a partition of an interval in $\mathbb{R}$ which defines the set of basic labels. The partition is defined by a set of real landmarks. A general algebraic structure called qualitative algebra is defined; it provides a mathematical structure that combines sign algebra and interval algebra. This structure has been extensively studied by Travé-Massuyès et al. (2005).

Definition 1 Let $[a_1, a_{n+1}]$ be a real interval and $\{a_1,\ldots,a_{n+1}\}$ a set of real landmarks, with $a_1 < \cdots < a_{n+1}$. The basic labels are defined by $B_i = [a_i, a_{i+1}]$, $i = 1,\ldots,n$.

Each basic label B_i corresponds to a linguistic term. In a generic sense, if $r < s$, then $B_r < B_s$, meaning that B_s is strictly preferred to B_r, such as "extremely bad" < "very bad."

Definition 2 The non-basic labels describing different levels of precision are defined as $[B_i, B_j] = [a_i, a_{j+1}]$ where $i, j = 1,\ldots,n$, and $i < j$. The label $[B_i, B_j]$ corresponds to the concept "between B_i and B_j."

In 2012, Agell et al. introduced a qualitative approach for ranking alternatives described qualitatively that was inspired by the reference point method. This approach ranks a set of alternatives $\{A_1,\ldots,A_l\}$ by using a distance function. This technique uses qualitative linguistic assessments of alternatives and minimizes the distance between them and a certain target point that models the best performance for each criterion considered. The approach considers that each alternative is defined by a set of r criteria, and each criterion is evaluated by the judgments of a team of m experts. These evaluations are given by means of a set of qualitative labels with different levels of precision belonging to a certain order-of-magnitude space $\mathbb{S}_n = \{[B_i, B_j] | i,j = 1,\ldots,n+1, i \leq j\}$, considering $[B_i, B_i] = B_i$.

In this way, each alternative A_i, $i = 1,\ldots,l$, is represented by a k-dimensional vector of labels in $(\mathbb{S}_n)^k$, $A_i \leftrightarrow (A_{i_{11}}, \ldots, A_{i_{1m}}, \ldots, A_{i_{r1}}, \ldots, A_{i_{rm}})$, k being the product of the number of criteria and the number of experts: $k = r{\cdot}m$. Distances between linguistic k-dimensional vectors of basic and non-basic labels are computed by using the location function in $\mathbb{S}_n$, which enables one to move from an ordinal scale to a cardinal scale and is defined as follows.

Definition 3 The location function definition in $\mathbb{S}_n$ is the function $l : \mathbb{S}_n \to \mathbb{Z}^2$ such that:

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

where μ is any measure defined over the set of basic labels, for instance, $(B_i) = ([a_i, a_{i+1}]) = a_{i+1} - a_i$.

In other words, the location function of a qualitative label $[B_i, B_j]$ is defined as a pair of real numbers whose components are, respectively, the opposite of the addition of the measures of the basic labels to its left and the addition of the measures of the basic labels to its right.

By applying a function l to each component of the k-dimensional vector of labels, each alternative A_i is codified via a $2k$-dimensional vector of real numbers: $L(A_i) = (l(A_{i_{11}}), \ldots, l(A_{i_{1m}}), \ldots, l(A_{i_{r1}}), \ldots, l(A_{i_{rm}}))$.

AHP method to compute weights

Special attention has been paid to the definition of the criteria weights for aggregation functions in the MCDM literature. Weights given to different criteria are particularly important to obtain the overall preferential value of the alternatives (Choo et al. 1999). Based on aggregation procedures of MCDM models, the criteria weights can be used in different ways. Weights can be defined as trade-off or importance coefficients. In MCDM methods based on distance functions, weights are obtained by trade-off among criteria such as pair-wise comparison. In particular, in this study, the well-known analytical hierarchy process (AHP) is used to obtain weights of criteria to evaluate energy alternatives.

AHP was developed by Saaty in the late 1980s (Saaty 1980, 1990). It evaluates the importance of each criterion in relation to the others in a hierarchical manner. The AHP method is based on structure of the model, comparative judgment of criteria and synthesis of the priorities (Karimi et al. 2011). In the first step, a complex problem is broken into a hierarchy with goal as an objective, criteria and sub-criteria at levels and sub-levels like a family tree. The second step begins with prioritization procedure in order to determine the relative importance of the criteria within each level. The evaluation of the hierarchy is based on pairwise comparison to assess the DM preferences from the second level to lowest one (Amiri 2010). At the last step, the relative weights for each matrix have been found and normalized. The AHP is considered a single synthesizing criterion approach (Ishizaka and Nemery 2013).

This process can be performed with both qualitative and quantitative criteria. In addition, to deal with the uncertainty involved in some complex problems, a fuzzy approach of AHP method, where linguistic variables are used to represent the experts' opinion, was developed (Laarhoven and Pedrycz 1983). The fuzzy AHP considers the fuzziness and vagueness of the decision makers (Kuo et al. 2015; Russo and Camanho 2015). In general, experts use linguistic terms, which are translated into fuzzy evaluation scores and weights are finally expressed via triangle fuzzy numbers.

The proposed Q-TOPSIS method

The TOPSIS method proposed in this paper, called "Q-TOPSIS," can process information represented by qualitative terms in the absolute order-of-magnitude model that was introduced in Subsection *Absolute qualitative order-of-magnitude models*.

Let us consider a set of alternatives $\{A_1,\ldots, A_l\}$, each one defined by a set of r criteria, with each criterion assessed by a team of m experts. These assessments are given by means of a set of qualitative labels with different levels of precision belonging to a certain order-of-magnitude space $\mathbb{S}_n$. Therefore, each alternative A_i, $i = 1,\ldots,l$ is represented by a k-dimensional vector of labels, k being the product of the number of criteria and the number of experts:

$$A_i \leftrightarrow (A_{i_{11}}, \ldots, A_{i_{1m}}, \ldots, A_{i_{r1}}, \ldots, A_{i_{rm}}),$$
$$A_{i_{jh}} \in \mathbb{S}_n, i = 1, \ldots, l, \quad j = 1, \ldots, r, h = 1, \ldots, m$$

We consider the qualitative positive reference label (QPRL) as the k-dimensional vector $A^* = (B_n, \ldots, B_n)$, and the qualitative negative reference label (QNRL) as the k-dimensional vector $A^- = (B_1,\ldots,B_1)$, which are considered as reference labels to compute distances. Their location function values are in:

$$L(A^*) = \left(-\sum_{s=1}^{n-1} \mu(B_s), 0, \ldots, -\sum_{s=1}^{n-1} \mu(B_s), 0 \right) \quad (2)$$

$$L(A^-) = \left(0, \sum_{s=2}^{n} \mu(B_s), \ldots, 0, \sum_{s=2}^{n} \mu(B_s) \right) \quad (3)$$

Both the Euclidean weighted distances of each alternative location $L(A_i)$, $i = 1,\ldots,l$, to A^* and A^- locations are then calculated, thus $d(L(A_i), L(A^*))$ and

$d(L(A_i), L(A^-))$, by applying Eq. 4 to the vectors $(X, Y) = d(L(A_i), L(A^*))$ and $(X, Y) = d(L(A_i), L(A^-))$ respectively:

$$d(X, Y) = \sqrt{\sum\nolimits_{i=1}^{r} w_i \sum\nolimits_{j=1}^{2m} \left(X_{ji} - Y_{ji}\right)^2} \quad (4)$$

where w_i is the weight corresponding to the ith indicator, and X_{ij}, Y_{ji}, $j = 1,\ldots,2\ m$, $i = 1,\ldots,r$, are, respectively, the components of X and Y. Finally, the qualitative closeness coefficient of each alternative is obtained by Eq. 5, and the alternatives are ranked according to the decreasing order of QCCi values.

$$\mathrm{QCC}_i = \frac{d_i^-}{d_i^* + d_i^-}, \quad i = 1, 2\ldots, l. \quad (5)$$

where d_i^* and d_i^- are, respectively, the distance between the alternative location $L(A_i)$ and the QPRL location $L(A^*)$ and the QNRL location $L(A^-)$. The ranking of alternatives can be determined according to the pre-order defined by the values of QCC$_i$, and the closer to A^* and further from A^- the alternative A_i, the greater the value of QCC$_i$. In such a case, common in TOPSIS methodology, the alternative A_i with the maximum QCC$_i$ is chosen as the best option.

Results and discussion

A case example application of Q-TOPSIS for selecting sustainable energy alternatives

To demonstrate the potential of this methodology, an application for selecting sustainable energy alternatives is presented. A case example, based on data provided in a paper by Kaya and Kahraman (2011), is used to illustrate the introduced approach. This case example enables us to show the main advantages of the Q-TOPSIS method with respect to the existing methods, i.e., classic TOPSIS and fuzzy TOPSIS. Specifically, the ability of the proposed method is to capture the uncertainty inherent in human reasoning and by allowing experts to use "different levels of precision" in their assessments. Although this is not specific for energy issues, and it may applicable in general for selecting the best from a set of alternatives, its suitability for selecting sustainable energy alternatives is clearly shown. Using linguistic labels with different levels of precision for expert assessment is crucial when some experts do not have enough knowledge about some aspect.

Alternatives, criteria, and indicators for sustainability assessment

Seven alternatives were examined in the current paper: conventional (A_1), nuclear (A_2), solar (A_3), wind (A_4), hydraulic (A_5), biomass (A_6) and combined heat and power (CHP) (A_7). Nine indicators, with reference to the most frequently used technical, economic, environmental, and social criteria in evaluating energy options, were selected to assess the given alternatives. Note that in this study in order to compare results with Kaya and Kahraman (2011), the same indicators have been selected and other important indicators, such as environmental and health risk, and environmental emissions such as CO, SO_2 and SPM, were not considered. For this reason, the Q-TOPSIS method is performed on the basis of these nine indicators, as weighted by a group of three experts.

The considered indicators according to each criterion are: efficiency (I_1) and exergy (rational efficiency) (I_2) as technological indicators; investment cost (I_3) and operation and maintenance cost (I_4) as economic indicators; NO_X emission (I_5), CO_2 emission (I_6), and land use (I_7) as environmental indicators; and social acceptability (I_8) and job creation (I_9) as social indicators.

The considered indicators' weights are: $w_1 = 0.09$; $w_2 = 0.1$; $w_3 = 0.1$; $w_4 = 0.11$; $w_5 = 0.13$; $w_6 = 0.15$; $w_7 = 0.11$; $w_8 = 0.09$; and $w_9 = 0.12$ using fuzzy AHP method. It is assumed that all the criteria are benefit criteria. For instance, if energy source is evaluated as "very good" in terms of "CO_2 emission," this means that the CO_2 emission level for energy option is "very low."

Results

Once the criteria evaluation is determined and the indicators, weights, and alternatives are specified, the Q-TOPSIS algorithm steps are executed. The Q-TOPSIS approach considered in this example uses seven basic qualitative labels. Table 3 shows these qualitative labels together with their locations, considering the measure μ over the set of basic labels $\mu(B_i) = 1$, for all $i = 1,\ldots,7$.

Each expert assesses each alternative by means of nine qualitative labels (one for each indicator). Therefore, each alternative A is represented by a 27-dimensional vector of qualitative labels.

Table 3 Evaluation scores

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)

$$A \leftrightarrow \left(E_{1,1}, \ldots, E_{1,9}, E_{2,1}, \ldots, E_{2,9}, E_{3,1}, \ldots, E_{3,9}\right) \quad (6)$$

As mentioned, the location function then codifies each alternative by a 54-dimensional vector of real numbers.

$$A \leftrightarrow \left(X_{1,1}, \ldots, X_{1,18}, X_{2,1}, \ldots, X_{2,18}, X_{3,1}, \ldots, X_{3,18}\right) \quad (7)$$

Note that the vector in Eq. 7 for each alternative A_i is obtained by combining the ith rows of the three matrices given in Table 4. Considering separately the assessments made by the three energy planning experts (E_1, E_2, and E_3), Table 4 shows the alternatives' evaluation matrices via the locations of the nine indicators.

The two vectors $L(A^-) = L(B_1,\ldots,B_1) = (0,\ 6,\ldots,0,\ 6)$ and $L(A^*) = L(B_7,\ldots,B_7) = (-6, 0, \ldots, -6, 0)$ are considered as the reference labels to compute distances. The qualitative Euclidean distance of each alternative from the QPRL and QNRL is then calculated by means of (Eq. 8):

$$d\left(A, \tilde{A}\right) = \sqrt{\sum\nolimits_{i=1}^{9} w_i \sum\nolimits_{j=1}^{6} \left(X_{ji} - \tilde{X}_{ji}\right)^2} \quad (8)$$

Weights mentioned in the previous subsection are considered: $w_1 = 0.09$; $w_2 = 0.1$; $w_3 = 0.1$; $w_4 = 0.11$; $w_5 = 0.13$; $w_6 = 0.15$; $w_7 = 0.11$; $w_8 = 0.09$; and $w_9 = 0.12$; and the procedure detailed in Subsection *Q-TOPSIS method* was applied. Table 5 shows the values of the distances to the QPRL and QNRL of each alternative together with the values of the QCC_i

According to the QCC_i values, the best alternative is A_4 (wind energy). The order of the remaining alternatives is biomass (A_6), solar (A_3), CHP (A_7), nuclear (A_2), hydraulic (A_5) and conventional energy (A_1).

Comparing Q-TOPSIS with modified fuzzy TOPSIS

Q-TOPSIS is compared with the modified fuzzy TOPSIS methodology in two different aspects. In the first subsection, we compare theoretically the two methodologies, and in the second subsection, we compare the results obtained in Subsection *A case example application of Q-TOPSIS for selecting sustainable energy alternatives* with the results obtained in Kaya and Kahraman (2011) using the modified fuzzy TOPSIS developed by Chen (2000). The main reasons for comparing the proposed method with modified fuzzy TOPSIS are that both methods are TOPSIS methods, and both capture uncertainty through linguistic labels. Therefore, as modified fuzzy TOPSIS method in some theoretical points is close to Q-TOPSIS, it has been selected for this comparison in order to show the new contribution of our method.

Table 4 Qualitative decision matrices

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
E_1									
A_1	(−5, 1)	(−5, 1)	(−4, 2)	(−4, 2)	(0, 6)	(0, 6)	(−1, 5)	(−2, 4)	(−4, 2)
A_2	(−6, 0)	(−3, 3)	(0, 6)	(−6, 0)	(−2, 4)	(−2, 4)	(−2, 4)	(−1, 5)	(−5, 1)
A_3	(−3, 3)	(−3, 3)	(−3, 3)	(−3, 3)	(−6, 0)	(−5, 1)	(−6, 0)	(−5, 1)	(−3, 3)
A_4	(−2, 4)	(−4, 2)	(−5, 1)	(−5, 1)	(−5, 1)	(−6, 0)	(−6, 0)	(−6, 0)	(−3, 3)
A_5	(−4, 2)	(−5, 1)	(−4, 2)	(−3, 3)	(−2, 4)	(−1, 5)	(−2, 4)	(−3, 3)	(−5, 1)
A_6	(−3, 3)	(−4, 2)	(−3, 3)	(−3, 3)	(−5, 1)	(−5, 1)	(−4, 2)	(−5, 1)	(−5, 1)
A_7	(−3, 3)	(−4, 2)	(−3, 3)	(−2, 4)	(−3, 3)	(−3, 3)	(−4, 2)	(−5, 1)	(−4, 2)
E_2									
A_1	(−6, 0)	(−4, 2)	(−5, 1)	(−3, 3)	(0, 6)	(−2, 4)	(0, 6)	(−1, 5)	(−5, 1)
A_2	(−5, 1)	(−6, 0)	(−2, 4)	(−6, 0)	(−2, 4)	(−2, 4)	(0, 6)	(−2, 4)	(−5, 1)
A_3	(−2, 4)	(−3, 3)	(−4, 2)	(−3, 3)	(−6, 0)	(−5, 1)	(−5, 1)	(−5, 1)	(−4, 2)
A_4	(−3, 3)	(−4, 2)	(−5, 1)	(−5, 1)	(−5, 1)	(−6, 0)	(−5, 1)	(−6, 0)	(−3, 3)
A_5	(−3, 3)	(−5, 1)	(−4, 2)	(−3, 3)	(−2, 4)	(−1, 5)	(−2, 4)	(−3, 3)	(−4, 2)
A_6	(−3, 3)	(−3, 3)	(−4, 2)	(−3, 3)	(−5, 1)	(−5, 1)	(−4, 2)	(−5, 1)	(−5, 1)
A_7	(−4, 2)	(−3, 3)	(−3, 3)	(−2, 4)	(−3, 3)	(−3, 3)	(−5, 1)	(−4, 2)	(−4, 2)
E_3									
A_1	(−6, 0)	(−6, 0)	(−4, 2)	(−4, 2)	(−2, 4)	(−2, 4)	(−1, 5)	(−2, 4)	(−4, 2)
A_2	(−6, 0)	(−6, 0)	(0, 6)	(−6, 0)	(−1, 5)	(−2, 4)	(−2, 4)	(−2, 4)	(−5, 1)
A_3	(−3, 3)	(−3, 3)	(−3, 3)	(−3, 3)	(−5, 1)	(−5, 1)	(−5, 1)	(−5, 1)	(−3, 3)
A_4	(−1, 5)	(−4, 2)	(−5, 1)	(−6, 0)	(−6, 0)	(−6, 0)	(−5, 1)	(−6, 0)	(−3, 3)
A_5	(−5, 1)	(−5, 1)	(−4, 2)	(−3, 3)	(−2, 4)	(−1, 5)	(−2, 4)	(−3, 3)	(−5, 1)
A_6	(−3, 3)	(−4, 2)	(−3, 3)	(−4, 2)	(−5, 1)	(−5, 1)	(−4, 2)	(−5, 1)	(−4, 2)
A_7	(−4, 2)	(−3, 3)	(−4, 2)	(−3, 3)	(−3, 3)	(−3, 3)	(−4, 2)	(−5, 1)	(−4, 2)

Table 5 Q-TOPSIS results

	d_i^-	d_i^*	QCCi
A_1	8.514	9.033	0.485
A_2	9.278	8.657	0.517
A_3	10.528	5.420	0.660
A_4	12.119	4.435	0.732
A_5	8.204	7.973	0.507
A_6	10.490	4.876	0.682
A_7	9.136	6.495	0.584

Methods comparison

The modified fuzzy TOPSIS developed by Chen (2000) that takes an evaluated fuzzy decision matrix as input is a popular tool to analyze the ideal alternative. This MCDM technique determines the best alternative by calculating the distances from the fuzzy positive and fuzzy negative ideal solutions according to an aggregation of the expert fuzzy evaluation scores. In modified fuzzy TOPSIS, linguistic preferences are converted to fuzzy triangle numbers (π_1, π_2, π_3). Table 6 shows the main differences between Q-TOPSIS and the modified fuzzy TOPSIS method. The differences noted in Table 6 represent four significant improvements over modified fuzzy TOPSIS.

Generally speaking, both methods use linguistic variables, but in different ways: Q-TOPSIS in the form of qualitative labels with different levels of precision and fuzzy TOPSIS by means of linguistic labels corresponding to triangle fuzzy numbers. Furthermore, the final aggregation process of both methods finds the distance between each alternative and the best and worst solutions. However, there are some differences between these two methods. Firstly, the Q-TOPSIS method does not require any previous discretization or definition of landmarks for defining initial qualitative terms because the calculations are performed directly with the labels through the location functions. In contrast, in the modified fuzzy TOPSIS, fuzzy labels are defined by means of cut-points that have to be set before any aggregate triangle fuzzy numbers. Secondly, the Q-TOPSIS method can address different levels of precision, from the most precise and basic labels to the least precise label [B_1, B_n], which can be used to represent unknown values. In this way, experts are not forced to make more precise judgments than they are capable of; as mentioned earlier, sometimes decision makers can make mistakes if they are required to make more precise judgments than the available information allows. Finally, the Q-TOPSIS methodology computations do not need to use an aggregation of expert assessments or a prior normalization. The former involves a loss of information, and the latter concentrates expert assessments into a given range, which causes reduced differences. However, as can be seen in the next subsection, the results obtained by applying both methodologies are similar.

Results comparison and sensitivity analysis

Modified fuzzy TOPSIS has been applied to the data summarized in Subsection *A case example application of Q-TOPSIS for selecting sustainable energy alternatives*. Three experts evaluated the seven energy alternatives [conventional, nuclear, solar, wind, hydraulic, biomass and combined heat and power (CHP)] with respect to each one of the nine technical, economic, environmental, and social indicators using linguistic terms defined by the triangle fuzzy numbers given in Table 7.

For the particular scenario ($w_1 = 0.09; w_2 = 0.1; w_3 = 0.1; w_4 = 0.11; w_5 = 0.13; w_6 = 0.15; w_7 = 0.11; w_8 = 0.09$; and $w_9 = 0.12$), the modified fuzzy TOPSIS provided the following alternatives ranking: wind > biomass > solar > CHP > hydraulic > nuclear > conventional energy. Both algorithms were implemented using the same data, and wind energy was found to be the best alternative among other energy technologies on both studies for this particular scenario. Although both MCDM linguistic approaches process uncertainty in different ways, their results produce the similar rankings.

In addition, a sensitivity analysis that considered the four other scenarios, changing the weights considered for each criterion (Table 8), was carried out to analyze the results when applying both approaches. It is a crucial issue in any multi-criteria method to determine whether the final ranking is dependent and sensitive to the estimates of the criteria weights.

The results of applying both approaches are summarized in Table 9. Differences were found just in the shaded cells. In each shaded cell, the first item always shows the Q-TOPSIS result and the second item shows the modified fuzzy TOPSIS result.

Table 6 Differences between the two methods

Differences	Q-TOPSIS	Fuzzy TOPSIS
Scale	Qualitative labels	Fuzzy triangle numbers
Granularity	Multi-granularity	Fixed granularity
Aggregation step	Without prior aggregation	Weighted mean
Normalization	Without prior normalization	Normalization

Table 7 Fuzzy evaluation scores for the alternatives

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)

Table 8 Different weights of indicators for five scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
C_1	0.09	0.2	0.2	0.05	0.3
C_2	0.1	0.1	0.15	0.05	0.05
C_3	0.1	0.05	0.05	0.1	0.05
C_4	0.11	0.05	0.05	0.1	0.05
C_5	0.13	0.1	0.2	0.15	0.2
C_6	0.15	0.1	0.05	0.15	0.05
C_7	0.11	0.1	0.05	0.15	0.05
C_8	0.09	0.1	0.05	0.15	0.05
C_9	0.12	0.2	0.2	0.1	0.2

Table 9 shows that the results obtained from both methodologies always coincide in the first option, and in general, they produce compatible rankings of alternatives. In particular, in Scenario 2, both methodologies produce exactly the same ranking. Greater differences were found in the last scenario. A plausible reason for this finding is that the variability (standard deviation) of the weights used in the last scenario is significantly greater than in the rest of the scenarios. Moreover, increasing the criteria weight of C_1 changes the position of the wind energy alternative in the last scenario, meaning that this option is largely dependent on the weights of efficiency indicator. The alternatives which are changed in the positions were more sensitive to the criteria weights changes.

Finally, to study the similarity between both ranking methods, a simulation was conducted including 30 other scenarios in which the weights considered changed randomly for each criterion. Figure 1 shows the correlation coefficient values obtained in the 30 scenarios. To this end, the Spearman's rho and the Kendall's tau correlation coefficients were computed for each of the 30 scenarios. In all the scenarios, highly significant values (p value < 0.05) were obtained. The mean and the standard deviation for these coefficients were: $\bar{\rho} = 0.97$ and $\bar{\tau} = 0.93$, and $S_\rho = 0.037$ and $S_\tau = 0.082$, respectively. The results indicate a high correlation between the results obtained using both methods.

Table 9 Sensitivity analysis

Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Wind	Biomass	Biomass	Wind	Biomass
Biomass	Wind	Wind	Biomass/Solar	Solar
Solar	Solar	Solar	Solar/Biomass	Wind
CHP	CHP	CHP/Nuclear	CHP	CHP/Nuclear
Nuclear/Hydra	Nuclear	Nuclear/CHP	Hydra	Nuclear/CHP
Hydra/Nuclear	Hydra	Hydra	Nuclear	Hydra/ Convent.
Convent.	Convent.	Convent.	Convent.	Convent./Hydra

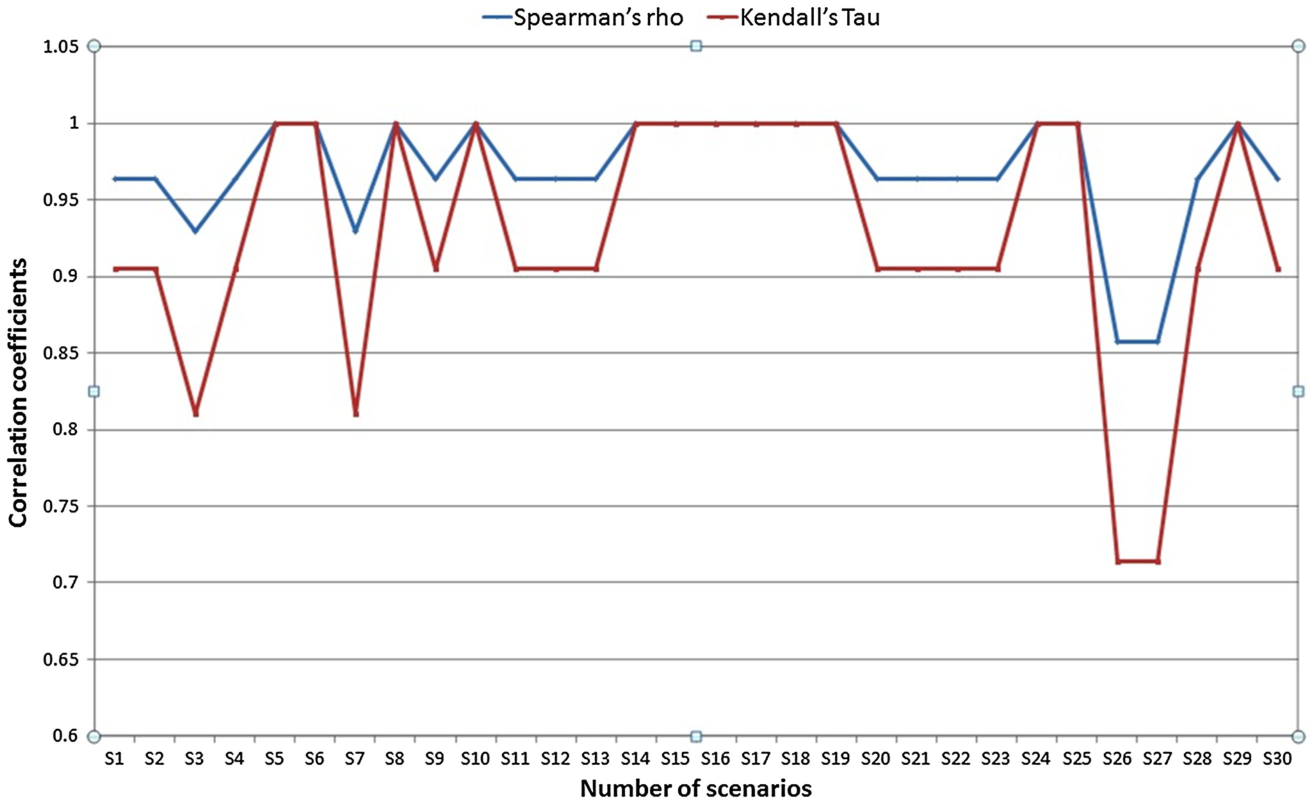

Fig. 1 Spearman's rho and Kendall's tau correlation coefficients

Table 10 Expert 1 assessment using non-basic labels

E_1	C_3		C_4		C_8		C_9	
	Basic labels	Non-basic labels	Basic labels	Non-basic labels	Basic labels	Non-basic labels	Basic labels	Non-basic labels
A_1	B_5	$[B_2–B_6]$	B_5	B_5	B_3	B_3	B_5	$[B_3–B_6]$
A_2	B_1	B_1	B_7	B_7	B_2	$[B_1–B_3]$	B_6	B_6
A_3	B_4	$[B_3–B_5]$	B_4	$[B_3–B_5]$	B_6	B_6	B_4	$[B_3–B_5]$
A_4	B_6	B_6	B_6	B_6	B_7	B_7	B_4	B_4
A_5	B_5	$[B_4–B_6]$	B_4	$[B_1–B_7]$	B_4	$[B_3–B_5]$	B_6	B_6
A_6	B_4	$[B_3–B_5]$	B_4	$[B_3–B_5]$	B_6	$[B_5–B_6]$	B_6	B_6
A_7	B_4	$[B_1–B_7]$	B_3	$[B_1–B_4]$	B_6	B_6	B_5	$[B_4–B_5]$

Allowing experts to use different levels of precision

To highlight the ability of the method presented to capture the inherent uncertainty existing in human reasoning, we present a simulated extension of the previous Scenario 1 where experts are allowed to use different levels of precision in their assessments. In general, costs, social acceptability and job creation are usually the criteria involving more uncertainty, meaning that their results and predictions can present greater differences. For this reason, we consider that Expert 1 expresses uncertain judgments when assessing criteria (C_3, C_4, C_8 and C_9) in Scenario 1. Table 10 presents the previous values considered for Expert 1 assessments with respect to these four criteria, whose locations are presented in Table 4, along with the new assessments allowing different levels of precision.

Considering these new assessments of Expert 1, the final order of ranking is the same as the previous one: wind > biomass > solar > CHP > nuclear > hydraulic > conventional energy (see Table 9). Note that the modified fuzzy TOPSIS method is not able to deal with these types of

Table 11 Expert 1 assessment using more non-basic labels

E_1	C_3		C_4		C_8		C_9	
	Basic labels	Non-basic labels	Basic labels	Non-basic labels	Basic labels	Non-basic labels	Basic labels	Non-basic labels
A_1	B_5	$[B_4–B_6]$	B_5	B_5	B_3	B_3	B_5	$[B_3–B_5]$
A_2	B_1	$[B_1,B_2]$	B_7	$[B_1–B_3]$	B_2	$[B_1–B_3]$	B_6	$[B_4–B_6]$
A_3	B_4	$[B_4–B_7]$	B_4	$[B_4–B_6]$	B_6	$[B_6–B_7]$	B_4	$[B_4–B_6]$
A_4	B_6	$[B_6,B_7]$	B_6	$[B_6,B_7]$	B_7	B_7	B_4	$[B_4–B_6]$
A_5	B_5	$[B_5–B_6]$	B_4	$[B_4–B_6]$	B_4	$[B_4–B_6]$	B_6	$[B_4–B_7]$
A_6	B_4	B_4	B_4	$[B_3–B_5]$	B_6	$[B_4–B_6]$	B_6	$[B_4–B_6]$
A_7	B_4	$[B_2–B_6]$	B_3	$[B_4–B_5]$	B_6	B_6	B_5	$[B_4–B_6]$

assessments; therefore, these results can only be computed using the method proposed in this paper.

This example clearly shows the originality and the contribution of the proposed method because, although it allows experts to express their uncertainty through imprecise assessments, it yields the same final ranking; thus, the same results can be obtained with less information. In addition, this reinforces the idea that the proposed method is more adaptable to real situations and requires less cognitive effort on the part of the experts. However, obviously, if the assessments are more imprecise, the obtained ranking can be different, as can be seen in the situation presented in Table 11.

The ranking based on these new assessments is wind > solar > biomass > CHP > hydraulic > nuclear > conventional energy. In the new order the respective places of solar/biomass and hydra./nuclear are switched.

Conclusion

When considering environmental, technical, economic and social aspects, it is crucial to analyze and quantify different types of variables involving imprecision. These factors, especially social ones, are not always precise, as imprecisions and uncertainties are features of the real world. Therefore, in order to provide useful data from experts' assessments, a new MCDM method to support decision makers in all stages of the decision-making process with uncertain values is presented. This imprecision is captured by using linguistic variables involving qualitative labels with different levels of precision. This approach, based on order-of-magnitude QR, provides a model that can obtain results from non-numeric variables.

The main contribution of this paper is the qualitative TOPSIS method, which is introduced and applied in an energy case study. Sustainable energy planning problems require critical decisions in a variety of dynamic complexities with respect to conflicting environmental, economic, social and technical criteria. This method takes into account intensity of preferences and gives experts the capability to assess alternatives under uncertainty by expressing their judgments using linguistic variables involving qualitative labels. As an advantage of this method, the use of qualitative labels with different levels of precision is essential to obtaining user-friendly systems to be used by energy planners for evaluation processes. This method is able to capture the existing ambiguity inherent in human reasoning and addresses the problem in such a way that the principle of relevance is preserved: each variable is valued with the level of precision required.

In this paper, the proposed Q-TOPSIS method is compared with the modified fuzzy TOPSIS method, which uses another type of linguistic variables. The modified fuzzy TOPSIS approach utilizes fuzzy linguistic variables for evaluating alternatives. For further research, the proposed Q-TOPSIS method will be applied to real data to determine the most appropriate sustainable energy alternative in a specific geographical area. Moreover, regarding the application for selecting sustainable energy alternatives, the theoretical framework can be deeply extended to include more indicators such as waste management, other environmental pollutions (SO_2, GHG, CO emissions and SPM), public health and environmental risk and the impact of possible accidents, which are crucial in energy studies. Other parameters such as internal rate of return and payback period are important economic parameters for investment on any energy sources that will be considered in future applications.

Acknowledgments This research was partially supported by the SENSORIAL research Project (TIN2010-20966-C02-01 and TIN2010-20966-C02-02), funded by the Spanish Ministry of Science and Information Technology. Partial support was also provided by a doctoral fellowship awarded to one of the authors at the ESADE Business School, with additional support from Ramon Llull University.

References

Afsordegan A, Sánchez M, Agell N, Aguado JC, Gamboa G (2016) Absolute order-of-magnitude reasoning applied to a social multi-criteria evaluation framework. J Exp Theor Artif Intell 28(1–2):261–274

Agell N, Sánchez M, Prats F, Roselló L (2012) Ranking multi-attribute alternatives on the basis of linguistic labels in group decisions. Inf Sci 209:49–60

Akash BA, Mamlook R, Mohsen MS (1999) Multi-criteria selection of electric power plants using analytical hierarchy process. Electr Power Syst Res 52(1):29–35

Amiri MP (2010) Project selection for oil-fields development by using the AHP and fuzzy TOPSIS methods. Expert Syst Appl 37:6218–6224

Aras H, Erdomu S, Koç E (2004) Multi-criteria selection for a wind observation station location using analytic hierarchy process. Renew Energy 29:1383–1392

Ashtiani B, Haghighirad F, Makui A, Montazer GA (2009) Extension of fuzzy TOPSIS method based on interval-valued fuzzy sets. Appl Soft Comput 9(2):457–461

Baños R, Manzano-Agugliaro F, Montoya F, Gil C, Alcayde A, Gómez J (2011) Optimization methods applied to renewable and sustainable energy: a review. Renew Sustain Energy Rev 15(4):1753–1766

Beccali M, Cellura M, Ardente D (1998) Decision making in energy planning: the ELECTRE multicriteria analysis approach compared to a FUZZY-SETS methodology. Energy Convers Manag 39(16–18):1869–1881

Beccali M, Cellura M, Mistretta M (2003) Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology. Renew Energy 28(13):2063–2087

Begic F, Afgan N (2007) Sustainability assessment tool for the decision making in selection of energy system—Bosnian case. Energy 32:1979–1985

Behzadian M, Khanmohammadi Otaghsara S, Yazdani M, Ignatius J (2012) A state-of the-art survey of TOPSIS applications. Expert Syst Appl 39(17):13051–13069

Belton V, Stewart T (2002) Multiple criteria decision analysis: an integrated approach. Kluwer Academic Publications, Boston

Boran F, Boran K, Menlik T (2012) The evaluation of renewable energy technologies for electricity generation in turkey using intuitionistic fuzzy TOPSIS. Energy Sources Part B 7(1):81–90

Buehring W, Foell W, Keeney R (1978) Examining energy/environment policy using decision analysis. Energy Policy 2(3):341–367

Carlsson C, Fuller R (1996) Fuzzy multiple criteria decision making: recent developments. Fuzzy Sets Syst 78:139–153

Cavallaro F (2010a) A comparative assessment of thin-film photovoltaic production processes using the ELECTRE III method. Energy Policy 38(1):463–474

Cavallaro F (2010b) Fuzzy TOPSIS approach for assessing thermal-energy storage in concentrated solar power (CSP) systems. Appl Energy 87(2):496–503

Chang NB, Parvathinathan G, Breeden JB (2008) Combining GIS with fuzzy multicriteria decision-making for landfill siting in a fast-growing urban region. J Environ Manag 87(1):139–153

Chen CT (2000) Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets Syst 114(1):1–9

Cherubini F, Strømman AH (2011) Life cycle assessment of bioenergy systems: state of the art and future challenges. Bioresour Technol 102(2):437–451

Choo EU, Schoner B, Wedley WC (1999) Interpretation of criteria weights in multicriteria decision making. Comput Ind Eng 37(3):527–541

Dai J, Qi J, Chi J, Chen S, Yang J (2010) Integrated water resource security evaluation of Beijing based on GRA and TOPSIS. Front Earth Sci China 4(3):357–362

Doukas H, Andreas BM, Psarras JE (2007) Multi-criteria decision aid for the formulation of sustainable technological energy priorities using linguistic variables. Eur J Oper Res 182(2):844–855

Doukas H, Karakosta C, Psarras J (2010) Computing with words to assess the sustainability of renewable energy options. Expert Syst Appl 37(7):5491–5497

Doumpos M, Grigoroudis E (2013) Multicriteria decision aid and artificial intelligence: links, theory and applications. Wiley, Hoboken

Dubois D, Prade H (1980) Fuzzy sets and systems: theory and applications. Academic press, New York

Evans TJ, Strezov V, Annette E (2009) Assessment of sustainability indicators for renewable energy technologies. Renew Sustain Energy Rev 13:1062–1088

Forbus K (1984) Qualitative process theory. Artif Intell 24(1–3):85–168

Georgopoulou E, Sarafidis Y, Diakoulaki D (1998) Design and implementation of a group DSS for sustaining renewable energies exploitation. Eur J Oper Res 109:483–500

Goumas M, Lygerou V (2000) An extension of the PROMETHEE method for decision making in fuzzy environment: ranking of alternative energy exploitation projects. Eur J Oper Res 123(3):606–613

Herrera F, Herrera-Viedma E, Martínez L (2008) A fuzzy linguistic methodology to deal with unbalanced linguistic term sets. IEEE Trans Fuzzy Syst 16(2):354–370

Hwang C, Yoon K (1981) Multiple attribute decision making: methods and applications, a state of the art survey, vol 1. Springer, Berlin

Hwang C, Yoon K (2005) Multiple attribute decision making. Quant Appl Soc Sci 7–104:53–62

Ishizaka A, Nemery P (2013) Multi-criteria decision analysis: methods and software. Wiley, Hoboken

Jebaraj S, Iniyan S (2006) A review of energy models. Renew Sustain Energy Rev 10(4):281–311

Jing YY, Bai H, Wang JJ (2012) A fuzzy multi-criteria decision making model for CCHP systems driven by different energy sources. Energy Policy 42:286–296

Kablan M (2004) Decision support for energy conservation promotion. Energy Policy 32(10):1151–1158

Kahraman C (2008) Fuzzy multi-criteria decision making: theory and applications with recent developments. Springer, New York

Kahraman C, Cebi S, Kaya I (2010) Selection among renewable energy alternatives using fuzzy axiomatic design: the case of Turkey. J Univers Comput Sci 16(1):82–102

Kara SS, Onut S (2010) A stochastic optimization approach for paper recycling reverse logistics network design under uncertainty. Int J Environ Sci Technol 7(4):717–730

Karimi AR, Mehrdadi N, Hashemian SJ, Nabi Bidhendi G, Tavakkoli Moghadam R (2011) Selection of wastewater treatment process based on the analytical hierarchy process and fuzzy analytical hierarchy process methods. Int J Environ Sci Technol 8(2):267–280

Kaya I, Kahraman C (2011) Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. Expert Syst Appl 38(6):6577–6585

Kowkabi L, Setayesh SR, Badri A, Rajaee A (2013) The application of fuzzy multi-attribute group decision making to prioritize the landscapes with high ecological value: Khoshk river in Shiraz. Int J Environ Res 7(2):423–434

Kuo RJ, Hsu CW, Chen YL (2015) Integration of fuzzy ANP and fuzzy TOPSIS for evaluating carbon performance of suppliers. Int J Environ Sci Technol. doi:10.1007/s13762-015-0819-9

Laarhoven V, Pedrycz W (1983) A fuzzy extension of Saaty's priority theory. Fuzzy Sets Syst 11(1–3):199–227

Liu KFR (2007) Evaluating environmental sustainability: an integration of multiple-criteria decision-making and fuzzy logic. Environ Manag 39(5):721–736

Loken E (2007) Use of multicriteria decision analysis methods for energy planning problems. Renew Sustain Energy Rev 11(7):1584–1595

Meier PM, Hobbs BF (1994) Multicriteria methods for resource planning: an experimental comparison. IEEE Trans Power Syst 9(4):1811–1817

Moghaddam NB, Nasiri M, Mousavi SM (2011) An appropriate multiple criteria decision making method for solving electricity planning problems, addressing sustainability issue. Int J Environ Sci Technol 8(3):605–620

Mosadeghi R, Warnken J, Tomlinson R, Mirfenderesk H (2015) Comparison of fuzzy-AHP and AHP in a spatial multi-criteria decision making model for urban land-use planning. Comput Environ Urban Syst 49:54–65

Nieto-Morote A, Ruz-Vila F, Cánovas-Rodríguez F (2010) Selection of a trigeneration system using a fuzzy AHP multi-criteria decision-making approach. Int J Energy Res 35:781–794

Nigim K, Munier N, Green J (2004) Pre-feasibility MCDM tools to aid communities in prioritizing local viable renewable energy sources. Renew Energy 29(11):1775–1791

Oberschmidt J, Geldermann J, Ludwig J, Schmehl M (2010) Modified PROMETHEE approach for assessing energy technologies. Int J Energy Sect Manag 4(2):183–212

Opricovic S, Tzeng GH (2004) Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. Eur J Oper Res 156(2):445–455

Pan J, Rahman S (1998) Multiattribute utility analysis with imprecise information: an enhanced decision support technique for the evaluation of electric generation expansion strategies. Electr Power Syst Res 46(2):101–109

Parreiras RO, Ekel PY, Martini JSC, Palhares RM (2010) A flexible consensus scheme for multicriteria group decision making under linguistic assessments. Inf Sci 180(7):1075–1089

Pohekar S, Ramachandran M (2004) Application of multi-criteria decision making to sustainable energy planning: a review. Renew Sustain Energy Rev 8(4):365–381

Polatidis H, Haralambopoulos D, Munda G, Vreeker R (2006) Selecting an appropriate multi-criteria decision analysis technique for renewable energy planning. Energy Sources Part B 1(2):181–193

Rovere E, Soares J, Oliveira L, Lauria T (2010) Sustainable expansion of electricity sector: sustainability indicators as an instrument to support decision making. Renew Sustain Energy Rev 14:422–429

Russo R, Camanho R (2015) Criteria in AHP: a systematic review of literature. Procedia Comput Sci 55:1123–1132

Saaty TL (1980) The analytic hierarchy process. McGraw-Hill, New York

Saaty TL (1990) Decision making by the analytic hierarchy process: theory and applications. Eur J Oper Res 48(1):9–26

San Cristóbal J (2012) A goal programming model for the optimal mix and location of renewable energy plants in the north of Spain. Renew Sustain Energy Rev 16(7):4461–4464

Stamford L, Azapagic A (2011) Sustainability indicators for the assessment of nuclear power. Energy 36:6037–6057

Streimikiene D, Balezentis T, Krisciukaitien I, Balezentis A (2012) Prioritizing sustainable electricity production technologies: mCDM approach. Renew Sustain Energy Rev 16(5):3302–3311

Topcu Y, Ulengin F (2004) Energy for the future: an integrated decision aid for the case of Turkey. Energy 29(1):137–154

Travé-Massuyès L, Prats F, Sánchez M, Agell N (2005) Relative and absolute order-of-magnitude models unified. Ann Math Artif Intell 45(3–4):323–341

Tsoutsos T, Drandaki M, Frantzeskaki N, Iosifidis E, Kiosses I (2009) Sustainable energy planning by using multi-criteria analysis application in the island of Crete. Energy Policy 37(5):1587–1600

Tuzkaya G, Ozgen A, Ozgen D, Tuzkaya UR (2009) Environmental performance evaluation of suppliers: a hybrid fuzzy multi-criteria decision approach. Int J Environ Sci Technol 6(3):477–490

Tzeng GH, Ta Shiau, Lin CY (1992) Application of multicriteria decision making to the evaluation of new energy system development in Taiwan. Energy 17(10):983–992

Varun S, Bhat IK, Prakash R (2009) LCA of renewable energy for electricity generation systems—a review. Renew Sustain Energy Rev 13:1067–1073

Wang JJ, Jing YY, Zhang CF, Shi GH, Zhang XT (2008) A fuzzy multi-criteria decision-making model for trigeneration system. Energy Policy 36(10):3823–3832

Wang JJ, Jing YY, Zhang CF, Zhao JH (2009) Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew Sustain Energy Rev 13(9):2263–2278

Yeh TM, Huang YL (2014) Factors in determining wind farm location: integrating GQM, fuzzy DEMATEL, and ANP. Renew Energy 66:159–169

Yilmaz B, Dadeviren M (2011) A combined approach for equipment selection: F-PROMETHEE method and zeroone goal programming. Expert Syst Appl 38(9):11641–11650

Zadeh L (1965) Fuzzy sets. Inf Control 8:338–353

Zadeh L (1975) The concept of a linguistic variable and its application to approximate reasoning. Inf Sci 8(3):199–249