Chapter 11
Strategic Renewable Energy Source Selection for Turkey with Hesitant Fuzzy MCDM Method

Gülçin Büyüközkan, Yağmur Karabulut and Merve Güler

Abstract Renewable energy sources (RES) strengthen their hold on emerging economies. Record numbers of newly installed RES capacity are being observed in recent years. In 2016, the addition of renewable resources were more than 60% of new capacity investments globally, surpassing fossil fuel-based investments. The majority of these additions take place in developing countries, indicating the vital importance of selecting the best RES technologies for Turkey, an emerging economy. RES is not only becoming less expensive, they also contribute to employment and environmental protection. Selecting the most appropriate RES strategy among alternatives involves many criteria. This chapter introduces a novel RES evaluation model that can guide investors in identifying the most suitable RES strategy from a sustainability perspective. Complex socio-economic decision problems often make it more difficult for Decision Makers to consider different aspects, and to provide exact numerical values. Considering many, usually conflicting sustainability factors that affect this selection process, the chapter proposes a Multi-Criteria Decision-Making (MCDM) model by implementing hesitant fuzzy linguistic term sets (HFLTS) for an effective RES strategy evaluation problem. Group Decision Making (GDM) is also integrated to the method, as it is capable to offset individual DMs' bias and partiality. HFLTS enables DMs to accurately provide their linguistic expressions. An integrated HFL SAW method (Simple Additive Weighting) and HFL TOPSIS method (Technique for Order Performance by Similarity to Ideal Solution) are employed for this purpose. The criteria priorities are determined with the HFL SAW method and the final RES strategy ranking results are determined with HFL TOPSIS method. The plausibility of the proposed framework is tested in a case study. This combination of MCDM techniques is applied for the first time in the literature for dealing with this problem setting.

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11.1 Introduction

Today, around 1 billion people globally have no access to electricity. Providing these people, and the other parts of the world, with clean, affordable and sustainable electricity still remains a challenge today. Despite many challenges, Renewable Energy Sources (RER) have become the strategic first choice of investors in recent years. In 2016 alone, renewables accounted for more than 60% of new capacity additions globally. Most of this addition came from solar PV for the first time, which accounts for about 47% of new renewable power capacity additions in 2016, while wind and hydropower contributed 34 and 15.5%, respectively (REN 21 2017). This sustained growth and geographical expansion can be mostly attributed to the continued decline of installation costs, particularly for wind and solar PV, as wells as continually increasing power demand in developing countries and governmental support mechanisms. Innovations in solar PV manufacturing and installation techniques, as well as cell and module efficiency and performance, are major causes for this wide adoption. Similarly, recent improvements in wind turbine materials, design, operation, and maintenance lead to lower operational costs and higher energy generation for the same wind turbine capacity. New advances in power grids are able to support more RES plants. Improvements in the production of advanced biofuels are also observed.

Today, the world is adding renewable power capacity at unprecedented rates, it even surpasses all fossil fuels combined (International Energy Agency 2015). Some mature RES options, such as hydropower and geothermal energy, are already competitive in terms of costs with thermal power plants run with fossil fuels. Solar PV and wind power are converging to these well-known and established power sources due to recent technological developments. Moreover, the flexibility of capacity, ease of deployment in remote areas and low maintenance requirements increasingly favor such newer RES technologies. Distributed, off-grid RES projects in rural areas present strategic sustainable alternatives over conventional power plants not only thanks to their competitive capital investment and low maintenance costs but also their environmental benefits and new job creation opportunities locally. The development of these community RES investments continued in 2016. Moreover, these emerging RES alternatives bring about significant employment opportunities, technology transfer, local economic activity, lower greenhouse gas emissions, less environmental footprint and many other co-benefits.

This trend is especially true for developing countries. In 2016, most of new RES capacity installations took place in developing countries. For the first time, developing economies overtook the level of RES investment of developed countries in 2015. Although developed countries took the lead back the next year, developing countries are becoming a significant market for the RES industry due to natural potential and willingness of investors. This is also true for Turkey, an emerging economy. Turkey takes steps to minimize its dependency on unsustainable fossil fuels and to reduce pollution caused by power generation (Büyüközkan and Güleryüz 2017). Together with Indonesia, Turkey is leading the world in new geothermal power installations by adding 10 new geothermal plants in 2016 to its existing cohort of 10 plants. For the wind industry, Turkey had a record year in 2016 as well. It added ca. 1.4 GW new wind power capacity and ranked among the top 10 countries globally (REN 21 2017). This also reflected in employment numbers in this industry. As of 2016, more than 1 million people around the world are employed in businesses related to wind power. More than half a million of this employment takes place in China, followed by Germany, the United States, India, and Turkey. In the face of high energy prices, global warming, lack of decent employment opportunities, ecologic deterioration and development priorities, the selection of the most sustainable RES strategy is becoming a key decision problem in Turkey that can ensure environmental protection, lower pollution, and new jobs. These developments lead to higher interest by investors, who seek to strategically balance profits, good governance, community dialogue, environmental integrity and compliance with national policies at the same time.

Low-cost and environmentally friendly energy supply is a pre-requisite for a sustainable power supply. There exist many RES strategies, each having their advantages and disadvantages. Investors, as Decision Makers (DMs) of RES projects, are therefore faced with a multitude of factors that shall be considered to come to a thorough decision. As the number of RES options expand, this decision process also becomes more complex for DMs. The long-term value of this RES strategy selection problem necessitates powerful decision support systems to aid DMs in determining which RES is the best by considering qualitative and quantitative sustainability aspects.

Decision-making activities aim to select the best from two or more of alternatives. Deciding on a suitable RES strategy is a complex process, and can be overwhelming for DMs in the presence of many decision factors, if not treated with proper methods. Traditional single-criterion decision-making approaches are unable to cope with such complex systems, as the problem involves the assessment of many criteria which shall be assisted by DMs (Taha and Daim 2013; Ishizaka and Nemery 2013; Kahraman et al. 2015). To address this need, the literature offers to treat it as a Multi-Criteria Decision-Making (MCDM) problem (Iskin et al. 2012; Kabak and Dağdeviren 2014; Pak et al. 2015; Şengül et al. 2015; Ishizaka et al. 2016). MCDM methods can solve various energy management and planning problems, especially complex issues that feature low certainty, conflicting goals, multiple interests and differing points of view. They provide researchers with many effective tools that can be used individually or in combination for reaching the intended results. In MCDM, criteria and alternatives should be determined at the beginning and evaluated one by one by DMs in a particular way.

MCDM processes can be improved with Group Decision Making (GDM) approaches by involving several DMs at once that possess different notions and ideas. Each DM can approach the decision problem from different angles, and their collective assessments can be integrated into the procedure. Furthermore, there are many MCDM techniques offered in the literature. While DMs evaluate the alternatives, they might be guided by their personal feelings, uncertainty, and hesitancy in their opinions. To add to these challenges, DMs can have difficulty in expressing their assessment numerically, especially for qualitative criteria.

This chapter presents an integrated MCDM model that addresses these complications. This approach consists of HFL SAW (Simple Additive Weighting) method and HFL TOPSIS method (Technique for Order Performance by Similarity to Ideal Solution). HFL SAW method is applied for determining the criteria weights, while HFL TOPSIS is employed for obtaining the final RES strategy rankings. The alternatives are ranked according to their proximity to the positive ideal solution and negative ideal solution (Chen et al. 1992). This approach can sort and select the best RES from a number of alternatives by comparing their sustainability performance. This chapter discusses this new approach, which integrates SAW and TOPSIS under a hesitant fuzzy environment with GDM. It differentiates from the literature by using HFL SAW and HFL TOPSIS with GDM approach for the RES strategy selection problem with technical, social, environmental and economic aspects in a developing country setting.

The chapter continues with Sect. 11.2 to give a snapshot of the state of the art. Then, Sect. 11.3 will follow, where the methods are described in detail. Section 11.4 demonstrates the proposed method's application on a case study from Turkey, while Sect. 11.5 summarizes the results and concludes this chapter.

11.2 Literature Review

There is extensive research in the literature that deploy MCDM tools, e.g. AHP, TOPSIS, DEMATEL, ELECTRE, PROMETHEE, and VIKOR, as well as fuzzy logic and GDM applications, to deal with RES strategy selection problems. In this field, Kumar et al. (2017) recently reviewed the literature on MCDM applications for sustainable RES strategy selection and provided a good overview of the state of the art. Suganthi et al. (2015) reviewed the literature on the fuzzy logic application in RES problems and found that fuzzy-based MCDM methods are applied for RES site assessment, strategy selection, and optimization of conflicting criteria, among others. Considering the multitude of research, readers are kindly referred to these articles.

Among the publications that use MCDM methods for selecting RES strategies with a specific focus on Turkey, Önüt et al. (2008) applied ANP to assess RES strategies for the Turkish manufacturing industry. Kahraman et al. (2009) deployed a fuzzy AHP approach for selecting the most suitable renewable energy strategy for Turkey and came to the conclusion that wind energy generates the best effects. In a study by Kaya and Kahraman (2011), a new fuzzy TOPSIS technique is presented for energy planning. Kabak and Dağdeviren (2014) employed a hybrid ANP model to consider the benefits, opportunities, costs, and risks of RES strategies in Turkey. Büyüközkan and Güleryüz (2014) constructed an evaluation method to rank alternative strategies for RES. In another paper, Erdogan and Kaya (2015) first deployed fuzzy AHP using interval type-2 fuzzy sets to calculate the priorities of the evaluation criteria. Then, they fuzzified the TOPSIS method by interval type-2 fuzzy sets to put strategic alternatives into order. Şengül et al. (2015) utilized fuzzy TOPSIS technique to rank RES strategies for Turkey. A similar goal was pursued by Büyüközkan and Güleryüz (2016), who combined DEMATEL with ANP for identifying the best RES option in Turkey from an investor point of view. Recently, Büyüközkan and Karabulut (2017) came up with an evaluation method fusing AHP with VIKOR for selecting energy projects from a sustainability point of view, and Büyüközkan and Güleryüz (2017) applied linguistic interval fuzzy preferences with DEMATEL, ANP, and TOPSIS to pinpoint the most appropriate energy strategy for Turkey. The same objective was explored by Çolak and Kaya (2017), who merged AHP based on interval type-2 fuzzy sets with hesitant fuzzy TOPSIS methods, as well as Balin and Baraçli (2017), who integrated fuzzy AHP-based type-2 fuzzy sets with interval type-2 TOPSIS method.

Publications that use the techniques proposed in this chapter are also reviewed. In literature, those papers that integrate HFLTS and MCDM are dispersed to a few fields, such as finance, technology, and management. The integrated use of HFLTS and MCDM tools began in 2013 with the studies of Zhang and Beg. Zhang and Wei (2013) developed the HFL VIKOR technique, an effective MCDM method for determining the best compromise solution by collecting linguistic expressions. They also compared this method to HFL TOPSIS. In another article, Beg and Rashid (2013) proposed Hesitant Fuzzy Linguistic TOPSIS for aggregating the opinions of experts and DMs on various criteria by GDM. Senvar et al. (2016) applied Hesitant Fuzzy TOPSIS to pinpoint to the best hospital site. Zhang et al. (2015) applied Hesitant Fuzzy TOPSIS and linear programming for selecting the best supplier. Onar et al. (2016) employed Hesitant Fuzzy Linguistic AHP, Hesitant Fuzzy Linguistic TOPSIS, and QFD methods and explored the applicability and effectiveness of their approach by a case study. Zhou et al. (2016) proposed Hesitant TOPSIS and Hesitant TODIM and combined it with linguistic hesitant fuzzy sets (LHFS) with the evidential reasoning (ER) approach. Since it is a very new combined method, HFL TOPSIS's applications are limited. One example is by Cevik Onar et al. (2014), who developed a Hesitant Fuzzy TOPSIS model that considers the complexity and imprecision of strategic decisions and presented a case study for an electronics company. Büyüközkan and Güler (2017) integrated HFLTS, OWA operator and TOPSIS method for evaluating smart glasses alternatives.

Chou et al. (2008) used SAW method in fuzzy environment. However, the integrated use of HFLTS and SAW method is a research gap in the literature. Therefore, this is the first publication in the literature that integrates HFLTS, SAW and TOPSIS methods in the field of energy in general, and for RES strategy selection more specifically. Furthermore, HFLTS, SAW and TOPSIS methods are not operated before with GDM in any publication, marking another scientific contribution of this chapter.

11.3 Proposed RES Strategy Selection Model

RES can be defined as energy sources that are continually replenished by nature, such as the solar radiation, wind, water and geothermal heat. These resources do not originate from fossil fuels, have lower emissions, are renewed in continuous cycles and are available in nature to utilize (Şengül et al. 2015). The most important RES strategies for Turkey are wind, solar PV, biogas, geothermal and hydro energy (Büyüközkan and Güleryüz 2017).

The RES model introduced in this chapter is based on a set of evaluation criteria and an integrated MCDM method for processing the criteria evaluations of the DMs. MCDM allows DMs to have a systematic overview of the decision problem so that the problem can be investigated and scaled according to specific needs (Işıklar and Büyüközkan 2007). The proposed RES strategy selection model is based on the criteria introduced in Sect. 11.3.1.1, and on a combination of MCDM techniques. In this approach, MCDM methods will be deployed in a certain order and pre-defined setting. This approach applies HFL SAW and HFL TOPSIS techniques in a GDM environment. HFL SAW is put into use for finding the weights of the evaluation criteria, and HFL TOPSIS is used for ranking the energy strategy alternatives in an optimal manner. This algorithm can be described with the following phases:

1. **Problem definition**: Initially, the goal of the decision problem is determined. Then, the DMs, who will be involved in the process, are chosen. Next, available RES strategies to be considered are defined. At the final stage of this first phase, the evaluation criteria are established.
2. **Criteria weights**: In this second phase, HFL SAW will be applied. First, linguistic opinions of DMs are gathered for each criterion about their perceived impact on the group decision. Based on these data, the criteria decision matrix is constructed. Then, linguistic data are transformed into HFLTS, which are then converted to trapezoidal fuzzy numbers (TFNs). The aggregated fuzzy weights are calculated, and criteria weights are eventually found by de-fuzzifying and normalizing them.
3. **Ranking of alternatives**: In this third phase, HFL TOPSIS will be deployed. First, linguistic opinions of DMs are gathered for each alternative, according to each criterion about how well the alternatives fare. Once the evaluation alternative matrix is constructed, the linguistic judgment matrix is converted into the HFLTS judgment matrix. The standardized decision matrix and weighted standardized decision matrix are constructed. Then, the positive and negative ideal solutions are determined and the distance between alternatives are computed using a special distance measure named as Hamming distance. The proximity coefficients of the alternatives are calculated, which are then ranked according to their proximity coefficients.

The research methodology of the study is provided in Fig. 11.1.

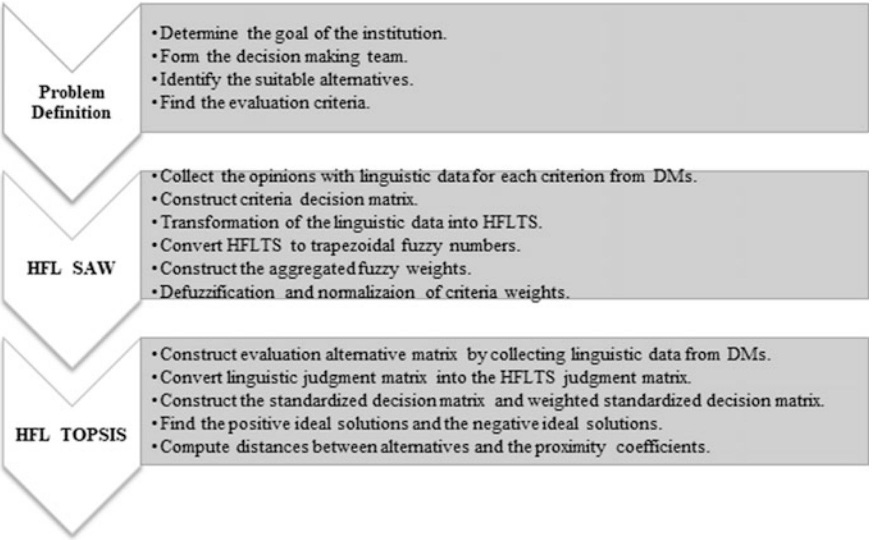

Fig. 11.1 Research methodology of the proposed model

11.3.1 Problem Definition

In this first phase of the model, the goal is determined as selecting the most appropriate RES strategy by taking various aspects, including sustainability-related factors, into account from an investor point of view. This decision will be taken with the support of industry experts. While RES strategies can be expanded according to local circumstances and availability of natural resources, usually these options include wind, solar PV, biogas, hydropower and geothermal alternatives.

11.3.1.1 Evaluation Criteria

Evaluation criteria are identified based on a detailed literature survey of existing models and consultations with three experts from the energy industry.

Compared to conventional energy strategies, RES offers many economic, social and environmental benefits. Each type of RES has its own attributes, as benefits or harms, that make it uniquely suitable for the specific use (Kabak and Dağdeviren 2014). Certainly, the identification of suitable criteria is one of the most important prerequisites for DMs (Pak et al. 2015). For this model, evaluation criteria from the literature, mostly from Ishizaka et al. (2016), Taha and Daim (2013), Kahraman et al. (2015), and Wang et al. (2009) are compiled, and then adapted to RES strategies with DMs' guidance and feedback. This chapter thus provides a novel criteria structure for assessing RES strategies. Eventually, 10 selection criteria are determined, as described as Table 11.1.

The model's general overview is provided in Fig. 11.2.

11.3.2 Criteria Weights

The evaluation criteria can have different levels of impact on the ultimate decision. Therefore, in this second phase of the proposed model, the selected DMs are asked to provide their opinions about which criteria has what level of influence on the decision outcomes. This process is accomplished with HFL SAW technique in a GDM environment. The GDM, HFLTS, and HFL SAW techniques are explained next.

11.3.2.1 Group Decision Making

RES strategies are inherently subject to different opinions and views. This subjectivity embedded in human judgments can lead to biased perception in individual decisions, even for experts, as an expert might not always have the necessary knowledge about the problem. Different DMs can provide different points of view (Pohekar and Ramachandran 2004). Depending on a single DM, therefore, poses subjectivity risks due to limited experiences and personal preferences. These risks can effectively be reduced by including more than one DM in the process. A GDM process involves two or more industry specialists, who understand the common problem and have a common interest in reaching a collective decision (Herrera et al. 1995). Therefore, GDM is often superior for evading the prejudice and subjectivity of individual DMs.

11.3.2.2 Hesitant Fuzzy Linguistic Term Sets

In decision-making processes, experts are usually inclined to express their judgments with words, which correspond to imprecise, and unquantifiable ratings, since it might be difficult for DMs to precisely estimate their preference degrees numerically. Values of linguistic information can include words, phrases or sentences instead of numbers (Tapia Garcı´a et al. 2012). Linguistic assessment tend to be more flexible, practical and suitable for the real world (Rodríguez et al. 2013). These linguistic judgments can be taken into account with the fuzzy set theory, developed by Zadeh (1965), to deal with the uncertainty and vagueness.

Table 11.1 Evaluation criteria of the proposed model

Criterion		Explanation
C_1	Investment and O&M Costs	Investment costs represent those expenditures that occur at the beginning for establishing the energy strategy alternative. Operation and maintenance (O&M) costs refer to production costs that are associated with running a power plant
C_2	Price tariff and incentives	RES strategies are often supported with attractive legal and financial mechanisms to stabilize cash inflows for investors and reduce various costs and red tape. This criterion affects the return on investment and the economic success of the strategy
C_3	Maturity and serviceability	Maturity is related to technological penetration, availability of and maintenance knowhow and services, familiarity of investors and suppliers and technical development for reliable operation. Serviceability becomes especially important for remote RES installations, where a breakdown may not be fixed locally
C_4	Grid connectivity	RES strategies are often halted due to unavailable capacity at local power grids. Many RES strategies are not able to carry the base load in a grid, therefore additional transformer capacity can be needed to connect renewables. The lack of such capacity can delay, or prevent, the realization of RES strategies
C_5	Greenhouse gas emissions	RES strategies reduce greenhouse gas emissions indirectly by substituting electricity in the grid generated with fossil fuels. However, the manufacturing of RES equipment (steel, silicon wafers, concrete etc.) has a carbon footprint, as does the operation (e.g. hydropower plants with shallow reservoirs, or geothermal power plants). Therefore, the emission reductions shall incorporate a Life Cycle Analysis (LCA) approach
C_6	Land use and ecologic footprint	Most RES strategies are bound to specific geographies and locations, so that their impact on their immediate surroundings can vary according to the regional ecologic sensitivity. This impact is amplified, as the physical size of the RES facility increases (such as solar PV covering large areas, or high wind turbines in bird migration routes)
C_7	Job creation	Creation of decent, full-time, diverse, and permanent employment opportunities for local communities is a central priority for sustainable development
C_8	Social acceptability	Many energy facilities are subject to opposition by residents for a new development because it is close to them, which can be due to environmental pollution, poor air quality, increased traffic, visual beauty, sharing of limited local resources etc. These challenges shall be overcome by enhanced dialogue, voluntary actions and social responsibility
C_9	Supply security	Energy supply in a grid is expected to be resilient to international political developments, price volatility of fuels and market shortages. The supply of natural resources is prone to such shocks, but can be sensitive to ecologic and climatic variations
C_{10}	Policy compatibility	The RER strategy shall be in line with national energy policies, compatible with regional priorities and relevant legislation. These policies can aim to improve international competitiveness, technology transfer, trade balance, job creation and environmental protection, among others

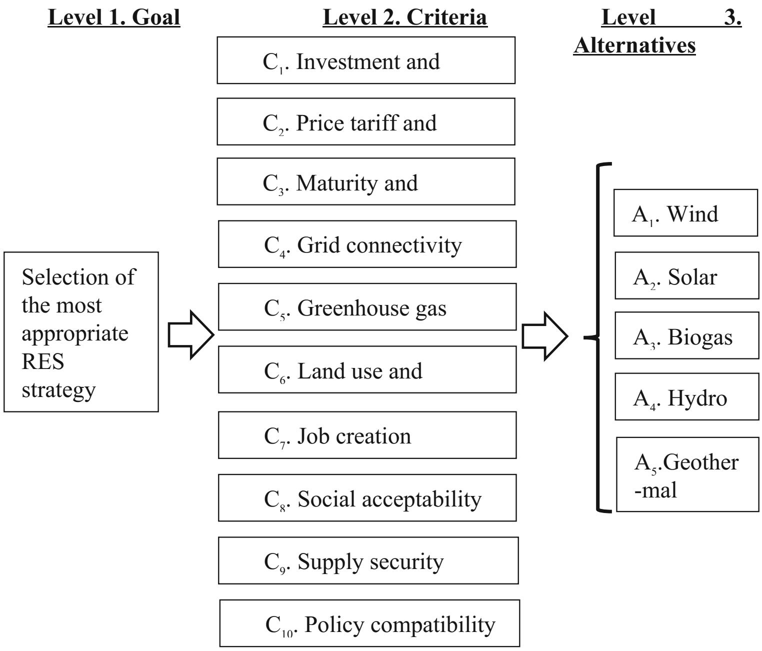

Fig. 11.2 The overall structure of the proposed model

However, DMs also can find it difficult to identify the best fitting linguistic term for voicing their opinions in. Hesitant Fuzzy Sets (HFS), which constitute the extension of classical fuzzy sets, prove helpful in such settings.

Extending the classical fuzzy set theory to the HFS method is first developed by Torra and Narukawa (2009). It defines the degree of adhesion of an element with a set of possible values between 0 and 1. This method is useful when DMs hesitate in expressing a certain evaluation. It is based on the following definitions:

Definition 1 Let X be a universal set. HFS over X is defined as ssa function that will render a subset of [0, 1] when applied to X, which is defined as the following (Torra 2010):

$$\mathrm{E} = \{\langle \mathrm{x}, \mathrm{h}_{\mathrm{E}}(\mathrm{x})\rangle \mathrm{x} \in \mathrm{X} \tag{11.1}$$

In this definition, *H* is the set of all Hesitant Fuzzy Element (HFE), with HFEs $h_E(x)$ between [0, 1]. Possible degrees of adhesion of the element $x \in X$ to the set *E* are specified.

Definition 2 X is defined as a reference set. HFS over *X* is a function *h* which assigns values between [0, 1]:

$$h: X \rightarrow \{[0,1]\} \tag{11.2}$$

Then, an HFS is represented with the union of their membership functions.

Definition 3 $M = \{\mu 1, \mu 2, \ldots, \mu n\}$ is defined as a set of membership functions n. HFS is linked to *M*. Here,, h_M gives values between 0 and 1:

$$h_M : M \rightarrow \{[0,1]\} \tag{11.3}$$

$$h_M(x) = U_{\mu \in M}\{\mu(x)\} \tag{11.4}$$

Definition 4 The lower and upper boundaries of *h*, an HFS, are defined as (Torra 2010):

$$h^-(x) = \min\ h(x) \tag{11.5}$$

$$h^+(x) = \max\ h(x) \tag{11.6}$$

Definition 5 When *h* is defined as an HFS, its envelope $A_{env}(h)$ is defined as:

$$A_{env(h)} = \{x,\ \mu_A(x), \nu_A(x)\} \tag{11.7}$$

Where $A_{env(h)}$ is an intuitionistic fuzzy set of *h*. Accordingly, μ and *v* are represented as:

$$\mu_A(x) = h^-(x) \tag{11.8}$$

$$\nu_A(x) = 1 - h^+(x) \tag{11.9}$$

Rodriguez et al. (2012) developed an MCDM method, where DMs voice their evaluations with linguistic expressions as HFLTS.

Definition 6 $S = \{s_0, \ldots, s_g\}$ is defined as a set of linguistic expressions. An HFLTS, H_s, is an ordered finite subset of the consecutive linguistic elements of *S*, which can also be shown as a subscript-symmetric linguistic term set as $S = \{s_i| i = -\tau, \ldots, -1, 0, 1, \ldots, \tau\}$.

Definition 7: HFLTS's upper and lower bounds, H_s, H_{s+} and H_{s-} respectively, are formulated as:

$$H_{s+} = \max\ (s_i) = s_j, s_i \in H_S \text{ et } s_i \leq s_j \forall\, i \tag{11.10}$$

$$H_{s-} = \min(s_i) = s_j, s_i \in H_S \text{ et } s_i \leq s_j \forall\, i \tag{11.11}$$

Definition 8 E_{GH} is defined as a function which transforms linguistic expressions into HFLTS, $H_{S.}$ Then, G_H is defined as an out-of-context grammar that utilizes the linguistic term set in S. S_{ll} is defined as the expression domain generated by G_H. This mapping can be represented as:

$$\mathrm{E_{GH}}: \mathrm{S_{ll}} \rightarrow \mathrm{H_s} \tag{11.12}$$

Comparative linguistic expressions are converted into HFLTS with the following formulae;

$$\mathrm{E_{GH}}(\mathrm{s_i}) = \{\mathrm{s_i} | \mathrm{s_i} \in \mathrm{S}\} \tag{11.13}$$

$$\mathrm{E_{GH}}(\text{at most } \mathrm{s_i}) = \{\mathrm{s_j} | \mathrm{s_j} \in \mathrm{S} \text{ et } \mathrm{s_j} \leq \mathrm{s_i}\} \tag{11.14}$$

$$\mathrm{E_{GH}}(\text{lower than } \mathrm{s_i}) = \{\mathrm{s_j} | \mathrm{s_j} \in \mathrm{S} \text{ et } \mathrm{s_j} < \mathrm{s_i}\} \tag{11.15}$$

$$\mathrm{E_{GH}}(\text{at least } \mathrm{s_i}) = \{\mathrm{s_j} | \mathrm{s_j} \in \mathrm{S} \text{ et } \mathrm{s_j} \geq \mathrm{s_i}\} \tag{11.16}$$

$$\mathrm{E_{GH}}(\text{greater than } \mathrm{s_i}) = \{\mathrm{s_j} | \mathrm{s_j} \in \mathrm{S} \text{ et } \mathrm{s_j} > \mathrm{s_i}\} \tag{11.17}$$

$$\mathrm{E_{GH}}\left(\text{between } \mathrm{s_i} \text{ and } \mathrm{s_j}\right) = \{\mathrm{s_k} | \mathrm{s_k} \in \mathrm{S} \text{ et } \mathrm{s_i} \leq \mathrm{s_k} \leq \mathrm{s_j}\} \tag{11.18}$$

Definition 9 When H_s is defined as an HFLTS, based on H_{s+} and H_{s-} as introduced in *Definition* 7, its envelope $env(H_s)$ is shown as:

$$\mathrm{env}(\mathrm{H_S}) = [\mathrm{H_{s-}}, \mathrm{H_{s+}}], \quad \mathrm{H_{s-}} \leq \mathrm{H_{s+}} \tag{11.19}$$

11.3.2.3 HFL SAW Method

Simple Additive Weighting (SAW) method is developed by Hwang and Yoon (1981). Still, it is counted among the most popular MCDM techniques thanks to its simplicity. It is based on a simple aggregation concept that is useful for positive values only. This makes it mandatory to transform negative criteria into positive values first with a normalization process. As an extension of SAW, Chou et al. (2008) introduced the combined Fuzzy Simple Additive Weighting (FSAW) technique as a way to approach decision problems with fuzzy aspects. Similarly, the SAW method is combined with HFLTS in this chapter, the steps of which are explained next in consecutive steps (Chou et al. 2008).

Step 1. DMs voice their opinions, in words, about the importance of the evaluation criteria. These opinions are expressed with a context-free grammar, as shown in *Definition* 6 and Table 11.2.

Table 11.2 Linguistic terms for HFL SAW (Chou et al. 2008)

Linguistic term	S_i	Abb.	Fuzzy numbers
Very low	s_{-2}	VL	(0, 0, 0, 3)
Low	s_{-1}	L	(0, 3, 3, 5)
Medium	s_0	M	(2, 5, 5, 8)
High	s_1	H	(5, 7, 7, 10)
Very high	s_2	VH	(7, 10, 10, 10)

Step 2. Linguistic judgment matrix is transformed into HFLTS judgment matrix on the basis of the scale provided in Table 11.2 by using the conversion function E_{GH}, as in *Definition* 8.

Step 3. The alternatives are formulated as $A_i = \{a_1, a_2,\ldots, a_I\}$ with I members. The evaluation criteria are represented as $C_j = \{c_1, c_2,\ldots, c_J\}$ with J members. The decision committee is formulated as $D_t = \{d_1, d_2,\ldots, d_k\}$ with k DMs. The DMs do not necessary possess equal say on the decision, and I_t delineates the degree of importance of each DM, with $0 \leq I_t \leq 1$, $t = 1, 2,\ldots, k$, and $\sum_{t=1}^{k} I_t = 1$, $\widetilde{\omega}_t$ being the fuzzy weight of the DMs. I_t is found as:

$$I_t = \frac{d(\widetilde{w}_t)}{\sum_{t=1}^{k} d(\widetilde{w}_t)}, \quad t = 1, 2, \ldots, k \tag{11.20}$$

Here, $d(\widetilde{w}_t)$ stands for the de-fuzzified value of the fuzzy weight according to its signed distance.

Step 4. Aggregated fuzzy weights of the evaluation criteria $C_j, \widetilde{w}_j = (a_j, b_j, c_j, d_j)$, are computed:

$$\widetilde{W}_j = (I_1 \otimes \widetilde{W}_{j1}) \oplus (I_2 \otimes \widetilde{W}_{j2} \oplus \ldots \oplus (I_k \otimes \widetilde{W}_{k1}) \tag{11.21}$$

Here, $a_j = \sum_{t=1}^{k} I_t a_{jt}$, $b_j = \sum_{t=1}^{k} I_t b_{jt}$, $c_j = \sum_{t=1}^{k} I_t c_{jt}$, $d_j = \sum_{t=1}^{k} I_t d_{jt}$.

Step 5. Criteria's fuzzy weights are de-fuzzified. The de-fuzzified $\widetilde{W}_j$, shown as $d(\widetilde{W_j})$, is calculated as:

$$d\left(\widetilde{W}_j\right) = \frac{1}{4}(a_j + b_j + c_j + d_j), \quad \text{where } j = 1, 2, \ldots, n \tag{11.22}$$

Step 6. Normalized weight of the criteria C_j, shown as W_j, is calculated as:

$$W_j = \frac{d(\widetilde{w}_j)}{\sum_{j=1}^{n} d(\widetilde{w}_j)}, \quad j = 1, 2, \ldots, n \tag{11.23}$$

Here, the normalized weights add to 1, i.e. $\sum_{j=1}^{n} W_j = 1$. Eventually, the weight vector $W = (W_1, W_2, \ldots, W_n)$ is established.

11.3.3 Ranking of Alternatives

After criteria weights are known, DMs are asked to rate the RES strategy alternatives according to the evaluation criteria, one by one. This 3rd phase is guided by HFL TOPSIS technique, again in a GDM environment with consensus process. HFLTS and GDM approach are explained in Sect. 11.3.2. Therefore, the algorithmic steps of HFL TOPSIS are described next.

11.3.3.1 HFL TOPSIS Method

Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method is presented by Chen and Hwang (1992). It is based on the concept that the chosen alternative should have the smallest geometric distance from the positive ideal solution (PIS) and the largest geometric distance from the negative ideal solution (NIS).

Cevik Onar et al. (2014) came up with a Hesitant Fuzzy TOPSIS model that considers the complexity and imprecision of strategic decisions and presented a case study for an electronics company.

The steps of HFL TOPSIS method are:

Step 1. DMs express their opinions by using linguistic expressions about criteria. The linguistic expression is voiced by the DM based on a context-free grammar, as shown in *Definition 6*.

Step 2. The linguistic judgment matrix is converted to the HFLTS judgment matrix with the help of the transformation function E_{GH} as given in *Definition 8*. Table 11.3 shows the scale used in HFL TOPSIS method.

Table 11.3 Linguistic terms for HFL TOPSIS (Beg and Rashid 2013)

Linguistic term	S_i	Abb.	Fuzzy numbers
None	s_{-3}	N	(0, 0, 0.17)
Very bad	s_{-2}	VB	(0, 0.17, 0.33)
Bad	s_{-1}	B	(0.17, 0.33, 0.5)
Medium	s_0	M	(0.33,0.5,0.67)
Good	s_1	G	(0.5, 0.67, 0.83)
Very good	s_2	VG	(0.67, 0.83, 1)
Perfect	s_3	P	(0.83, 1, 1)

Step 3. The positive and negative ideal solutions are determined as:

$$A^* = \{h_1^*, h_2^*, \ldots, h_n^*\} \tag{11.24}$$

where $h_j^* = \cup_{i=1}^{m} h_{ij} = \cup_{\gamma_{1j} \in h_{1j},\ldots,\gamma_{mj} \in h_{mj}} \max\{\gamma_{1j}, \ldots, \gamma_{mj}\} \quad j = 1, 2, \ldots, n$

$$A^- = \{h_1^-, h_2^-, \ldots, h_n^-\} \tag{11.25}$$

where $h_j^* = \cap_{i=1}^{m} h_{ij} = \cap_{\gamma_{1j} \in h_{1j},\ldots,\gamma_{mj} \in h_{mj}} \min\{\gamma_{1j}, \ldots, \gamma_{mj}\} \quad j = 1, 2, \ldots, n$

Step 4. Separation measures of each alternative from the ideal solution are calculated. As the separation measure, the weighted hesitant normalized Hamming distance is applied. The proximity of an alternative to the positive ideal is calculated as:

$$D_i^+ = \sum_{j=1}^{n} w_j \left\| h_{ij} - h_j^* \right\| \tag{11.26}$$

where w_j is the weight of the jth criterion determined by hesitant AHP. The distance from the negative ideal solution is given as:

$$D_i^- = \sum_{j=1}^{n} w_j \left\| h_{ij} - h_j^- \right\| \tag{11.27}$$

The distance between two hesitant fuzzy numbers is found as:

$$\|h_1 - h_2\| = \frac{1}{1} \sum_{j=1}^{1} w_j \left| h_{1\sigma(j)} - h_{2\sigma(j)} \right| \tag{11.28}$$

Step 5. The relative proximity to the ideal solution is found as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{11.29}$$

Step 6. The alternatives are ranked in increasing order, based on their relative closeness index. The alternative that has the highest value is determined to be the best alternative.

With this step, the ranking of RES strategies is accomplished.

11.4 Case Study

The proposed model is applied on a case study, in which a number of RES strategies from Turkey are assessed and then ranked. The most important alternative strategies for Turkey, i.e. wind, solar PV, biogas, hydro, and geothermal, are chosen for this comparison.

Energy demand in Turkey, electricity consumption, in particular, grows at high rates since decades, requiring continuous new capacity additions. The rapidly increasing electricity need is covered by installing large fossil fuel-powered power plants, mostly coal and natural gas. Due to their environmental impacts, such as greenhouse gas emissions and pollution, as well as social impacts, such as local acceptability, renewables remain top on the energy agenda of Turkey, which has abundant natural resources and willingness of investors. While RES strategies, in general, are considered to be a priority, investors find it difficult to select which RES strategy to prioritize in their investment decisions.

The integrated MCDM model presented previously is applied for finding the most suitable RES strategy by first forming a decision committee with 3 industry experts. These experts support the process of defining the criteria set, weighing these criteria, and rating the alternatives. All three DMs have sufficient knowledge about energy strategies and are adequately qualified for this evaluation.

11.4.1 Application of the Proposed Model

The criteria are introduced next. C1 is Investment and O&M cost, C2 is Price tariff and incentives, C3 is Maturity and serviceability, C4 is Grid connectivity, C5 is LCA greenhouse gas emissions, C6 is Land use and ecologic footprint, C7 is Job creation, C8 is Social acceptability, C9 is Supply security and C10 is Policy compatibility.

There are five possible alternatives: A1 is Wind, A2 is Solar, A3 is Biogas, A4 is Hydro and A5 is Geothermal.

11.4.1.1 Criteria Weight Calculation with HFL SAW Method

In the first stage, DMs evaluated the criteria by using linguistic term sets given in Table 11.2. Table 11.4 shows the assessments of DMs.

Table 11.4 DMs evaluation about criteria

Criteria	DM1	DM2	DM3
C1	Between H and VH	At least VH	At least H
C2	Between H and VH	Between L and H	Between L and H
C3	At most VL	At most VL	Between L and H
C4	Between L and H	Between L and H	At most VL
C5	At most VL	between VL and L	between L and H
C6	At most VL	Between VL and L	Between L and H
C7	Between VL and L	between VL and L	between VL and L
C8	Between VL and L	Between VL and L	Between VL and L
C9	At most VL	Between VL and L	Between L and H
C10	Between VL and L	Between VL and L	Between VL and L

Table 11.5 Criteria weights

Criteria	Defuzzified value	Normalized value	Ranking
C1	7.917	0.215	1
C2	5.750	0.156	2
C3	2.833	0.077	4
C4	3.583	0.097	3
C5	2.833	0.077	4
C6	2.833	0.077	4
C7	2.750	0.075	8
C8	2.750	0.075	8
C9	2.833	0.077	4
C10	2.750	0.075	8
Total	36.833		

Based on these assessments in Table 11.4, the linguistic expressions are converted into HFLTS by using (11.13)–(11.18). The HFLTS are converted into fuzzy numbers by using the scale given in Table 11.1. Based on these numbers, the fuzzy weights of individual criteria are calculated by (11.21). The de-fuzzified values of the aggregated fuzzy weights are computed using (11.22) and the normalized weights of criteria are found using (11.23). Table 11.5 depicts the criteria weights.

The most important criterion is Investment, O&M cost (C1), and the second important criterion is Price tariff and incentives (C2).

11.4.1.2 Ranking E-Health Technology Alternatives with HFL TOPSIS Method

Initially, the DMs evaluated the alternatives with regard to criteria via comparative linguistic expressions and the linguistic scale given in Table 11.3.

In the initial phase, the DMs reached consensus by using Delphi Method and a series of questionnaires (Hsu and Sandford 2007; Marchais-Roubelat and Roubelat 2011). The consensus evaluation with linguistic expressions is listed in Table 11.6.

Linguistic expressions are converted into HFLTS by using Eqs. (11.13)–(11.18). The positive ideal and the negative ideal solution are found with Eqs. (11.24) and (11.25). The Hamming distances are calculated by using Eqs. (11.26) and (11.27). The distance between two hesitant fuzzy numbers is found with Eq. (11.28). Finally, the proximity to the ideal solution is found with Eq. (11.29). Table 11.7 shows the results of HFL TOPSIS methodology and ranking of alternatives.

The results about alternatives give an idea to find the best alternative. As a result, Hydro (A4) is the most desirable energy alternative through these alternatives, with the nearest competitor Geothermal (A5). Solar (A2) has become the third, and the fourth one is Wind (A1), as depicted in Table 11.6.

Table 11.6 DMs evaluation about alternatives

Ai	C1	C2	C3	C4	C5
A1	Between VB and M	Between VB and M	Between B and G	At most VB	Between B and G
A2	Between VB and M	Between M and VG	Between VB and M	Between VB and M	Between B and G
A3	Between VB and M	Between M and VG	Between VB and M	Between B and G	At least VG
A4	At least VG	At most VB	Between M and VG	Between M and VG	Between B and G
A5	Between B and G	At least VG	Between B and G	Between M and VG	At most N
Ai	C6	C7	C8	C9	C10
A1	Between B and G	Between B and G	At most VB	Between VB and M	Between VB and M
A2	At most N	At most VB	At least VG	At least VG	Between VB and M
A3	At least VG	Between M and VG	Between M and VG	Between VB and M	Between M and VG
A4	At most VB	Between B and G	At most N	Between VB and M	Between B and G
A5	At least VG	Between B and G	At least VG	Between B and G	At least VG

Table 11.7 Ranking of alternatives

Ai	Di+	Di−	Ci	Ranking
A1	0.403	0.440	0.522	4
A2	0.354	0.489	0.580	3
A3	0.412	0.431	0.511	5
A4	0.312	0.540	0.634	1
A5	0.360	0.535	0.598	2

The main ranking list of alternatives is:
A4 ≻ A5 ≻ A2 ≻ A1 ≻ A3

11.5 Conclusion

The main objective of this chapter is to identify the most applicable RES strategy with a sustainability point of view and developing country perspective. This decision-making process is governed by a set of evaluation factors that are assessed by a decision committee. In such complex problems with conflicting criteria, uncertainty, and vagueness MCDM methods can prove very useful. For this reason, this decision-making problem is approached by proposing a new set of criteria and integrating it with MCDM methods in a GDM setting. The proposed model is based on 10 criteria, the weights of which are determined with HFL SAW method. The results are then fed into the HFL TOPSIS to find the ranking of selected RES strategies. The combined method offers superior solutions, as it is able to successfully capture DMs' opinions.

The plausibility and practical usefulness of the proposed model are shown in a case study from Turkey. The case study revealed Hydro to be the best RES strategy for Turkey, followed by Geothermal and Solar. These findings can be associated with legal difficulties for getting permits for wind farms in Turkey in recent years, as well as the economic performance of hydro energy plants. Investors can benefit from these results by applying similar practices in comparing different RES strategies available to them.

Individually, HFL SAW and HFL TOPSIS techniques are recent and novel methods. In the literature, publications applying these methods are very few. Using these methods together with GDM, therefore, presents a scientific contribution. Therefore, this model is unique in its application of HFL SAW and HFL TOPSIS in combination in a GDM setting for the RES strategy selection problem. It not only contributes to the RES strategy evaluation literature by developing a new evaluation model, it also provides a case study to illustrate how the proposed method can be utilized to solve real problems. The introduction of a new criteria set, adapted to developing economies, adds to its research value. The proposed model can be applied in other developing countries as well by re-weighing the criteria and assessing different alternative RES strategies with other experts.

The proposed model also has some limitations. One of these limitations is its focus on developing countries when it comes to selecting evaluation criteria, which can show differences from a developed country perspective. Future research therefore can consider the adaptation of these criteria to other circumstances and geographies. Moreover, the criteria set consists of one level, with no hierarchical structure. In the future, the criteria set can be extended. In terms of MCDM methods, future research can also use other similar techniques, such as HFL VIKOR, instead of HFL TOPSIS, and compare the findings.

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References

Balin, A., & Baraçli, H. (2017). A fuzzy multi-criteria decision making methodology based upon the interval Type-2 fuzzy sets for evaluating renewable energy alternatives in Turkey. *Technological and Economic Development of Economy, 23,* 742–763. https://doi.org/10.3846/20294913.2015.1056276.

Beg, I., & Rashid, T. (2013). TOPSIS for hesitant fuzzy linguistic term sets. *International Journal of Intelligent Systems, 28,* 1162–1171. https://doi.org/10.1002/int.21623.

Büyüközkan, G., & Güler, M. (2017). Hesitant fuzzy linguistic VIKOR method for e-health technology selection (in Press).
Büyüközkan, G., & Güleryüz, S. (2017). Evaluation of Renewable Energy Resources in Turkey using an integrated MCDM approach with linguistic interval fuzzy preference relations. *Energy, 123,* 149–163. https://doi.org/10.1016/j.energy.2017.01.137.
Büyüközkan, G., & Güleryüz, S. (2014). A new GDM based AHP framework with linguistic interval fuzzy preference relations for renewable energy planning. *Journal of Intelligent & Fuzzy Systems, 27,* 3181–3195.
Büyüközkan, G., & Güleryüz, S. (2016). An integrated DEMATEL-ANP approach for renewable energy resources selection in Turkey. *International Journal of Production Economics, 182,* 435–448. https://doi.org/10.1016/j.ijpe.2016.09.015.
Büyüközkan, G., & Karabulut, Y. (2017). Energy project performance evaluation with sustainability perspective. *Energy, 119,* 549–560. https://doi.org/10.1016/j.energy.2016.12.087.
Cevik Onar, S., Oztaysi, B., & Kahraman, C. (2014). Strategic decision selection using hesitant fuzzy TOPSIS and interval type-2 fuzzy AHP: A case study. *International Journal of Computational intelligence systems, 7,* 1002–1021.
Chen, S.-J. J., Hwang, C.-L., Beckmann, M. J., & Krelle, W. (1992). *Fuzzy multiple attribute decision making: Methods and applications*. New York Inc: Springer.
Chou, S.-Y., Chang, Y.-H., & Shen, C.-Y. (2008). A fuzzy simple additive weighting system under group decision-making for facility location selection with objective/subjective attributes. *European Journal of Operational Research, 189,* 132–145. https://doi.org/10.1016/j.ejor.2007.05.006.
Çolak, M., & Kaya, İ. (2017). Prioritization of renewable energy alternatives by using an integrated fuzzy MCDM model: A real case application for Turkey. *Renewable and Sustainable Energy Reviews, 80,* 840–853. https://doi.org/10.1016/j.rser.2017.05.194.
Erdogan, M., & Kaya, I. (2015). An integrated multi-criteria decision-making methodology based on type-2 fuzzy sets for selection among energy alternatives in Turkey. *Iranian Journal of Fuzzy Systems, 12,* 1–25.
Herrera, F., Herrera-Viedma, E., & Verdegay, J. L. (1995). A sequential selection process in group decision making with a linguistic assessment approach. *Information Sciences, 85,* 223–239.
Hsu, C.-C., & Sandford, B. A. (2007). The Delphi technique: Making sense of consensus. *Practical assessment, research & evaluation, 12,* 1–8.
Hwang, C., & Yoon, K. (1981). Multiple attribute decision making. *Lecture notes in Economics and Mathematical Systems*. http://www.doi.org/10.1007/978-3-642-48318-9.
International Energy Agency (Ed.). (2015). *World energy outlook 2016*. Paris: OECD.
Ishizaka, A., Nemery, P. (2013). *Multi-criteria decision analysis: Methods and software*. Wiley.
Ishizaka, A., Siraj, S., & Nemery, P. (2016). Which energy mix for the UK (United Kingdom)? An evolutive descriptive mapping with the integrated GAIA (graphical analysis for interactive aid)–AHP (analytic hierarchy process) visualization tool. *Energy, 95,* 602–611. https://doi.org/10.1016/j.energy.2015.12.009.
Işıklar, G., & Büyüközkan, G. (2007). Using a multi-criteria decision making approach to evaluate mobile phone alternatives. *Computer Standards & Interfaces, 29,* 265–274. https://doi.org/10.1016/j.csi.2006.05.002.
Iskin, I., Daim, T., Kayakutlu, G., & Altuntas, M. (2012). Exploring renewable energy pricing with analytic network process—Comparing a developed and a developing economy. *Energy Economics, 34,* 882–891. https://doi.org/10.1016/j.eneco.2012.04.005.
Kabak, M., & Dağdeviren, M. (2014). Prioritization of renewable energy sources for Turkey by using a hybrid MCDM methodology. *Energy Conversion and Management, 79,* 25–33. https://doi.org/10.1016/j.enconman.2013.11.036.
Kahraman, C., Kaya, İ., & Cebi, S. (2009). A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process. *Energy, 34,* 1603–1616. https://doi.org/10.1016/j.energy.2009.07.008.

Kahraman, C., Onar, S. C., & Oztaysi, B. (2015). Fuzzy multicriteria decision-making: A literature review. *International Journal of Computational Intelligence Systems, 8,* 637–666. https://doi.org/10.1080/18756891.2015.1046325.

Kaya, T., & Kahraman, C. (2011). Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. *Expert Systems with Applications, 38,* 6577–6585. https://doi.org/10.1016/j.eswa.2010.11.081.

Kumar, A., Sah, B., Singh, A. R., et al. (2017). A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews, 69,* 596–609. https://doi.org/10.1016/j.rser.2016.11.191.

Marchais-Roubelat, A., & Roubelat, F. (2011). The Delphi method as a ritual: Inquiring the Delphic Oracle. *Technological Forecasting and Social Change, 78,* 1491–1499.

Onar, S. Ç., Büyüközkan, G., Öztayşi, B., & Kahraman, C. (2016). A new hesitant fuzzy QFD approach: An application to computer workstation selection. *Applied Soft Computing, 46,* 1–16.

Önüt, S., Tuzkaya, U. R., & Saadet, N. (2008). Multiple criteria evaluation of current energy resources for Turkish manufacturing industry. *Energy Conversion and Management, 49,* 1480–1492. https://doi.org/10.1016/j.enconman.2007.12.026.

Pak, B. K., Albayrak, Y. E., & Erensal, Y. C. (2015). Renewable energy perspective for Turkey using sustainability indicators. *International Journal of Computational Intelligence Systems, 8,* 187–197. https://doi.org/10.1080/18756891.2014.963987.

Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and Sustainable Energy Reviews, 8,* 365–381. https://doi.org/10.1016/j.rser.2003.12.007.

REN 21. (2017). Renewables 2017 Global Status Report. REN 21, Paris, France.

Rodriguez, R. M., Martinez, L., & Herrera, F. (2012). Hesitant fuzzy linguistic term sets for decision making. *IEEE Transactions on Fuzzy Systems, 20,* 109–119. https://doi.org/10.1109/tfuzz.2011.2170076.

Rodríguez, R. M., Martínez, L., & Herrera, F. (2013). A group decision making model dealing with comparative linguistic expressions based on hesitant fuzzy linguistic term sets. *Information Sciences, 241*, 28–42. https://doi.org/10.1016/j.ins.2013.04.006.

Şengül, Ü., Eren, M., Eslamian Shiraz, S., et al. (2015). Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. *Renewable Energy, 75,* 617–625. https://doi.org/10.1016/j.renene.2014.10.045.

Senvar, O., Otay, I., & Bolturk, E. (2016). Hospital site selection via hesitant fuzzy TOPSIS. *IFAC-PapersOnLine, 49,* 1140–1145. https://doi.org/10.1016/j.ifacol.2016.07.656.

Suganthi, L., Iniyan, S., & Samuel, A. A. (2015). Applications of fuzzy logic in renewable energy systems—A review. *Renewable and Sustainable Energy Reviews, 48,* 585–607. https://doi.org/10.1016/j.rser.2015.04.037.

Taha, R. A., & Daim, T. (2013). Multi-criteria applications in renewable energy analysis, a literature review. In T. Daim, T. Oliver & J. Kim (Eds.), *Research and technology management in the electricity industry* (pp. 17–30). London: Springer.

Tapia Garcı´a, J. M., del Moral, M. J., Martínez, M. A., Herrera-Viedma, E. (2012). A consensus model for group decision making problems with linguistic interval fuzzy preference relations. *Expert Systems with Applications, 39*, 10022–10030. https://doi.org/10.1016/j.eswa.2012.02.008.

Torra, V. (2010). Hesitant fuzzy sets. *International Journal of Intelligent Systems, 25,* 529–539. https://doi.org/10.1002/int.20418.

Torra, V., Narukawa, Y. (2009). On hesitant fuzzy sets and decision. In: *2009 IEEE International Conference on Fuzzy Systems*, pp. 1378–1382.

Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., & Zhao, J.-H. (2009). Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews, 13,* 2263–2278. https://doi.org/10.1016/j.rser.2009.06.021.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8,* 338–353.

Zhang, N., & Wei, G. (2013). Extension of VIKOR method for decision making problem based on hesitant fuzzy set. *Applied Mathematical Modelling, 37,* 4938–4947. https://doi.org/10.1016/j.apm.2012.10.002.

Zhang, Y., Xie, A., & Wu, Y. (2015). A hesitant fuzzy multiple attribute decision making method based on linear programming and TOPSIS**This work was supported by the Specialized Research Fund for the Doctoral Program of Higher Education under Project No. 20130009120040. *IFAC-PapersOnLine, 48,* 427–431. https://doi.org/10.1016/j.ifacol.2015.12.165.

Zhou, H., Wang, J., Zhang, H., & Chen, X. (2016). Linguistic hesitant fuzzy multi-criteria decision-making method based on evidential reasoning. *International Journal of Systems Science, 47,* 314–327.