

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

A. Afsordegan<sup>1</sup> · M. Sánchez<sup>2</sup> · N. Agell<sup>1</sup>  · S. Zahedi<sup>3</sup> · L. V. Cremades<sup>4</sup>

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**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

<sup>1</sup> ESADE Business School, Ramon Llull University, Av. Pedralbes, 60, 08034 Barcelona, Spain

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

<sup>3</sup> Department of Business Administration, Universitat Politècnica de Catalunya, UPC-BarcelonaTech, Av. Diagonal, 647, 08028 Barcelona, Spain

<sup>4</sup> 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 Iniyar (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<sub>x</sub> emission; CO<sub>2</sub> 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)
Goal Programming	Strategic energy planning	Pan and Rahman (1998)
	Energy resource planning	Meier and Hobbs (1994)
TOPSIS	Renewable energy planning	San Cristóbal (2012)
	Evaluating renewable energy	Cavallaro (2010b) and Boran et al. (2012)
PROMETHEE II	Assessing energy policy objectives	Doukas et al. (2010)
	Selecting the best energy alternative	Kaya and Kahraman (2011); Proposed method
PROMETHEE I and II	Ranking energy alternatives	Georgopoulou et al. (1998) and Goumas and Lygerou (2000)
ELECTRE III	Assessing renewable energies	Topcu and Ulengin (2004)
	Sustainable energy planning	Tsoutsos et al. (2009)
ELECTRE III	Assessing energy technologies	Tzeng et al. (1992) and Oberschmidt et al. (2010)
	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)
Environmental	Availability of funds	Stamford and Azapagic (2011)
	NO <sub>x</sub> emission	Kaya and Kahraman (2011) and Rovere et al. (2010)
	CO <sub>2</sub> 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)
Social	Environmental risk	Rovere et al. (2010)
	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 tri-generation 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  $\{a_1, \dots, a_{n+1}\}$  a set of real landmarks, with  $a_1 < \dots < a_{n+1}$ . The basic labels are defined by  $B_i = [a_i, a_{i+1}]$ ,  $i = 1, \dots, n$ .

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  $i, j = 1, \dots, n$ , 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  $\{A_1, \dots, A_l\}$  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  $\mathbb{S}_n = \{[B_i, B_j] | i, j = 1, \dots, n+1, i \leq j\}$ , considering  $[B_i, B_i] = B_i$ .

In this way, each alternative  $A_i$ ,  $i = 1, \dots, l$ , is represented by a  $k$ -dimensional vector of labels in  $(\mathbb{S}_n)^k$ ,  $A_i \leftrightarrow (A_{i1}, \dots, A_{im}, \dots, A_{i1}, \dots, A_{im})$ ,  $k$  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  $l : \mathbb{S}_n \rightarrow \mathbb{Z}^2$  such that:

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

where  $\mu$  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:  $L(A_i) = (l(A_{i1}), \dots, l(A_{im}), \dots, l(A_{i1}), \dots, l(A_{im}))$ .

**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  $\{A_1, \dots, A_l\}$ , 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  $A_i, i = 1, \dots, l$  is represented by a  $k$ -dimensional vector of labels,  $k$  being the product of the number of criteria and the number of experts:

$$A_i \leftrightarrow (A_{i1}, \dots, A_{im}, \dots, A_{i1}, \dots, A_{im}),$$

$$A_{jh} \in \mathbb{S}_n, i = 1, \dots, l, j = 1, \dots, r, h = 1, \dots, m$$

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

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

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

Both the Euclidean weighted distances of each alternative location  $L(A_i), i = 1, \dots, l$ , 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:

$$d(X, Y) = \sqrt{\sum_{i=1}^r w_i \sum_{j=1}^{2m} (X_{ji} - Y_{ji})^2} \tag{4}$$

where  $w_i$  is the weight corresponding to the  $i$ th indicator, and  $X_{ij}, Y_{ji}, j = 1, \dots, 2m, i = 1, \dots, r$ , 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 QCC $_i$  values.

$$QCC_i = \frac{d_i^-}{d_i^* + d_i^-}, \quad i = 1, 2, \dots, l. \tag{5}$$

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 be 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  $\mu$  over the set of basic labels  $\mu(B_i) = 1$ , for all  $i = 1, \dots, 7$ .

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)

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

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

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

Note that the vector in Eq. 7 for each alternative  $A_i$  is obtained by combining the  $i$ th 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  $L(A^-) = L(B_1, \dots, B_1) = (0, 6, \dots, 0, 6)$  and  $L(A^*) = L(B_7, \dots, B_7) = (-6, 0, \dots, -6, 0)$  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):

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

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

	$d_i^-$	$d_i^+$	QCC $_i$
A <sub>1</sub>	8.514	9.033	0.485
A <sub>2</sub>	9.278	8.657	0.517
A <sub>3</sub>	10.528	5.420	0.660
A <sub>4</sub>	12.119	4.435	0.732
A <sub>5</sub>	8.204	7.973	0.507
A <sub>6</sub>	10.490	4.876	0.682
A <sub>7</sub>	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 ( $\pi_1, \pi_2, \pi_3$ ). 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 ( $w_1 = 0.09; w_2 = 0.1; w_3 = 0.1; w_4 = 0.11; w_5 = 0.13; w_6 = 0.15; w_7 = 0.11; w_8 = 0.09; w_9 = 0.12$ ), 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

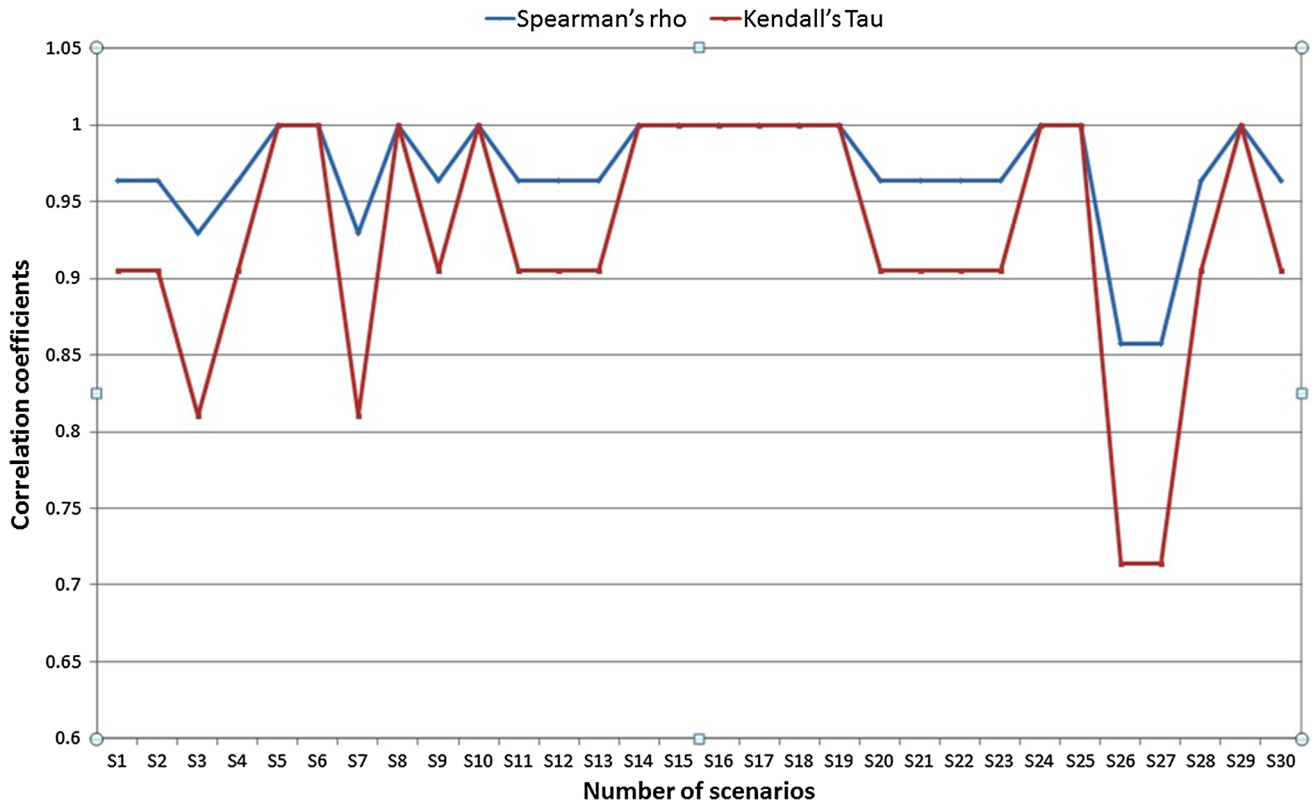


Fig. 1 Spearman's rho and Kendall's tau correlation coefficients

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 hydro./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 pay-back period are important economic parameters for investment on any energy sources that will be considered in future applications.

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