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Energy planning under uncertain decision-making environment: An evidential reasoning approach to prioritize renewable energy sources

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Abstract Nowadays, making strategic decisions in a sensitive sector such as energy planning that usually requires allocating huge funds, time, and resources is a difficult task. For instance, prioritizing a set of Renewable Energy Sources (RES) is a complex multi-dimensional task that typically involves a range of conflicting criteria featuring different forms of evaluation data in an uncertain decision-making environment. This process is aligned with several sources that can be uncertain, including imprecise information, limited domain knowledge from decision-makers, and failures to provide accurate judgments from experts. In this study, we propose to use the Evidential Reasoning (ER) approach to manage the expanding complexities and uncertainties in RES prioritization problem. The ER approach is employed as a multiple criteria framework to assess the appropriateness regarding the use of different renewable energy technologies. A case study is provided to illustrate the implementation process. Results show that using the ER approach when assessing the sustainability of different RES under uncertainty allows providing robust decisions, which brings out a more accurate, effective, and better-informed decision-making tool to conduct the evaluation process.

Keywords: Renewable energy, Strategic decision-making, Multi-criteria analysis, Evidential reasoning, Uncertainty.

Nomenclature

D-S	Dempster–Shafer
DSS	Decision Support System
EPDM	Energy Planning Decision-Making
EfW	Energy-from-Waste
ER	Evidential Reasoning
FMCDM	Fuzzy based Multiple Criteria Decision Making
MCA	Multiple Criteria Analysis
MCDM	Multiple Criteria Decision-Making
MCS	Monte Carlo Simulation
RES	Renewable Energy Sources

1 Introduction

Energy use is the essential instrument for worldwide economic growth. Rapid technological advances— in the twentieth century —improved individuals' life quality, and high economic development has amplified the population rate, which significantly increased the energy demand across the world [1]. The international energy association (IEA) expected that global energy demand set to grow by 37% by 2040 [2]. The efficient, clean, and renewable energy was distinguished as the key success to strongly activate the sustainability vision for future life. The last two decades have seen an important increased use of renewable energy sources (RES). Recently, resources such as solar energy, wind power, hydropower, geothermal power, and biomass started to effectively

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replace the conventional sources and to provide better resources use, better cost-effectiveness, better efficiency, and better environment [3]. Despite the obvious advantages of RES, they present considerable drawbacks, such as the discontinuity of generation, as most RES depend on the climate. This is one of many reasons why their exploitation requires complex design, planning, and control optimization methods [4].

Energy planning, exploitation, and management have attracted the attention of decision makers for a long time. Typically, energy planning endeavour involves decision makers investigating the exploitation of RES in a particular area to meet energy demand in an optimal manner. Consequently, this process has been applied in different forms in order to deal with the increasing energy planning issues. For instance, (i) to assess energy policies, (ii) to rank sustainable energy planning strategies, (iii) to prioritize the most suitable and innovative RES in a given area, and last but not least (iv) to select the best site location for power plant and renewable energy projects. A great deal of research has already devoted to designing techniques that aid in handling this set of energy planning decision-making (EPDM) problems. Particularly, to support the sustainability vision of energy, scholars have proposed several decision-making tools. According to earlier literature reviews [5–8], multiple criteria decision-making (MCDM) methods have been applied to deal with the complexity of renewable energy planning and policy, RES evaluation and prioritization, projects selection, and environmental considerations. The majority of those proposed methods have been applied to deal with the problem of RES prioritization.

The process of prioritizing RES consists on evaluating diverse sources of energy while taking into consideration different assessment levels that certainly include- in most scenarios -but not limited to the technical, environmental, and socio-economic considerations. This multi-dimensionality nature of prioritizing available RES, in addition to the latest advancements taking place in information and communication technologies, confirm the fact that decision support systems (DSSs) using MCDM methods is still challenging in EPDM domain. Although, decision-making for sustainable energy planning and development requires methods that allow to handle complexities of specific management situations, and to address uncertainties of long-term consequences. The EPDM in general, involves many sources of uncertainty due to internal and external factors. Long time frame planning, financial issues, as well as unknown future conditions need to be considered [1]. Particularly, the RES prioritization problem especially decision makers' judgments are usually vague and prone to a high degree of uncertainty. It is difficult for decision makers to provide exact values in the evaluation data depending on different criteria. Moreover, ambiguity, experts' knowledge, and decision makers' preferences might be inadequate for a particular decision situation, which often lead to biased and uncertain decisions with respect to the evaluated alternatives and criteria [1,3,10]. However, even if many sources of uncertainty are recognized, there is still a lack of agreement on a unified typology, characteristics, relative magnitudes, and available approaches for dealing with them [29]. Fuzzy techniques have been used recently in several EPDM situations under uncertainty [11]. Consequently and during the past two decades fuzzy AHP, fuzzy ANP, and fuzzy VIKOR, and fuzzy TOPSIS have been strongly used to deal with uncertainty in RES prioritization problem [12–14].

Although much work has been done in this area of research, the following three practical issues were not fully addressed in literature and deserve more considerations. (1) Incomplete and imprecise information exist in evaluation data. Reasons are mainly: (i) the inability of decision makers to provide judgments with confidence due to the lack of required knowledge, and (ii) the complexity of providing the exact statistics of optimal RES. (2) Evaluation data could be in various forms, including quantitative information (e.g., statistics, interval ranges, and probability distributions), and human qualitative judgments (e.g., linguistic variables or grades). A real life assessment problem might include all these forms of information. As a result, a comprehensive method is needed to deal with these various forms in a unified format [15]. (3) Fuzzy based MCDM (FMCDM) approaches are now being used in a wide range of applications in the renewable energy sector (e.g., energy systems, smart grid and micro-grid management applications, demand side management, etc.). However, these solutions are classified as "complex" [11]. They require specialists to run the process and to interpret the results. Besides, the application of FMCDM in EPDM problems is questionable. The fact that dealing with a sensitive strategic sector such as energy planning that requires allocating huge funds, time, and resources with the decision-making tools based on classical fuzzy models is an unsafe call. Furthermore, outcomes based on these decision models might be undesirable. They should be referred as decision aid tools rather than decision-making tools.

Accordingly, for improved energy planning outcomes and optimal selection of RES under uncertain environment, and in view of all shortcomings discussed above, this study proposes the application of a recently developed decision-making approach. In this paper we propose to use the Evidential Reasoning (ER) approach [19] to assess potential RES in a given area in order to provide a final ranking that might help involved decision makers to prioritize such energy sources. This includes explicitly dealing with information under ignorance, fuzziness, and vagueness. This paper is a step towards initiating a new generation of intelligent, robust, and effective decision-making tools to deal with the complexity of EPDM and to fully exploiting potentials from RES [20].

The rest of the paper is organized as follows. Section 2 gives the basic description and identification of the RES prioritization problem. Then, the ER approach will be fully investigated in Sect. 3, including the identification of assessment attributes, the determination of their weights, the ER distributed modelling framework, the description of the recursive ER algorithm, and the utility based ER ranking method. Section 4 presents the examination of a real case study with real data using the proposed approach. The paper is concluded in Sect. 5 with both discussions about features of the ER approach and future works.

2 Renewable Energy Sources Prioritization: Problem Identification

2.1 Uncertain decision-making environment

An EPDM process usually consists in solving a well-defined decision-making problem to fulfil the main objectives of the energy plan in a given area (e.g. regional or nationwide). This process usually involves solving several energy-related problematic such energy management system, energy demand and supply, and strategic decision-making situations. Prioritizing RES is one of the active research topics in this area. In light of strong incentives for investment, technical potentials, and environmental restrictions, the evaluation and selection of RES are multiple criteria analysis (MCA) problems. It is a multi-dimensional decision-making problem that consists of evaluating diverse sources of energy while taking into consideration different assessment levels that certainly include— in most scenarios —but not limited to the technical, environmental, and socio-economic considerations. Typically, a decision maker is responsible of providing an evaluation matrix usually referred as a decision matrix in which rows are alternatives (i.e., RES), columns are the assessment criteria or attributes, and finally each cell represents the corresponding assessment value of the alternative on a given criterion. One of the most challenging tasks in this area of research is how to rationally handle various types of uncertainties, incomplete information in evaluation data, and the subjectiveness in-group judgments [21]. Furthermore, the assessment values could be in various forms, including quantitative information (e.g., statistics, interval ranges, and probability distributions), and human qualitative judgments (e.g., linguistic variables or grades). A real life assessment problem might include all these forms of information in an uncertain decision making environment. As a result, a comprehensive method is needed to deal with these various forms in a unified format [15].

2.2 Problem identification: Conventional decision matrix Vs. Belief decision matrix

To manage the expanding complexity and uncertainties in assessment problems, the ER approach for multiple attribute decision analysis is developed based on evidence theory [22] and belief decision matrix [15]. Compared with other MCDM methods, the ER approach is able to deal with the uncertainty and diversity originally due to the deployment of the belief decision matrix to model the multiple criteria problems. In a belief decision matrix, the performance of an alternative on a given criterion is represented by a distribution instead of a single value as in a conventional decision matrix [21]. For example, several experts were asked to assess different sources of energy with respect to the relevant criteria in Turkey. Based on the evaluation of the participants, the performance of “oil” option on the criterion “National economic benefits” can be modelled by the following distribution [10]:

$$\{(very\ low, 22\%), (low, 44\%), (medium, 33\%), (high, 0\%), (very\ high, 0\%)\} \tag{1}$$

Using a conventional decision matrix to model this assessment problem means that the above distribution is most likely to be estimated by a single value such as “low”, which means that performance distributions of “oil” alternative on all other criteria may also need to be estimated to single values. Such approximations introduce information loss or distortion. Moreover, the accumulated imprecisions may impact the whole assessment analysis process to become unreliable. As a consequence, decision makers may lose confidence in and become less committed to the decisions made on the basis of such approximated or distorted evaluation values. Instead of a conventional decision matrix, the belief decision matrix can deal with the above shortcomings, for modelling MCA problems. The subsequent research on the ER approach demonstrates that the use of the belief decision matrix also provides several additional advantages [15,18,19,21,23–25]. For instance, the belief decision matrix provides a novel structure to model MCA problems, by assessing each alternative based on a two-dimensional variable (i.e., as explained above, assessment grades and their associated degrees of belief) while dealing with both quantitative and qualitative criteria with uncertainties, fuzziness, and even incomplete evaluation values.

The ER approach, as outlined in the following section, is designed to fully use information in data from different sources with different type of uncertainties to generate rational, reliable, and informative decisions. The ER approach is discussed in details in [19].

3 The Evidential Reasoning Approach for RES Prioritization

The ER approach was proposed and developed to model various uncertainties on the basis of decision theory and the Dempster–Shafer (D–S) theory of evidence [16–19]. ER approach allows mapping different formats of attributes using a unified distributed modelling framework. The distributed assessment concept enables various types of information to be incorporated into a decision-making process without pre-aggregation, in contrary to the single assessment value approaches [28]. As a consequence, a belief decision matrix concept was conceived. Each attribute is characterized by a set of collectively exhaustive assessment grades and probabilistic uncertainty. Then, the D–S combination rule of evidence is modified and used to aggregate the assessment attributes. The ER approach has been widely used in various areas such as motorcycle evaluation [19], bridge condition assessment [24], nuclear waste repository assessment [21], environmental impact assessment [23], weapon system capability assessment [15], and recently in a combined medical quality assessment [25]. Due to the distributed modelling capability and belief structure, we chose the ER to model the RES prioritization problem. This consists of five main parts: (1) the selection of assessment attributes (2) the determination of weights and assessment grades for each attribute (3) the identification of the distributed modelling framework (4) the application of the recursive ER analytical algorithm for aggregating multiple assessment attributes and finally, (5) the prioritization of RES in terms of their overall assessment performances using the concept of expected and interval utility based ranking method. The following sections discuss the previous five main components of the ER approach.

3.1 Identification of RES assessment attributes

A set of criteria or generally referred as attributes need to be first investigated and carefully identified. These attributes enable a comparison of the alternatives from different perspectives. Several examples from studies in the literature have already tried to capitalize all existing attributes used to compare different RES (e.g. [6]). However, only a few works proposed to deal with both quantitative and qualitative criteria under uncertainty [9]. For comparison reasons and as a basis for formulating the attributes and evaluation data, we chose [9]. Eleven renewable energy technologies have been identified from the Scottish Government's 2020 route map for renewable energy [27] including onshore wind, offshore wind, hydropower, wave power, tidal power, geothermal power, photovoltaic, solar thermal, dedicated biomass, energy-from-waste, heat pumps. The evaluation data used in this study represents the maturity scores assigned to each technology and these have been determined based on literature information and through dialogue with relevant stakeholders as explained in [9]. Nine attributes are selected comprising three different levels of assessment: technical, environmental and socio-economic. The selected attributes are summarized in Table 1. The values and associated ranges for each selected attribute assigned to the different renewable technologies are given in detail in Table 2.

Table 1: Overview of the selected attributes ([9]).

Level	Attribute	Unit	Optimize*
Technical	T1. Potential total power generation	TW h/yr	Maximize
	T2. Technology maturity	Qualitative (1-5)	Maximize
	T3. Reliability of energy supply	Qualitative (1-5)	Maximize
Environmental	E1. Greenhouse gas emissions	g CO_2 eq/kW h	Minimize
	E2. Impacts on amenity	Qualitative (1-5)	Maximize
	E3. Area requirements	m^2/kW	Minimize
Socio-economic	SE1. Levelized energy cost	£/MW	Minimize
	SE2. Contribution to economy	Qualitative (1-5)	Maximize
	SE3. Social acceptability	Qualitative (1-5)	Maximize

*Optimize refers to whether a high or a low value for a given attribute is preferred.

Table 2: Best estimate, minimum and maximum attributes values for each of the renewable technologies ([9]).

Renewable technology	T1	T2	T3	E1	E2	E3	SE1	SE2	SE3
Onshore wind	45(25–125)	5 (4–5)	2 (2–4)	15(5–70)	2 (1–4)	200(10–1200)	70(25–125)	3 (2–4)	3 (1–4)
Offshore wind	80(25–150)	4 (3–4)	3 (2–4)	15(5–70)	3 (1–4)	200(10–1200)	110(50–190)	3 (2–5)	4 (2–5)
Hydro power	10(6–25)	5 (4–5)	4 (3–5)	20(2–60)	2 (1–4)	500(10–6500)	60(10–130)	3 (2–5)	4 (2–4)
Wave	20(5–60)	2 (2-3)	3 (2–4)	25(12–50)	4 (1–4)	150(10–300)	185(130–400)	4 (2–5)	4 (2–5)
Tidal	20(5–50)	2 (2–3)	3 (2–4)	25(10–80)	3 (1–4)	100(10–300)	160(80–350)	4 (2–5)	4 (2–5)
Geothermal	2.5(1–10)	4 (3–4)	5 (4–5)	40(10–80)	4 (1–4)	100(20–1000)	80(10–200)	3 (2–5)	3 (1–4)
Photovoltaic	20(2.5–70)	5 (4–5)	2 (1–3)	60(20–200)	5 (3–5)	150(10–500)	340(50–600)	4 (2–5)	5 (4-5)
Solar thermal	11(2.5–20)	5 (4-5)	2 (1–3)	40(15–150)	5 (3–5)	40(10–100)	200(50–450)	3 (2–4)	5 (4-5)
Dedicated biomass	15(5–45)	4 (4-5)	4 (3–5)	100(25–600)	2 (1–4)	4000(1000–6000)	130(40–250)	3 (2–5)	3 (1–4)
Energy-from-waste	3(2–10)	4 (4-5)	4 (3–5)	350(100-1000)	2 (1–4)	25(0–50)	80(50–170)	4 (2–5)	3 (1–4)
Heat pumps	10(5–20)	4 (4-5)	4 (3–5)	150(65–280)	5 (3–5)	50(10–300)	95(50–190)	3 (2–4)	5 (3–5)

3.2 Determination of weights and assessment grades

The identified attributes usually have different importance and play different roles in the assessment process of RES. Some of them are crucial, some of them are very important, some of them are important but not very important or crucial compared with the others. In this study, we assume that all attributes are equally important and they have therefore been assigned uniform weights [9]. We should notice that the focus here is specifically on the uncertainty in attributes performance values not on the applied weights, as in [9]. On the other side, assessment standards or generally known as evaluation grades need to be defined. There were several evaluation grades examples proposed and defined depending on the domain problem. Some studies have used 0 or 1 (i.e., yes or no) as a rating concept, some used good and worst to describe the performances, whilst others used three assessment grades: good, fair, and poor. What kind of standards should be used depends on the requirement from the problem at hand. The most used and preferred evaluation grades in the literature are: worst (W), poor (P), average (A), good (G), and excellent (E), (see e.g. [25]). So, for simplicity reasons, we propose to use the same set of evaluation grades in this study.

3.3 The ER approach

After identifying assessment attributes, weights, and grades, we are qualified now to employ the ER approach to aggregate evaluation data. Firstly, suppose we have N alternatives $A\ (A_1, A_2, \dots, A_N)$ that need to be appraised or ranked based on L attributes or criteria $C(C_1, C_2, \dots, C_L)$, the lth attribute $C_l\ (l = 1,2, \dots, L)$ can be either quantitative or qualitative, and each attribute C_l can be assessed through a set of M assessment grades $G(G_1, G_2, \dots, G_M)$ which are assumed to be collectively exhaustive and mutually exclusive. As mentioned in Sect. 3.2, the attributes may be of different importance, and attribute weight $\omega_l(l = 1,2, \dots, L)$ can be used to denote such unequal importance if it exists. In addition, these weights should meet the condition of $\omega_l \geq O$ and $\sum_{l=1}^{L} \omega_l = 1$. $\beta_{ml}(m = 1,2, \dots, M; l = 1,2, \dots, L)$ denotes the degree of belief in the mth assessment grade G_m on assessment of the lth attribute C_l, it can either be subjective if it quantifies a "personal belief" or objective if it is a computed probability on the basis of recorded data [25]. Next, a belief decision matrix can be used to represent the performance assessment of the given problem modelled by the ER approach as shown in Table 3 [19]. Based on the belief decision matrix, the ER algorithm can be used to aggregate the distributed assessments of all attributes and generate an overall assessment of each alternative. The recursive ER algorithm is as follows [17,19]. First, transform the degrees of belief $\beta_{ml}(m = 1,2, \dots, M; l = 1,2, \dots, L)$ into basic probability mass by combining the relative weights and the degrees of belief using the following equations:

$$\mathrm{m}_{\mathrm{m,l}} = \omega_{\mathrm{l}} \beta_{\mathrm{ml}} \tag{2}$$

$$\mathrm{m}_{\mathrm{G,l}} = 1 - \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{m}_{\mathrm{m,l}} = 1 - \omega_{\mathrm{l}} \sum_{\mathrm{m}=1}^{\mathrm{M}} \beta_{\mathrm{ml}} \tag{3}$$

$$\overline{\mathrm{m}}_{\mathrm{G,l}} = 1 - \omega_{\mathrm{l}} \tag{4}$$

$$\widetilde{\mathrm{m}}_{\mathrm{G,l}} = \omega_{\mathrm{l}} \left(1 - \sum_{\mathrm{m}=1}^{\mathrm{M}} \beta_{\mathrm{ml}}\right) \tag{5}$$

where $\mathrm{m}_{\mathrm{G,l}} = \bar{\mathrm{m}}_{\mathrm{G,l}} + \tilde{\mathrm{m}}_{\mathrm{G,l}}$ for all $l = 1, \dots, L$ and $\sum_{l=1}^{L} \omega_l = 1$. $\mathrm{m}_{\mathrm{m,l}}$ represents the basic probability mass of C_l being assessed to the assessment grade G_m. Furthermore, the probability mass assigned to the grade set G, which is unassigned to any individual attribute, is the sum of two parts: $\bar{\mathrm{m}}_{\mathrm{G,l}}$ caused by the relative importance of the lth attribute C_l and $\tilde{\mathrm{m}}_{\mathrm{G,l}}$ which reflects the importance of the lth attribute C_l. Then, all the L attributes are aggregated to generate the combined degree of belief in each possible grade G_m. Suppose $\mathrm{m}_{\mathrm{m,S(l)}}$ is the combined degree of belief in G_m by aggregating the first l attributes $(C_1, C_2, \dots, C_l)$, and $\mathrm{m}_{\mathrm{G,S(l)}}$ is the remaining degree of belief unassigned to any grade. Let $\mathrm{m}_{\mathrm{m,S(1)}} = \mathrm{m}_{\mathrm{m,1}}$ and $\mathrm{m}_{\mathrm{G,S(1)}} = \mathrm{m}_{\mathrm{G,1}}$. Then, the overall combined degree of belief β_m in G_m is calculated as follows:

$$\{\mathrm{G}_m\}: \ m_{\mathrm{m,S(l+1)}} = \mathrm{K}_{S(\mathrm{l}+1)}[m_{\mathrm{m,S(l)}} m_{\mathrm{m,l+1}} + m_{\mathrm{m,S(l)}} m_{\mathrm{G,l+1}} + m_{\mathrm{G,S(l)}} m_{\mathrm{m,l+1}}], l = 1,2, \dots, \mathrm{L}-1 \ m_{\mathrm{G,S(l)}} = \bar{m}_{\mathrm{G,S(l)}} + \tilde{\mathrm{m}}_{\mathrm{G,S(l)}}, l = 1,2, \dots, \mathrm{L} \tag{6}$$

$$\{\mathrm{G}\}: \ \tilde{m}_{\mathrm{G,S(l+1)}} = \mathrm{K}_{S(l+1)}[\tilde{m}_{\mathrm{G,S(l)}} \tilde{m}_{\mathrm{G,l+1}} + \bar{m}_{\mathrm{G,S(l)}} \tilde{m}_{\mathrm{G,l+1}} + \bar{m}_{\mathrm{G,S(l)}} \tilde{m}_{\mathrm{G,l+1}}], l = 1,2, \dots, \mathrm{L}-1 \tag{7}$$

$$\{\mathrm{G}\}: \ \bar{m}_{\mathrm{G,S(l+1)}} = \mathrm{K}_{S(l+1)}[\bar{m}_{\mathrm{G,S(l)}} \bar{m}_{\mathrm{G,l+1}}], l = 1,2, \dots, \mathrm{L}-1 \tag{8}$$

$$\mathrm{K}_{S(l+1)} = \left[1 - \sum_{m=1}^{M} \sum_{\substack{t=1 \\ t \neq m}}^{M} m_{\mathrm{m,S(l)}} m_{\mathrm{t,l+1}}\right]^{-1}, l = 1,2, \dots, \mathrm{L}-1 \tag{9}$$

$$\{\mathrm{G}_m\}: \beta_m = \frac{m_{\mathrm{m,S(L)}}}{1 - \bar{m}_{\mathrm{G,S(L)}}}, m = 1,2, \dots, \mathrm{M} \tag{10}$$

$$\{\mathrm{G}\}: \beta_{\mathrm{G}} = \frac{\tilde{m}_{\mathrm{G,S(L)}}}{1 - \tilde{m}_{\mathrm{G,S(L)}}} \tag{11}$$

β_{G} represents the remaining belief degrees unassigned to any G_m. It has been proven that $\sum_{m=1}^{M} \beta_m + \beta_{\mathrm{G}} = 1$ [19]. As a result, the aggregated assessment can be denoted by $\mathrm{O}(\mathrm{C}_l, \mathrm{l} = 1,2, \dots, \mathrm{L})) = \{(\mathrm{G}_m, \beta_m), m = 1,2, \dots, \mathrm{M}, \mathrm{l} = 1,2, \dots, \mathrm{L}\}$. The ER approach gives the opportunity to identify weak areas together with strengths for each alternative based on the distributed assessment of each attribute. In addition, to rank alternatives based on one or all attributes, a single score to represent the performance of each alternative is given. The distributed assessment results discussed above may not be directly used for ranking purpose. To do so, the concept of expected utility to generate a numerical value from each distributed assessment was proposed [19]. The next sub section describes the concept of the expected and utility interval.

Table 3: A belief decision matrix of the ER approach.

Evaluation grades	Belief degrees					
	$\omega_1(C_1)$	$\omega_2(C_2)$	…	$\omega_l(C_l)$	…	$\omega_L(C_L)$
G_1	β_{11}	β_{12}	…	β_{1l}	…	β_{1L}
G_2	β_{21}	β_{22}	…	β_{2l}	…	β_{2L}
⋮	⋮	⋮	…	⋮	…	⋮
G_{m}	$\beta_{\mathrm{m}1}$	$\beta_{\mathrm{m}2}$	…	$\beta_{\mathrm{m}l}$	…	$\beta_{\mathrm{m}L}$
⋮	⋮	⋮	…	⋮	…	⋮
G_{M}	$\beta_{\mathrm{M}1}$	$\beta_{\mathrm{M}2}$	…	$\beta_{\mathrm{M}l}$	…	$\beta_{\mathrm{M}L}$

3.4 Alternatives ranking

As aforementioned in Sect. 3.3, there may be situation where distributed assessments are not sufficient to demonstrate the difference between two alternatives. The concept of expected utility is used to overcome such problematic. As defined in [19], we suppose that $u(G_m)$ is the utility of the grade G_m with:

$$\mathrm{u}(\mathrm{G}_{m+1}) > u(\ \mathrm{G}_m)\ if\ \mathrm{G}_{m+1}\ is\ preferred\ to\ \mathrm{G}_m \tag{12}$$

If all assessments are complete and precise, then $\beta_G = 0$ and the expected utility of the attribute $\mathcal{y}$ can be used for ranking the alternatives, and given as follows:

$$\mathrm{u}(\mathcal{y}) = \sum_{m=1}^{M} \beta_m u(\mathrm{G}_m) \tag{13}$$

An alternative a is preferred to another alternative b on $\mathcal{y}$ if and only if $\mathrm{u}(a) > \mathrm{u}(b)$. On the other side, if any assessment for the attribute is incomplete, it will be proven that $\mathrm{G}_H > 0$. This means that the likelihood to which $\mathcal{y}$ may be assessed to G_m is not unique and can be a value in the interval $[\beta_m, (\beta_m + \beta_G)\ ]$. In such circumstances, [19] define three measures to characterize the assessment for $\mathcal{y}$, namely the minimum, maximum and average expected utilities. If all assessments $O(C_l)$ are complete, then $\beta_G = 0$ and $\mathrm{u}(\mathcal{y}) = \mathrm{u}_{min}(\mathcal{y}) = \mathrm{u}_{avg}(\mathcal{y}) = \mathrm{u}_{max}(\mathcal{y}) = 0$. Interested readers may refer to [19] for more details about the concept of expected and interval utility and the ranking of alternatives.

4 Results

The ER approach as explained above allows solving the RES prioritization problem. As already mentioned in Sect. 3.1, we chose [9] as basis for data collection and comparison.

4.1 Analysis

We conducted the data aggregation using the ER approach step by step as follows.

Step 1: Transform numerical values from quantitative/qualitative attributes to assessment grades with a belief structure.

To transform numerical values to distribute assessments with belief degrees, [25] proposed to calculate the benchmark values of E, G, A, P, and W grades for each attribute. For this purpose, they proposed a pragmatic method for transforming numerical values to assessment grades with a belief structure. Based on the data evaluation from [9], we should compute the minimum (denoted by a), the 25th percentile (b), the 50th percentile (c), the 75th percentile (d) and the maximum (e) for each attribute. As Table 1 indicates, there are both attributes to maximize and others to minimize. In [25], authors proposed to work only with minimizing attributes. In our case, we will explain briefly how to transform maximizing values to assessment grades with a belief structure. To do so, bigger attributes values mean better performance. Then the set of computed a,b,c, d, and e values for each attribute are used as benchmark values at E, G, A, P, and W grades respectively. Let z be a numerical value of an attribute and α,β,γ,δ and θ represent the degrees of belief in E, G, A, P and W grades respectively after transforming numerical value z to assessment grades. For instance, if z is less than the benchmark value at W grade (z < e), then the attribute can be definitely assessed as W grade, and z can be transformed to assessment with belief degree of 1 (θ=1) associated with worst. Belief degrees assigned to other grades: E, G, A, and P are all set to be 0 (α=0,β=0,γ=0,δ=0). Another illustrative example is: if z is equal or greater than the benchmark value for the W grade and less than the benchmark value for the P grade (e ≤ z < d), then z can be transformed to assessment with belief degrees (θ=(d-z)/(d-e)) and (δ=1-θ) associated with the W and P grades respectively. Belief degrees assigned to the other grades: A, G, and E (α=0,β=0,γ=0). This process continues until we transform each numerical value on a belief degree structure. Finally, we should notice that all assessments in this study are complete.

Step 2: Apply the ER approach to aggregate attributes.

Before data aggregation, we assigned equal weights to all attributes as mentioned in Sect. 3.2. The Java SE environment was used to develop a computerized program to calculate and aggregate all attributes automatically. Moreover, as already mentioned, the ER has the ability to assess the performance of alternatives while taking into consideration each evaluation level separately. Fig. 1 shows overall performances of the eleven alternatives while considering each level separately. After aggregating evaluation performances from all attributes in the three levels (i.e., technical, environmental, and socio-economic), we obtain distributed assessments about each renewable energy technology as shown in Table 4.

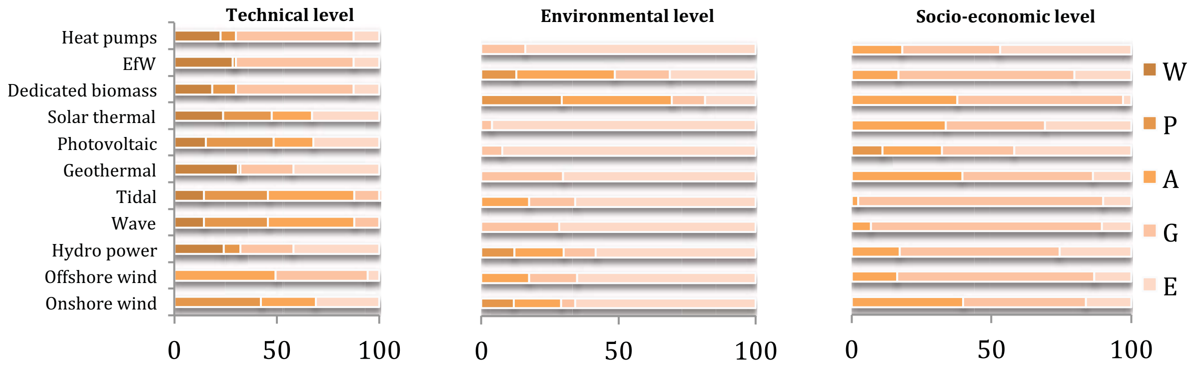

Figure 1. Distributed assessments for each level separately.

Table 4: Overall performances of the eleven renewable technologies.

Renewable technology	Distributed assessment
Onshore wind	(W, 0.00%), (P, 16.88%), (A, 28.69%), (G, 14.96%), (E, 39.46%)
Offshore wind	(W, 0.00%), (P, 0.00%), (A, 27.02%), (G, 46.65%), (E, 26. 31%)
Hydro power	(W, 7.08%), (P, 6.01%), (A, 10.78%), (G, 31.42%), (E, 44.68%)
Wave	(W, 4.50%), (P, 9.61%), (A, 15.54%), (G, 43.93%), (E, 26.40%)
Tidal	(W, 4.54%), (P, 9.68%), (A, 20.54%), (G, 40.65%),(E, 24.57%)
Geothermal	(W, 9.07%), (P, 0.37%), (A, 11.59%), (G, 35.12%), (E, 43.82%)
Photovoltaic	(W, 4.43%), (P, 13.11%), (A, 12.22%), (G, 9.83%), (E, 60.38%)
Solar thermal	(W, 6.98%), (P, 6.92%), (A, 16.58%), (G, 11.62%), (E, 57.86%)
Dedicated biomass	(W, 5.52%), (P, 12.58%), (A, 25.39%), (G, 45.88%), (E, 10.61%)
Energy-from-waste	(W, 8.32%), (P, 4.21%), (A, 16.30%), (G, 50.37), (E, 20.78%)
Heat pumps	(W, 6.46%), (P, 2.15%), (A, 5.21%), (G, 36.46%), (E, 49.70)

Step 3: Rank the eleven renewable technologies.

To rank different renewable technologies, it is necessary to generate numerical values that reflect the overall performances from the distributed assessments. As a consequence, the utilities of individual assessment grades need to be defined first [19]. More specifically, we assigned a performance score of 100 to excellent, 80 to good, 55 to average, 30 to poor, and 0 to worst. In this way, a distributed assessment can be transformed to a performance score (see Fig. 2). Finally, we present in Fig. 3 the final ranking of the renewable technologies on the basis of the computed scores.

4.2 Discussion

Figure 1 shows the distributed assessments of the eleven alternatives on each level separately. When considering each level separately this might help decision makers to obtain a clear vision of each alternative based on different perspectives. In addition, these results allow the decision-maker to directly examine with increased confidences which of the alternatives are the best or worst options given the selected level. For instance, considering the technical level, it is obvious that the hydropower, geothermal, and solar thermal are the technologies with the most interesting technology potentials whilst the energy-from-waste (EfW), biomass, tidal, and wave are immature choices. Moreover, the environmental level confirms that all the eleven renewable technologies are green and clean energies since all results are positive, with a small superiority for solar thermal, PV, heat pumps, and geothermal energy. The EfW and biomass are extending low performances even for this level. Furthermore, the socio-economic level presents the same conclusion as in the environmental level since the majority of renewable technologies can strongly contribute to the economic development and to the benefit of several parts, from community members, governments, until private sector investors. Although, we should mention the slight superiority of some RES such as heat pumps, photovoltaic, tidal, and wave. Moreover, the aggregated distributed assessments in Table 4 and the expected utilities in Fig. 2 confirm the analysis explained above (i.e., analysis based on each level separately). Heat pumps and offshore wind are the best options, whilst biomass and EfW are the least preferred options. However, it is still difficult to distinguish which alternative is the best or the worst without using the expected utility of each alternative as a numerical score to rank them (since all assessments are complete). Fig. 3 represents the ranking provided by three different approaches: the ER approach implemented in this study, the MCA using the best estimate criteria values from [9], and MCA using 10,000 Monte Carlo simulations (MCSs) to deal with uncertainty in attributes values variations over the estimated ranges from [9] too. Attribute values were defined by probability distributions and MCS has been used to run the MCA [9]. We note that there is a strong consensus between the ranking provided by the ER approach and the one using the 10,000 MCSs. When all attributes are considered equally important heat pumps, offshore wind, PV, and solar thermal are all the best options, while biomass and EfW are the least favoured options based on the selected nine attributes. Thus, there is a complete disagreement on the rank considered for geothermal in both approaches. The MCS ranked the geothermal as the 9th best option while the ER approach ranked it as the 3th best option, which seems more reasonable due to the good performances of this renewable technology as discussed above in all the three levels. In addition, this result agrees well with the findings from a recent MCA study by [26] in which it is concluded that geothermal is one of three RES that offer the most over-all benefits. However, when using the MCA based MCSs as indicated in [9], within the range of possible attributes values, almost any ranking of the eleven technologies is possible, which is confirmed when all of the technologies have been found to be the most and the least favoured option in some of the simulations, which is not the case when using the ER approach, only a single ranking scenario is provided. The objective when using the MCS approach is, however, to show the uncertainty in the ranking explicitly not to explicitly deal with this uncertainty. Thus, proposing to overcome this uncertainty in attribute values while producing another uncertainty issue is not reasonable. This is what explicitly explained by [9] authors: “Multi-criteria decision-making models, like the one developed here, can be used to assess, compare and rank different renewable energy technologies … Such models can therefore be useful for informing the selection of the most suitable renewable energy technology for a given area or location … However, the results from this study also demonstrate a clear limitation in the use of MCA for assessing and comparing the sustainability of different energy technologies and/or schemes due to the many uncertainties involved.” The distributed assessment framework which is the core of the ER approach handles such uncertainties, from the first step which is the selection of assessment attributes until the final one which is the prioritization and ranking of alternatives.

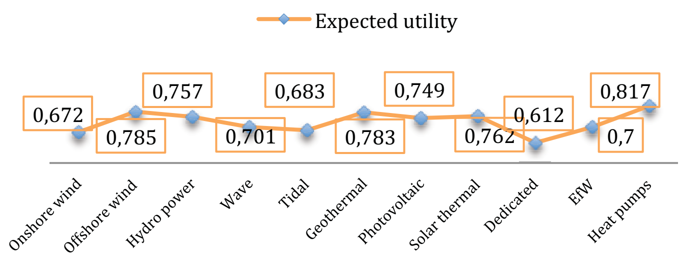

Figure 2. Expected utilities of the eleven renewable technologies.

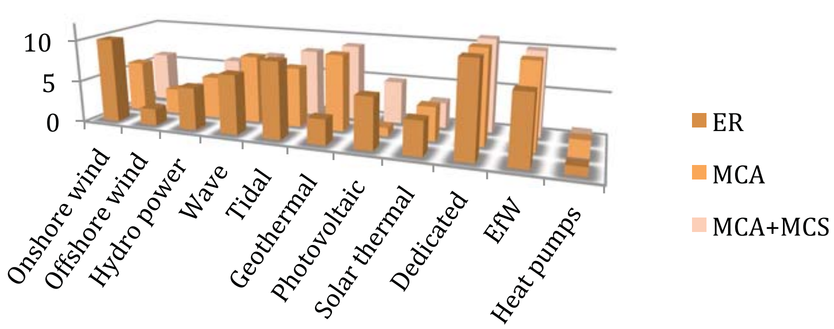

Figure 3. Ranking of the eleven renewable technologies

5 Conclusion and future works

This study investigated the main limitations of conventional decision-matrix in strategic EPDM problems. Most proposed approaches in this area are classical MCDM methods that are unable to manage the expanding complexities and uncertainties in RES prioritization problem. Fuzzy MCDM approaches are now being used in a wide range of applications in the renewable energy sector. However, these solutions are classified as “complex” since they require specialists to run the process and to interpret the results. The ER approach using belief structure and belief decision matrix can provide an appropriate and transparent MCDM approach not only for the selection and evaluation of the available energy resources but also for renewable energy management and other EPDM activities in general. The ER approach in contrast to existing MCA approaches is, therefore, applied to careful drawing conclusions and to explicitly address the associated uncertainties and sensitivities.

In this paper, we have developed an ER approach as a multiple criteria framework to assess the appropriateness regarding the use of different renewable energy technologies in an uncertain decision-making environment. A case study illustrates the implementation process. Results show that using the ER approach when prioritizing different RES under uncertainty allows providing robust decisions, which brings out a more accurate, effective, and better-informed EPDM tool to conduct the evaluation process.

In our future research, an intelligent web decision-making system will be developed, to automatically assist decision makers in EPDM problems using the ER approach. This tool might also be used to extract attributes and their associated weights, acquire expert judgments, collect decision-makers views and appreciation via an interactive user-friendly platform, and to finally produce in a representative form the assessment results.

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References

[1] Başar, Ö., Uğurlu, S., Kahraman, C.: Assessment of green energy alternatives using fuzzy ANP. In: Cavallaro, F. (ed.) Assessment and Simulation Tools for Sustainable Energy Systems. Green Energy and Technology Series, vol. 129, pp. 55–77. Springer, London (2013)

[2] International energy association (IEA), http://www.iea.org/textbase/npsum/weo2014sum.pdf, Accessed 11 June 2016

[3] Oberti, P., Muselli, M., Haurant, P.: Photovoltaic plants selection on an insular grid using multi-criteria outranking tools: application in Corsica Island (France). In: Cavallaro, F. (ed.) Assessment and Simulation Tools for Sustainable Energy Systems. Green Energy and Technology Series, vol. 129, pp. 27–54. Springer, London (2013)

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

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

[6] Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhao, J.H.: Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew. Sustain. Energy Rev. 13(9), 2263–2278 (2009). Elsevier

[7] Taha, R.A., Daim, T.: Multi-criteria applications in renewable energy analysis, a literature review. In: Daim, T., Oliver, T., Kim, J. (eds.) Research and Technology Management in the Electricity Industry, pp. 17–30. Springer, London (2013)

[8] Strantzali, E., Aravossis, K.: Decision making in renewable energy investments: a review. Renew. Sustain. Energy Rev. 55, 885–898 (2016). Elsevier

[9] Troldborg, M., Heslop, S., Hough, R.L.: Assessing the sustainability of renewable energy technologies using multi-criteria analysis: suitability of approach for national-scale assessments and associated uncertainties. Renew. Sustain. Energy Rev. 39, 1173–1184 (2014). Elsevier

[10] Kabak, Ö., Cinar, D., Hoge, G.Y.: A cumulative belief degree approach for prioritization of energy sources: case of Turkey. In: Cavallaro, F. (ed.) Assessment and Simulation Tools for Sustainable Energy Systems, pp. 129–151. Springer, London (2013)

[11] Suganthi, L., Iniyan, S., Samuel, A.A.: Applications of fuzzy logic in renewable energy systems–a review. Renew. Sustain. Energy Rev. 48, 585–607 (2015). Elsevier

[12] Kaya, T., Kahraman, C.: Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: the case of Istanbul. Energy 35(6), 2517–2527 (2010). Elsevier

[13] Tasri, A., Susilawati, A.: Selection among renewable energy alternatives based on a fuzzy analytic hierarchy process in Indonesia. Sustain. Energy Technol. Assessments 7, 34–44 (2014). Elsevier

[14] Shafiee, M.: A fuzzy analytic network process model to mitigate the risks associated with offshore wind farms. Expert Syst. Appl. 42(4), 2143–2152 (2015). Elsevier

[15] Jiang, J., Li, X., Zhou, Z.J., Xu, D.L., Chen, Y.W.: Weapon system capability assessment under uncertainty based on the evidential reasoning approach. Expert Syst. Appl. 38(11), 13773–13784 (2011). Elsevier

[16] Yang, J.B., Sen, P.: A general multi-level evaluation process for hybrid MADM with uncertainty. IEEE Trans. Syst. Man Cybern. 24, 1458–1473 (1994). IEEE

[17] Yang, J.B., Singh, M.G.: An evidential reasoning approach for multiple attribute decision making with uncertainty. IEEE Trans. Syst. Man Cybern. 24, 1–18 (1994). IEEE

[18] Yang, J.B., Wang, Y.M., Xu, D.L., Chin, K.S.: The evidential reasoning approach for MCDA under both probabilistic and fuzzy uncertainties. Eur. J. Oper. Res. 171, 309–343 (2006). Elsevier

[19] Yang, J.B., Xu, D.L.: On the evidential reasoning algorithm for multiple attribute decision analysis under uncertainty. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. 32(3), 289– 304 (2002). IEEE

[20] Sellak, H., Ouhbi, B., Frikh, B.: Towards an intelligent decision support system for renewable energy management. In: The 15th International Conference on Intelligent systems Design and Applications. IEEE, Marrakesh (2015)

[21] Xu, D.L.: Assessment of nuclear waste repository options using the ER approach. Int. J. Inf. Technol. Decis. Making 8(03), 581–607 (2009). World scientific

[22] Shafer, G.: A Mathematical Theory of Evidence, vol. 1. Princeton University Press, Princeton (1976)

[23] Wang, Y.M., Yang, J.B., Xu, D.L.: Environmental impact assessment using the evidential reasoning approach. Eur. J. Oper. Res. 174(3), 1885–1913 (2006). Elsevier

[24] Wang, Y.M., Elhag, T.M.: Evidential reasoning approach for bridge condition assessment. Expert Syst. Appl. 34(1), 689–699 (2008). Elsevier

[25] Kong, G., Xu, D.L., Yang, J.B., Ma, X.: Combined medical quality assessment using the evidential reasoning approach. Expert Syst. Appl. 42(13), 5522–5530 (2015). Elsevier

[26] Stein, E.W.: A comprehensive multi-criteria model to rank electric energy production technologies. Renew. Sustain. Energy Rev. 22, 640–654 (2013). Elsevier

[27] Scottish Government: 2020 Renewable Route Map for Scotland—Update. Scottish Government, Edinburgh (2012)

[28] Zhang, Z.J., Yang, J.B., Xu, D.L.: A hierarchical analysis model for multiobjective decision making. In: Analysis, Design and Evaluation of Man–Machine System 1989 (Selected Papers from the 4th IFAC/IFIP/IFORS/IEA Conference, Xian, PR China, September 1989), Pergamon, Oxford, UK, 1990, pp. 13–18 (1989)

[29] Ascough II, J. C., Maier, H. R., Ravalico, J. K., & Strudley, M. W. (2008). Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecological Modelling, 219(3–4), 383–399.