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A novel integrated decision-making approach for the evaluation and selection of renewable energy technologies

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Abstract
The decision-making in energy sector involves finding a set of energy sources and conversion devices to meet the energy demands in an optimal way. Making an energy planning decision involves the balancing of diverse ecological, social, technical and economic aspects across space and time. Usually, technical and environmental aspects are represented in the form of multiple criteria and indicators that are often expressed as conflicting objectives. In order to attain higher efficiency in the implementation of renewable energy (RE) systems, the developers and investors have to deploy multi-criteria decision-making techniques. In this paper, a novel hybrid Decision Making Trial and Evaluation Laboratory and analytic network process (DEMATEL-ANP) model is proposed in order to stress the importance of the evaluation criteria when selecting alternative REs and the causal relationships between the criteria. Finally, complex proportional assessment and weighted aggregated sum product assessment methods are used to assess the performances of the REs with respect to different evaluating criteria. An illustrative example from Costs assessment of sustainable energy systems (CASES) project, financed by European Commission Framework 6 programme (EU FM 6) for EU member states is presented in order to demonstrate the application feasibility of the proposed model for the comparative assessment and ranking of RE technologies. Sensitivity analysis, result validation and critical outcomes are provided as well to offer guidelines for the policy makers in the selection of the best alternative RE with the maximum effectiveness.

Keywords Multi-criteria decision-making · Renewable energy · Decision Making Trial and Evaluation Laboratory · Analytical network process

Introduction

Energy use, which is essential for the civilized activities, has economic, political, social and environmental aspects associated with it. One of the environmental impacts is the greenhouse effect due to the emission of the greenhouse gases. The use of renewable energy (RE) sources is one of the feasible options for sustainable development of the future (Şengül et al. 2015). There are various forms of Res, and most of them depend on the solar energy directly or indirectly. Solar energy is the direct conversion of sunlight, whereas bioenergy has derived from biomass, which is a product of photosynthesis. Geothermal energy comes from the natural heat of the Earth's core, and tidal energy is a converted form of gravitational energy.

Energy planning efforts involve the identification of a set of suitable energy resources and conversion appliances to meet the energy demands in the best possible way. Evaluation, justification and selection of the most appropriate REs is a multidimensional decision-making process, which involves balancing a number of distinguishing attributes at economic, technical, social and environmental view across space and time (Diakoulaki and Karangelis 2007). Usually, these four major aspects are represented in the form of multiple criteria and indicators that are often expressed by mutually conflicting objectives. Thus, the decision-making

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process can be viewed as a multi-criteria decision-making (MCDM) problem with correlating criteria and alternatives (Zavadskas et al. 2014; Yazdani and Payam 2015; Mardani et al. 2015a, b). Energy planning systems that are using multi-criteria analysis have attracted the attention of decision-makers (DMs) a few decades ago. In order to achieve higher efficiency in planning and executing RE systems, policy makers and investors have to deploy decision support tools to maximize the competent usage of these energies. In its most basic form, MCDM assumes that a DM must choose the best solution among a set of alternatives whose objective function values or attributes are certainly known. MCDM techniques are capable of dealing with multifaceted problems that are characterized by the mixture of both ordinal and cardinal objectives (Yazdani and Graeml 2014). This is achieved by recognizing the problem that should be analysed and developing alternative solutions to the problem based on some decision rules and problem constraints. In the next phase, the target problem is fragmented into some convenient small parts to allow incorporating data and judgments. This step is known as the development of decision matrix, which indicates the influencing alternative options and respective attribute values. Finally, the reassembling of broken parts by the application of an analytical model is performed (Chatterjee et al. 2011).

Hence, MCDM is the most efficient approach to provide decision support for the policy makers that are dealing with the problems of compromise selection of the best solution from a set of existing alternatives, according to the set objectives (Kaya and Kahraman 2010; Hiremath et al. 2007; Şengül et al. 2015; Santoyo-Castelazo and Azapagic 2014). Usually, neither of the alternatives satisfies all the objectives; therefore, satisfactory decision is made instead of the optimal one. Generally, MCDM problems are recognized by the following patterns: (1) choosing problem: choosing the best alternative, (2) sorting problem: classifying alternatives in relatively homogenous groups, (3) ranking problem: ranking alternatives from best to worst and (4) describing the problem: describing alternatives in terms of their peculiarities and features (Roy 1996; Tupėnaitė et al. 2010; Balezentiene et al. 2013).

The precedent researchers have developed and presented a number of numerical MCDM approaches and decision support systems (DSSs) for the assessment and selection of RE alternatives in a particular application. Over the last few decades, a variety of MCDM methods for RE project planning and policy assessment as well as computer-based DSS have been developed to address this problem and enable prospective policy makers to make multidimensional assessment of the techno-economic feasibility, before any huge investment is made. Şengül et al. (2015) proposed a fuzzy technique for preference order by similarity to ideal solution (TOPSIS) approach in order to rank RE supply systems in Turkey. The authors applied interval Shannon entropy method to determine the weights of decision attributes, and hydropower station has been selected as the best RE system among others. Santoyo-Castelazo and Azapagic (2014) conducted a sustainable appraisal of alternative energy systems using 17 criteria and three environmental, economic and social dimensions using multi-attribute value theory (MAVT) and simple multi-attribute rating technique (SMART). This study encouraged stakeholders to improve their energy policies. Streimikiene et al. (2012) employed TOPSIS and Multiple Objective Optimization based on Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) methods for selecting the most sustainable electricity and heat generation technology under economic, technological, social and political scenarios and identified water and solar thermal systems as the most suitable options. Another study by Georgiou et al. (2015) examined five alternative energy generation topologies with respect to economic, environmental, technological and societal factors, using the analytic hierarchy process (AHP) and preference ranking organization method for the enrichment evaluation (PROMETHEE) methods to arrive at the most effective decision. Troldborg et al. (2014) presented a probabilistic ranking of eleven RE technologies in Scotland considering nine evaluation criteria, including technical, environmental and socio-economic criteria, using PROMETHEE and Mont Carlo simulation in an uncertain situation. Ertay et al. (2013) evaluated RE alternatives, including solar, wind, hydropower and geothermal energies, for resolving energy-related challenges of Turkey using the measuring attractiveness by a categorical based evaluation technique (MACBETH) and fuzzy AHP approaches and considered five main attributes and fifteen sub-attributes. Streimikienė (2013) employed an interval TOPSIS method for the comparative assessment of electricity generation technologies and road transport technologies. Low carbon and targeting GHG reduction were considered as the most predominant criteria for the decision-making process. Yazdani-Chamzini et al. (2013) proposed an integrated AHP-complex proportional assessment (COPRAS) model to select the best RE project. AHP was used to estimate the weight of decision objectives, while COPRAS method was applied to rank the alternative energy systems. Ahmad and Tahar (2014) developed an AHP-based assessment model for prioritizing RE options. Four major RE resources, including hydropower, solar, wind, biomass (together with biogas and municipal solid waste), were evaluated with respect to technical, economic, social and environmental aspects of a Malaysian case study. Kabak and Dağdeviren (2014) presented another case study of selecting the most competent RE in Turkey using the analytic network process (ANP) and benefits, opportunities, costs and risks (BOCR) framework. Four RE sources like hydro, geothermal, solar, wind and biomass were assessed while taking different strategic criteria (technology, economy, security, global effects and human wellbeing) into consideration.

It has been observed from the literature survey presented above that the past researchers have mainly adopted AHP, TOPSIS and PROMETHEE methods for the evaluation of REs. Very few applications are related to MACBETH, COPRAS and MULTIMOORA methods. AHP is an established method of arranging an unstructured system or variables according to the hierarchy and assigning numerical values to subjective judgments depending on the relative importance of each variable and synthesizing the judgments to determine the highest priority variables. Conversely, the computational requirement of AHP is terrific, even for a small problem. The main drawback of this method is that it ignores the interrelationships among decision elements. The outcomes of this method may suffer due to the involvement of inconsistencies between judgment and ranking criteria. TOPSIS method is based on the concept that the best alternative has the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution by introducing two reference points using vector normalization. However, this method does not consider the relative significance of the distances from these reference points. It means that the best alternative of the TOPSIS method may not always be closest to the ideal solution. PROMETHEE method is a preference ranking method, which does not structure a decision-making problem. In the case of numerous criteria and alternatives, it may turn to complexities to obtain a clear view of the problem and assess the results due to the attachment of different preferential parameters like preference functions, which may be extremely tricky to define in the real time scenarios (Chatterjee et al. 2017). Moreover, the majority of these MCDM methods assume inter-criteria independence, which is not a pragmatic assumption in many real-world problems. Several forms of interactions among criteria might occur in the real life situations. Thus, more sophisticated and intelligent techniques are required to deal with such complexities. Unfortunately, the criteria interaction concept is scarcely discussed in the literature.

In order to overcome these difficulties, the present paper proposes a novel integrated hybrid model for multi-criteria assessment of RE systems, which combines the decision-making trial and evaluation laboratory (DEMATEL), ANP, COPRAS and weighted aggregated sum product assessment (WASPAS) methods. One of the benefits of ANP over AHP is that it permits feedback and interdependence among the criteria. In fact, ANP compensates the limitations of the AHP method by introducing interdependent relationships among the decision elements (Saaty 1996). This paper aims to form the influence relationship among RE selection dimensions/criteria with DEMATEL-ANP (D-ANP) to estimate criteria weight. D-ANP model successfully demonstrates the key influencing factors for RE planning by specifying the structure without dealing with complex, huge and time-consuming comparison matrix of ANP, and ultimately, COPRAS and WASPAS methods with D-ANP weightings are applied to determine the ranking preorders of the alternative REs. This model can help managers and decision-makers to devise appropriate strategies for the selection of the best RE system.

Proposed methodology

D-ANP is a new methodology, which was developed by applying a conjunctive form of the DEMATEL and ANP methods. DEMATEL is a method for constructing a structural model of a problem involving causal relationships among complex attributes. It works mainly through the collection of experts' opinions by observing the degree of influence between criteria, the use of matrix operations in order to obtain a causal relationship between the criteria and the establishment of structural network diagrams (Gabus and Fontela 1972; Yazdani et al. 2017). ANP, which is used to deal with different type of interdependency, was developed by Saaty (1996). This method is a general form of AHP, which enables decision-makers to define a complex relationship between the decision levels and the attributes (Tavana et al. 2017; Ignatius et al. 2016). ANP overcomes the drawbacks of AHP in handling interrelationship between decision levels as higher or lower and direct or indirect by using a super-matrix, which detects the composite weights (Shyur 2006). This super-matrix is a partitioned matrix when each matrix partition addresses a relationship between the levels or clusters in a system and has derived from the limiting powers of the priorities to calculate the overall priorities, and the cumulative influence of each element on every other element, with which it interacts, is obtained (Saaty 1996; Saaty and Vargas 1998). Moreover, in ANP, the matrix operations can be applied easily to the super-matrix, and undoubtedly, this super-matrix is a suitable option when the number of elements increases. Its distinguished benefits can be sorted as follows: (1) ANP transforms qualitative values into numerical values for a comparative analysis, (2) simple and intuitive structure and (3) participation of all stakeholders and experts in the decision process (Aras et al. 2004; Kabak and Dağdeviren 2014).

First, the combined D-ANP approach operates through constructing the impact-relations-map (IRM) among criteria by the DEMATEL technique and then by calculating the weights of each criterion by combined ANP based on the developed IRM. Researchers believe that although ANP determines identical weights in the cluster from the normalized super matrix, it neglects the influence in various degrees. Thus, D-ANP approach normalizes the total

Table 1 Indicator set for long-term sustainability assessment of electricity generation technologies (see footnotes 1, 2, 3, 4, 5, 6, 7)

Dimension	Criteria	Definition	Measurement unit	References
Environmental indicators (D_1)	C_1 (HEALTH)	Human health impact	EURcnt/kWh	CASES (2008a, b)
	C_2 (CO2eq)	GHG emissions	kg/kWh	CASES (2008a, b)
	C_3 (ENV)	Environmental external costs	EURcnt/kWh	CASES (2008a, b)
	C_4 (RADIO)	Radionuclide external costs	EURcnt/kWh	CASES (2008a, b)
Social indicators (D_2)	C_5 (ACC past)	Fatal accidents from the past experience	Fatalities/kWh	PSI (2003)
	C_6 (ACC fut)	Severe accidents perceived in the future	Point	PSI (2003)
	C_7 (food)	Food safety risk	Point	CASES (2008a, b)
	C_8 (EMPL)	Technology-specific job opportunities	Person-year/kWh	PSI (2003)
Economic indicators (D_3)	C_9 (grid cost)	Costs of grid connection	Point	CASES (2008a, b)
	C_{10} (available)	Average availability (load) factor	%	EUSUSTEL (2007)
	C_{11} (secure)	Security of supply	Point	NEEDS (2005, 2006, 2007)
	C_{12} (peak load)	Peak load response	Point	NEEDS (2005, 2006, 2007)
	C_{13} (PR cost)	Private costs (investments and operation costs)	EURcnt/kWh	CASES (2008a, b)

influence matrix of DEMETEL with dimensions and transposes it onto an un-weighted super-matrix of ANP thereafter normalizing it into a weighted super-matrix with the normalized influence matrix. The influential weights of the D-ANP can be obtained through self-multiplication multiple times (Hu et al. 2014; Hsu et al. 2012; Liu et al. 2012). Firstly, D-ANP method was developed by Tzeng et al. (2007) as a hybrid formula, which has been successfully applied to solve different problems, including the improvement of smart phone competitive advantage (Hu et al. 2014), choosing knowledge management strategies (Wu 2008), selecting vendor for conducting the recycled material (Hsu et al. 2012), supporting decisions in Taiwanese higher education (Chen and Chen 2010) and brand marketing (Wang and Tzeng 2012). In fact, the D-ANP approach decreases the large amount of ANP pairwise computations and indicates effective interrelationship among decision objectives.

The procedure of D-ANP model for estimating criteria weights is introduced in "Appendix 1". The results of D-ANP are used as input to WASPAS ("Appendix 2")- and COPRAS ("Appendix 3")-based calculations. COPRAS method was mainly developed by Zavadskas et al. (1994). It selects from alternatives in order to determine a solution with direct and proportional ratio to the best solution to the ratio with the ideal-worst solution.

A case study on the selection of renewable electricity generation technologies in EU

Over the last decade, the impact of "sustainability" on the development of national and international policy has increased. Efforts towards a sustainable energy system are progressively becoming an issue of paramount importance for DMs. Efficient production, distribution and use of energy resources and the provision of equitable and affordable access to energy while ensuring security of energy supply and environmental sustainability are the main energy policy objectives towards a sustainable energy system. The implementation of new energy technologies is a key strategy towards a sustainable energy system. Therefore, DMs have to choose the best option from an increasingly diverse mix of new energy technologies, which warrant support, including funding (e.g. R&D support) and other incentives for different sectors. However, the identification of these technologies that can comply with the emerging needs and opportunities in the three sustainable development dimensions, namely economic, environmental and social, is a very complex process. Thus, methods and tools are required to assist policy design in terms of establishing technological priorities towards a sustainable energy system. The multi-criteria methods can be an important supportive tool in decision-making, providing flexibility and capacity to assess the economic implications of the alternative technologies along with the environment and social inference.

A literature survey aiming at a review of published criteria and sub-criteria for the assessment of RE technologies was conducted. It enabled to identify the most important criteria for the comparison of RE generation technologies in electricity and heat sector. There are conducted several important EU projects[1,2,3,4,5,6,7] all of which are aiming at

[1] CASES (2008a).
[2] CASES (2008b).
[3] EUSUSTEL (2007).
[4] NEEDS (2005).
[5] NEEDS (2006).
[6] NEEDS (2007).
[7] PSI (2003).

Table 2 Electricity and heat generation technologies selected for the multi-criteria sustainability assessment

Technologies and types of power plants	Acronyms
Hydropower	
Run of river	
< 10 MW	HYD S (A_1)
< 100 MW	HYD M (A_2)
> 100 MW	HYD L (A_3)
Dam	HYD DAM (A_4)
Pump storage	HYD PMP (A_5)
Wind	
On shore	WIND ON (A_6)
Off shore	WIND OFF (A_7)
Solar PV	
Roof	PV ROOF (A_8)
Open space	PV OPEN (A_9)
Solar thermal	SOL TH (A_{10})
Biomass CHP with an extraction condensing turbine	
Straw	CHP STRAW (A_{11})
Wood chips	CHP WOOD (A_{12})

a comparative assessment of energy technologies. Table 1 was developed based on the analysis of those studies, which present the full set of sub-criteria covering economic, environmental and social aspects of a long-term sustainability assessment of energy technologies. The proposed indicator framework addresses the EU energy and environmental policy priorities and the three dimensions of sustainable development: economic, social and environmental.

The economic dimension in sustainability assessment of RE technologies is very important, as energy supply cost is the main driver of energy technology penetration in the markets. There are five sub-criteria selected to address the economic dimension of sustainability assessment in electricity and heat sector: private costs, average availability factor, costs of grid connection, peak load response, security of supply. The most important economic sub-criteria are private costs, availability factor and costs of grid connection. Security of supply is an important issue in terms of energy quality, regarding frequency, transient effects and voltage bands related to the specific RE generation sources.

The main environmental sub-criteria for RE technology assessment are human health impact, GHG emissions, environmental external costs and radionuclides external costs, whereas the main social sub-criteria selected for renewable electricity and heat technology assessment in this paper are fatal accidents from the past experience, severe accidents perceived in the future and technology-specific job opportunities. The major economic indicators that were considered are the costs of grid connection, the average availability (load) factor, security of supply, peak load response and private costs, including investments and operation costs. Table 2 summarizes renewable electricity and heat generation technologies, which are assessed based on the economic, social and environmental criteria, as summarized in Table 1. More details on methodologies and methods of calculation of sub-criteria presented in Table 1 can be found in the paper (Streimikiene et al. 2012).

The selected renewable electricity generation technologies (Table 2) and relevant data for the assessment were collected from EU Framework six project CASES databases developed for EU member states. The EU average data were applied to the case study developed in this paper (CASES 2008a, b). Thus, the decision matrix of the presented case study consists of twelve alternative RE technologies and thirteen criteria founded on multiple quantitative and qualitative economic, environmental and social aspects. Therefore, the appraising of RE technologies in terms of their sustainability and competitiveness is a complex task, considering the series of uncertainties and implications that are encountered to obtain realistic and transparent results. Advanced MCDM methods can help in addressing such difficult tasks.

In order to execute the proposed MCDM model for the considered case study and identify the most efficient alternative energy system based on defined dimension and criteria, the following steps have to be followed. Figure 1 shows the process in a comprehensive way.

Step 1 Introduction and historical review of the energy system planning, the evaluation of systems, main corresponded index, factors and aspects through previous studies.
Step 2 Finding research objectives based on the applied methodologies and different approaches.
Step 3 Clarifying essential dimensions, criteria, sub-criteria and candidate energy alternatives associated with a real case study in the EU as well as getting information and performance rate of each sub-criterion in front of energy source.
Step 4 Determining initial decision matrix and performing DEMATEL-ANP model to obtain criteria weights.
Step 5 Forming network relationship map and causal diagram by results of DEMATEL.
Step 6 Applying WASPAS and COPRAS methods in order to achieve the ranking of the candidate energy systems.
Step 7 Comparing results for the analytical validation.

Results and analysis

Solving REs selection problem

At the beginning, the initial relation matrix (A) of Table 3 is developed based on the presented extensive literature review,

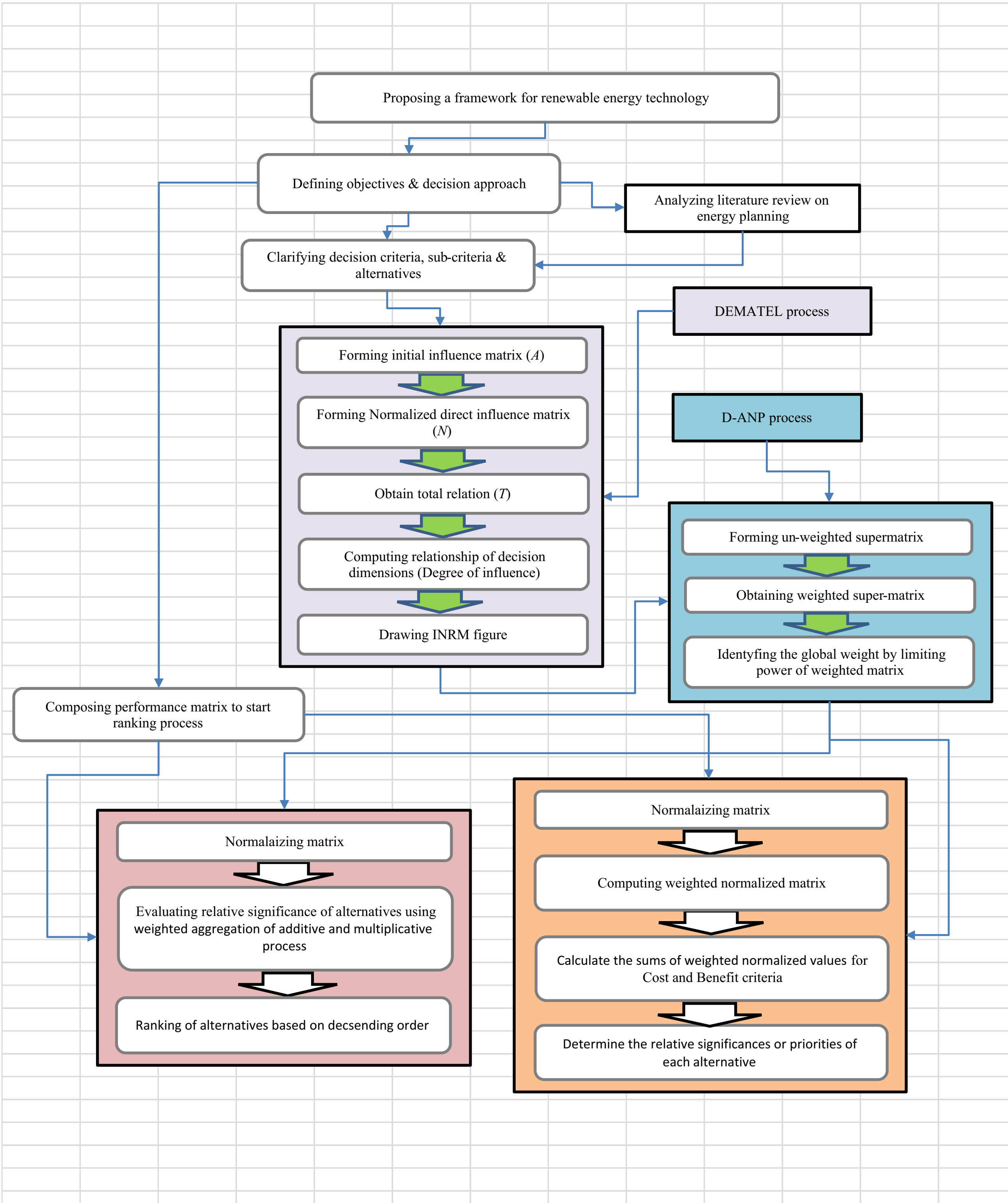

Fig. 1 Proposed hybrid framework

Table 3 Initial influence matrix (A)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0	0	3	1	2	3	3	3	0	1	4	0	1
C_2	4	0	4	1	4	4	4	2	2	0	3	1	3
C_3	2	4	0	4	3	3	4	3	3	2	4	1	4
C_4	3	2	4	0	3	3	2	2	1	1	4	1	3
C_5	4	2	2	1	0	4	4	2	1	1	3	1	4
C_6	4	1	2	3	4	0	4	4	1	2	4	1	4
C_7	4	1	2	3	0	4	0	4	1	2	4	1	4
C_8	4	4	3	1	1	1	3	0	1	1	3	1	4
C_9	0	1	1	1	1	1	1	4	0	2	4	2	3
C_{10}	2	4	4	3	2	2	3	4	2	0	4	4	4
C_{11}	3	3	4	4	4	4	3	4	2	2	0	2	4
C_{12}	1	3	3	3	3	3	3	3	4	4	4	0	4
C_{13}	3	3	2	2	3	3	4	4	2	2	4	2	0

Table 4 Normalized direct influence matrix (N)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0.000	0.000	0.067	0.022	0.044	0.067	0.067	0.067	0.000	0.022	0.089	0.000	0.022
C_2	0.089	0.000	0.089	0.022	0.089	0.089	0.089	0.044	0.044	0.000	0.067	0.022	0.067
C_3	0.044	0.089	0.000	0.089	0.067	0.067	0.089	0.067	0.067	0.044	0.089	0.022	0.089
C_4	0.067	0.044	0.089	0.000	0.067	0.067	0.044	0.044	0.022	0.022	0.089	0.022	0.067
C_5	0.089	0.044	0.044	0.022	0.000	0.089	0.089	0.044	0.022	0.022	0.067	0.022	0.089
C_6	0.089	0.022	0.044	0.067	0.089	0.000	0.089	0.089	0.022	0.044	0.089	0.022	0.089
C_7	0.089	0.022	0.044	0.067	0.000	0.089	0.000	0.089	0.022	0.044	0.089	0.022	0.089
C_8	0.089	0.089	0.067	0.022	0.022	0.022	0.067	0.000	0.022	0.022	0.067	0.022	0.089
C_9	0.000	0.022	0.022	0.022	0.022	0.022	0.022	0.089	0.000	0.044	0.089	0.044	0.067
C_{10}	0.044	0.089	0.089	0.067	0.044	0.044	0.067	0.089	0.044	0.000	0.089	0.089	0.089
C_{11}	0.067	0.067	0.089	0.089	0.089	0.089	0.067	0.089	0.044	0.044	0.000	0.044	0.089
C_{12}	0.022	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.089	0.089	0.089	0.000	0.089
C_{13}	0.067	0.067	0.044	0.044	0.067	0.067	0.089	0.089	0.044	0.044	0.089	0.044	0.000

energy expert opinions and knowledge. Normalized direct influence matrix (N) (Table 4) is derived by normalizing the values of matrix A using Eqs. (2, 3). This table shows the interrelation of all criteria. Then, the total influence matrix (T) and the degrees of influence are computed using Eq. (4), as shown in Table 5. Then, the values of Table 6 are computed using Eqs. (6) and (7). Table 7 shows the relationship of the three dimensions based on the expert cognition and also shows that the dimension environmental indicators (D_1) have the highest impact among the dimensions and are the most influential. Clearly, the degree of influence of economic indicators (D_3) is lowest among all the indicators.

DEMATEL technique is applied in order to determine the interactions among the criteria. This study forms a critical model for the RE systems, and the degree of influence of each criterion is obtained, as shown in Table 7.

Tables 6 and 7 provide helpful and beneficial information derived from DEMATEL method. Table 7 reveals that D_3 (economic indicators) have the largest positive value (net influence, indicating that it is the most important dimension). This signifies that D_3 will influence other dimensions more than the others influence it. On the other side, D_1 (environmental indicators) have the largest $r_i + y_i$ value, denoting that it has the largest total influence degree within all dimensions. In Table 6, C_{11} (security of supply) is the most important criterion due to the highest total degree ($r_i + y_i$) of influence based on the expert attitude. Moreover, the peak load response (C_{12}) has the least importance in comparison with the other criteria because of the lowest ($r_i + y_i$). Table 6 reveals that criterion with the maximum reason degree ($r_i - y_i$) is a peak load response (C_{12}), implying it is the most influential criterion. The criterion with the minimum reason degree ($r_i - y_i$) is human health impact (C_1), signifying that it is most influenced by the others. The network-influence relationship can be visualized by drawing an INRM of the criteria, as illustrated in Fig. 2. This figure pictured that C_2 (GHG emissions), C_5 (fatal accidents from the past experience) and C_{12} (peak load response) have the largest degrees

Table 5 Total-relation matrix of criteria (T)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0.106	0.080	0.156	0.103	0.128	0.165	0.174	0.173	0.050	0.072	0.206	0.042	0.139
C_2	0.234	0.108	0.214	0.134	0.206	0.233	0.244	0.201	0.113	0.074	0.243	0.079	0.224
C_3	0.217	0.212	0.157	0.211	0.206	0.234	0.266	0.245	0.146	0.125	0.291	0.093	0.270
C_4	0.203	0.148	0.209	0.106	0.181	0.202	0.194	0.190	0.090	0.089	0.250	0.077	0.213
C_5	0.223	0.143	0.165	0.125	0.113	0.220	0.231	0.190	0.086	0.089	0.229	0.076	0.227
C_6	0.244	0.142	0.187	0.181	0.212	0.158	0.253	0.251	0.096	0.119	0.274	0.086	0.253
C_7	0.226	0.131	0.174	0.171	0.122	0.222	0.152	0.236	0.089	0.112	0.255	0.080	0.234
C_8	0.212	0.180	0.180	0.117	0.130	0.152	0.202	0.136	0.084	0.083	0.217	0.073	0.216
C_9	0.105	0.107	0.118	0.101	0.109	0.123	0.133	0.195	0.053	0.095	0.208	0.089	0.177
C_{10}	0.222	0.225	0.250	0.200	0.196	0.223	0.257	0.275	0.136	0.091	0.302	0.159	0.281
C_{11}	0.245	0.200	0.247	0.218	0.234	0.262	0.258	0.274	0.131	0.131	0.220	0.116	0.280
C_{12}	0.199	0.202	0.226	0.198	0.212	0.238	0.253	0.255	0.173	0.172	0.300	0.078	0.280
C_{13}	0.224	0.183	0.188	0.162	0.194	0.221	0.253	0.252	0.119	0.120	0.275	0.107	0.182

Table 6 The sum of influences given/received on criteria

	r	y	$r+y$	$r-y$	Weight
C_1	1.456	1.595	4.255	− 1.065	0.071
C_2	2.082	2.306	4.366	0.246	0.073
C_3	2.403	2.673	5.143	0.202	0.086
C_4	1.939	2.152	4.178	0.126	0.070
C_5	1.890	2.117	4.361	− 0.126	0.073
C_6	2.202	2.454	5.107	− 0.199	0.085
C_7	1.970	2.203	5.074	− 0.668	0.085
C_8	1.766	1.982	4.856	− 0.891	0.081
C_9	1.437	1.614	2.980	0.248	0.050
C_{10}	2.534	2.816	4.189	1.443	0.070
C_{11}	2.536	2.816	6.086	− 0.454	0.101
C_{12}	2.508	2.788	3.942	1.633	0.066
C_{13}	2.298	2.480	5.455	− 0.496	0.091

of the net influence under the three main dimensions of environmental, social and economic indicators.

The D-ANP integrated tool provides the influential weights of criteria. After that, the un-weighted super-matrix (W) is obtained by transposing the normalized influence matrix T_C^{β} using Eq. (12), as shown in Table 8. The weighted super-matrix W^{β}, calculated using Eq. (16), is shown in Table 9. The influential weights (global weight) of the D-ANP can be achieved by limiting the power of the weighted super-matrix (a concept based on the Markov chain), as shown in Table 10.

As it is shown in Table 10, the global weights are computed to affect the decision-making process and play their role in the two MCDM techniques, i.e. WASPAS and COPRAS, that are used for determining the ranking preorder of the considered RE systems. The most important criterion among others is the peak load response (C_{12}) having the maximum weight of 0.1258. In this study, an attempt is made to validate the applicability and effectiveness of WASPAS and COPRAS methods as effective optimization tools to solve the considered RE system assessment and selection problem. WASPAS and COPRAS methods are adopted to aggregate the performance measures under different criteria into an overall performance score of renewable technologies. Optimization direction of criteria C_1–C_9 is non-beneficial; thus, lower values are expected, while that of C_{10}–C_{13} is beneficial in nature, and higher values are preferred. In case of WASPAS method, it has been noticed that due to the aggregated structure based on the concepts of WSM and WPM approaches its solution accuracy is expected to be better than that of any single method. The ranking order of the RE alternatives that was obtained by applying WASPAS method is as follows:

$$A_2 > A_3 > A_1 > A_4 > A_5 > A_{12} > A_{10} > A_{11} > A_7 > A_6 > A_9 > A_8.$$

Thus, "HYD M" (A_2) is considered the best RE technology among others. Moreover, the next two alternatives after "HYD M" are "HYD L" (A_3) and "HYD S" (A_1), while "PV

Table 7 The total influence matrix of dimensions and sum of influences given/received on dimensions

	D_1	D_2	D_3	r	y	$r+y$	$r-y$	w
D_1	0	4	3	1.883	2.429	4.313	0.546	**0.351**
D_2	2	0	1	2.715	1.286	4.001	− 1.429	**0.326**
D_3	3	4	0	1.546	2.429	3.975	0.883	**0.323**

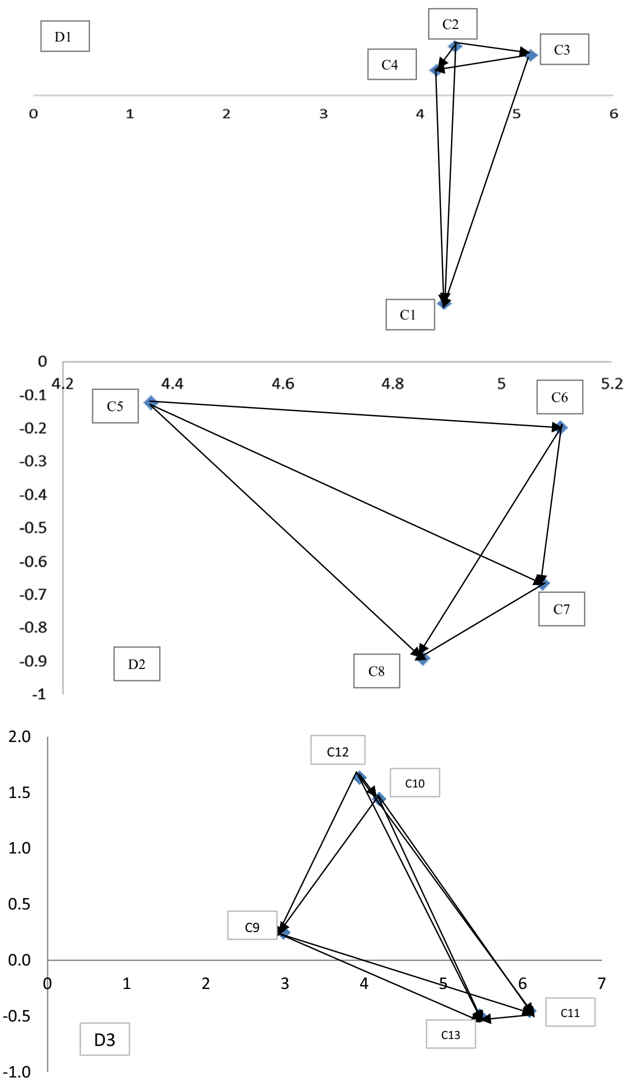

Fig. 2 Influential network relationship map (INRM) for RE criteria systems

ROOF" (A_8) and "PV OPEN" (A_9) are seen as the least preferred candidate for REs.

COPRAS method derives the following rank priorities of the alternative REs:

$$A_3 > A_2 > A_1 > A_{10} > A_6 > A_4 > A_5 > A_{12} > A_7 > A_{11} > A_8 > A_9.$$

COPRAS method suggests that "HYD L" (A_3) is the most preferred energy technology option, while "HYD M" (A_2) and "HYD S" (A_1) are the next two selected alternatives. Moreover, the lowest ranks are assigned to (A_8) and (A_9) as indicated by WASPAS method as well.

The validation of results

In this section, three tests have been performed to validate the results obtained by WASPAS and COPRAS methods. In order to accomplish this objective, the correlation coefficient between the two methods, consistency verification of WASPAS ranking index and sensitivity analysis of COPRAS method are performed. Both methods indicate that "HYDL, HYD M and HYD S" are the first three alternative energy technologies. Spearman correlation coefficient between these two methods is estimated at 0.82, which implies a strong agreement between the rankings provided by the two methods. Although the priority order of some intermediate alternatives has changed slightly, high correlation between these two methods establishes their effectiveness and applicability.

WASPAS method has a benefit in the optimization of problems. In WASPAS algorithm, λ index helps DMs to be flexible in their decision to get optimized solution. Table 11 presents the ranking of alternative REs for varying values of λ. It can be observed that WAPAS rankings for different λ values are consistent and quite similar with a Kendall tau rank correlation coefficient of 0.9391. The most significant

Table 8 The un-weighted super matrix of criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0.040	0.088	0.082	0.076	0.084	0.092	0.085	0.080	0.039	0.084	0.092	0.075	0.084
C_2	0.039	0.052	0.103	0.072	0.075	0.069	0.064	0.085	0.053	0.109	0.096	0.097	0.089
C_3	0.063	0.087	0.063	0.085	0.067	0.076	0.070	0.073	0.048	0.101	0.100	0.091	0.076
C_4	0.051	0.066	0.104	0.052	0.062	0.089	0.084	0.058	0.050	0.099	0.107	0.098	0.800
C_5	0.057	0.092	0.092	0.081	0.051	0.095	0.054	0.058	0.049	0.087	0.105	0.095	0.086
C_6	0.062	0.088	0.088	0.076	0.083	0.060	0.084	0.057	0.046	0.084	0.099	0.090	0.083
C_7	0.060	0.084	0.093	0.067	0.080	0.088	0.053	0.070	0.046	0.090	0.090	0.088	0.088
C_8	0.060	0.070	0.085	0.066	0.066	0.088	0.082	0.047	0.068	0.096	0.095	0.090	0.088
C_9	0.036	0.083	0.107	0.066	0.063	0.070	0.065	0.062	0.039	0.099	0.096	0.127	0.087
C_{10}	0.052	0.054	0.090	0.065	0.065	0.087	0.082	0.061	0.069	0.066	0.095	0.126	0.088
C_{11}	0.063	0.074	0.088	0.077	0.070	0.084	0.078	0.066	0.063	0.092	0.067	0.092	0.084
C_{12}	0.036	0.069	0.080	0.067	0.066	0.074	0.069	0.063	0.077	0.137	0.100	0.670	0.093
C_{13}	0.047	0.075	0.091	0.072	0.076	0.085	0.078	0.073	0.059	0.095	0.094	0.094	0.061

Table 9 The weighted super matrix for D-ANP process

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0.0028	0.0064	0.0070	0.0053	0.0061	0.0078	0.0072	0.0065	0.0019	0.0059	0.0093	0.0049	0.0076
C_2	0.0028	0.0038	0.0088	0.0050	0.0055	0.0059	0.0054	0.0069	0.0026	0.0076	0.0097	0.0064	0.0081
C_3	0.0045	0.0063	0.0054	0.0059	0.0049	0.0065	0.0059	0.0059	0.0024	0.0071	0.0101	0.0060	0.0069
C_4	0.0036	0.0048	0.0089	0.0036	0.0045	0.0076	0.0071	0.0047	0.0025	0.0069	0.0109	0.0064	0.0727
C_5	0.0040	0.0067	0.0079	0.0056	0.0037	0.0081	0.0046	0.0047	0.0024	0.0061	0.0107	0.0062	0.0078
C_6	0.0044	0.0064	0.0075	0.0053	0.0060	0.0051	0.0071	0.0046	0.0023	0.0059	0.0100	0.0059	0.0075
C_7	0.0043	0.0061	0.0080	0.0047	0.0058	0.0075	0.0045	0.0057	0.0023	0.0063	0.0091	0.0058	0.0080
C_8	0.0043	0.0051	0.0073	0.0046	0.0048	0.0075	0.0069	0.0038	0.0034	0.0067	0.0096	0.0059	0.0080
C_9	0.0026	0.0060	0.0092	0.0046	0.0046	0.0060	0.0055	0.0050	0.0019	0.0069	0.0097	0.0083	0.0079
C_{10}	0.0037	0.0039	0.0077	0.0045	0.0047	0.0074	0.0069	0.0049	0.0034	0.0046	0.0096	0.0083	0.0080
C_{11}	0.0045	0.0054	0.0075	0.0054	0.0051	0.0072	0.0066	0.0053	0.0031	0.0064	0.0068	0.0060	0.0076
C_{12}	0.0026	0.0050	0.0069	0.0047	0.0048	0.0063	0.0058	0.0051	0.0038	0.0096	0.0101	0.0440	0.0085
C_{13}	0.0033	0.0055	0.0078	0.0050	0.0055	0.0072	0.0066	0.0059	0.0029	0.0066	0.0095	0.0062	0.0055

point of this table is that when these results are compared with COPRAS method-based ranking, it is clear that the correlation coefficient between the COPRAS method-based ranking and WASPAS ($\lambda = 0.1$) is 0.76; for $\lambda = 0.5$, it is 0.80, and for $\lambda = 0.9$, it is 0.90. This correlation pattern signifies that the ranking accuracy of WASPAS method increases with the increase in λ value.

Sensitivity analysis is performed to check the consistency and robustness of COPRAS for the presented case study. Six different weight sets are used to obtain the ranking of the RE alternatives, as it is shown in Table 12.

The sensitivity analysis results of COPRAS method are given in Table 13. As observed from this table, the ranking preorders of the RE alternatives are very close to the original COPRAS method-based ranking (Table 10). Kendall tau rank correlation coefficient is computed between the ranking of Table 12 and original COPRAS method-based ranking of 0.9560, which indicates an extremely high agreement between the estimated ranking orders, and the higher one is observed in test 6 (0.9895). Although test 2 gives a slightly different ranking, all the other five tests are revealing almost similar priority of alternatives especially concerning best and worst options. The random sensitivity analysis tests, as they were adopted in this study, express the robust performance of COPRAS in the context of the RE selection problem.

Discussion

The results of ranking REs by applying the novel hybrid MCDM model provide precise outcomes for a comparative assessment. The D-ANP technique allows determining the interactions among the criteria and provides the degree of influence of each of three dimensions and thirteen criteria applied for REs technology ranking. The initial relation matrix was formed according to the energy expert opinions and knowledge. It showed that the environmental indicators have the highest impact among the three dimensions and are the most influential factor in REs technologies ranking, and the degree of influence of economic indicators is the lowest among all the indicators.

The D-ANP technique provided that economic indicators (D_3) have the largest positive value or net influence on REs ranking indicating that it is the most important dimension among three dimensions. This means that D_3 will influence other dimensions more than the others influence it. On the other side, environmental indicators (D_1) have the largest value meaning that they have the largest total influence degree within all the dimensions. The D-ANP technique indicated that the security of supply (C_{11}) is the most significant criterion due to its highest total degree of influence. Moreover, the peak load response (C_{12}) is of the least importance in comparison with the other criteria.

The criterion with the maximum reason degree is C_{12}, which easily influences other criteria. The criterion with the minimum reason degree is human health impact (C_1), which is mostly influenced by other criteria. GHG emissions (C_2), fatal accidents (C_5) from the past experience and C_{12} have the largest degrees of the net influence under the three main dimensions of environmental, social and economic indicators.

The ranking of REs alternatives by WASPAS and COPRAS models provided very similar results and concluded that the most attractive RE technology is hydro, and the least attractive is solar. According to WASPAS method-based analysis, "HYD M" is considered the best RE technology among others. The ranking of RE alternatives as given by COPRAS method indicates that "HYD L" is the most preferred energy alternative. "HYD M" and "HYD L" were selected as the best RE technologies, according to several criteria by WASPAS and

Table 10 Local and global weight with ranking of decision alternatives by COPRAS and WASPAS

Dimension/criteria	Local weight	Global weight	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
$\boldsymbol{D_1}$	**0.351**													
C_1	0.255	0.0894	0.198	0.142	0.127	0.245	0.251	0.142	0.173	0.479	1.082	0.105	1.691	0.639
C_2	0.237	0.0831	0.013	0.009	0.008	0.015	0.014	0.01	0.007	0.056	0.108	0.008	0.069	0.057
C_3	0.265	0.0931	7.229	4.519	4.519	7.35	7.35	6.019	6.143	25.14	20.829	11.969	4.751	3.791
C_4	0.243	0.0853	0.016	0.011	0.01	0.02	0.02	0.007	0.006	0.032	0.064	0.007	0.36	0.078
$\boldsymbol{D_2}$	**0.326**													
C_5	0.231	0.0753	0.0001	0.0001	0.0002	0.0002	0.0005	0.0004	0.0022	0.0028	0.0002	0.0002	0.0029	0.0028
C_6	0.254	0.0828	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.085	0.085
C_7	0.261	0.0849	1	1	1	2	2	1	1	1	1	1	2	2
C_8	0.254	0.0826	1	1	1	1	1	1	1	1	1	1	2	2
$\boldsymbol{D_3}$	**0.323**													
C_9	0.162	0.0523	3	3	3	3	3	4	5	3	3	3	4	4
C_{10}	0.160	0.0518	0.8	0.8	0.8	0.91	0.91	0.29	0.5	0.15	0.15	0.15	0.95	0.95
C_{11}	0.144	0.0465	5	5	5	5	5	5	5	5	5	5	5	5
C_{12}	0.389	0.1258	1.5	1.5	1.5	1.5	1.5	0	0	0	0	0	5	5
C_{13}	0.145	0.0471	1.2	1.2	1.2	1.2	1.2	0.36	0.36	6.6	6.6	6.6	4.4	4.4
WASPAS		Q_i	0.649	0.735	0.718	0.557	0.53	0.315	0.321	0.234	0.240	0.353	0.339	0.386
		Ranking	3	1	2	4	5	10	9	12	11	7	8	6
COPRAS		Q_i	0.1043	0.1196	0.1197	0.0884	0.0856	0.091	0.0684	0.0459	0.0433	0.0942	0.0663	0.0733
		Ranking	3	2	1	6	7	5	9	11	12	4	10	8

Bold values indicate the weight of the main criteria

Table 11 WASPAS ranking outcomes divided by λ values

Alternative RE	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
A_1	3	3	3	3	**3**	3	3	3	3
A_2	1	1	1	1	**1**	1	1	1	1
A_3	2	2	2	2	**2**	2	2	2	2
A_4	4	4	4	4	**4**	4	4	4	5
A_5	5	5	5	5	**5**	5	5	6	8
A_6	10	10	10	10	**10**	9	8	8	7
A_7	9	9	9	9	**9**	8	7	7	6
A_8	12	12	12	12	**12**	12	12	12	12
A_9	11	11	11	11	**11**	11	11	11	11
A_{10}	8	8	8	8	**7**	6	6	5	4
A_{11}	7	7	7	7	**8**	10	10	10	10
A_{12}	6	6	6	6	**6**	7	9	9	9

Bold values indicate ranking provided by WASPAS method with the most general λ value of 0.5

Table 12 Six tests for the sensitivity analysis of COPRAS method

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	w_{12}	w_{13}
Test 1	0.0831	0.0931	0.0894	0.0853	0.0828	0.0753	0.0849	0.0523	0.0826	0.0518	0.0471	0.0465	0.1258
Test 2	0.0831	0.0853	0.0894	0.0753	0.0523	0.0931	0.0826	0.0849	0.0828	0.0519	0.0465	0.1258	0.0471
Test 3	0.0518	0.0465	0.1258	0.0471	0.0894	0.0831	0.0931	0.0853	0.0753	0.0828	0.0849	0.0826	0.0523
Test 4	0.0471	0.0894	0.0831	0.0931	0.0853	0.0518	0.0465	0.1258	0.0753	0.0828	0.0849	0.0826	0.0523
Test 5	0.0465	0.0894	0.0831	0.0931	0.0853	0.0518	0.0471	0.0753	0.0828	0.0849	0.1258	0.0826	0.0523
Test 6	0.0518	0.0471	0.0753	0.0931	0.0853	0.0465	0.0894	0.0831	0.0828	0.0849	0.1258	0.0826	0.0523

Table 13 Results of sensitivity analysis for the COPRAS RE selection

RE alternatives	Rank					
	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
A_1	4	5	3	3	3	3
A_2	1	2	1	1	1	1
A_3	2	1	2	2	2	2
A_4	6	7	4	5	5	5
A_5	7	8	7	6	6	7
A_6	5	4	6	7	7	6
A_7	8	6	9	9	9	9
A_8	10	10	12	11	11	12
A_9	11	12	11	12	12	11
A_{10}	3	3	5	4	4	4
A_{11}	12	11	10	10	10	10
A_{12}	9	9	8	8	8	8

COPRAS methods, as these two technologies have very similar economic, social and environmental indicator values. However, MULTIMOORA and TOPSIS methods provided quite different results for the ranking of the same RE technologies in the other studies conducted by Streimikiene et al. (2012). In this study, MULTIMOORA suggested that "HYD M" (A_2) and "HYD L" (A_3) are the first two RE technologies, whereas TOPSIS method recommended CHP WOOD (A_{12}) and SOL TH (A_{10}) as the predominant alternatives. This difference in ranking may be attributed to the assumption of equal weights of criteria in the previous study.

Conclusions

1. This paper proposes a novel hybrid D-ANP model for the comparative assessment and ranking of RE technologies. The model combines ANP, WASPAS and COPRAS based on the DEMATEL technique. The D-ANP is applied to define the key influential factors in the RE technologies ranking.
2. WASPAS and COPRAS methods are adopted to aggregate the performance measures under different criteria into an overall performance score of RE technologies to provide a total ranking preorder and validate the results. Both these two methods assured that three first alternative energy technologies are hydro: "HYD L, "HYD M" and "HYD S".
3. In order to provide a better analysis, a comparative study consisting of several tests of the ranking performances of WASPAS and COPRAS methods was performed, which signify a strong acceptable agreement between the two methods.
4. The results of ranking RE technologies can be explained by analysing the most influential criteria and indicators obtained by D-ANP. As GHG emissions, fatal accidents from the past experience and peak load response have the largest degree of the net influence in scoring RE technologies under the three main dimensions of environmental, social and economic indicators, hydropower technologies received the highest scores because of the associated low life-cycle GHG emissions, low indicators of fatal accidents in the past and quite high peak load response.
5. The solar technologies were ranked as the worst among the analysed RE technologies because they are distinguished by higher lifetime GHG emissions and very low peak load response. In addition, solar energy technologies were the most expensive among the analysed technologies, though the solar energy technology is rapidly advancing with significant cost reduction in PV technologies and the associated balance of system components.
6. The medium run-of-river hydropower plants (< 100 MW) or HYD M and large run-of-river hydropower plants (> 100 MW) or HYD L were selected as the best RES technologies, according to several important criteria, as these technologies have exceptionally analogous economic, social and environmental indicators. These technologies have the same indicators of peak load response and the same indicators of fatal accidents in the past. The lifetime GHG emissions for these technologies are very similar as well (0.009 kgCO2/kWh for HYD M and 0.008 kgCO2/kWh for HYD L).
7. The proposed novel MCDM approach allows to systematically overcome all types of dependences among the decision elements and provides the maximum precise outcomes and explanations of impacts of various criteria and indicators in the RE technologies ranking. It is expected that the proposed model will effectively solve the dependency of criteria and provide quantified decision-making models to help policy makers in the selection of the best alternative with maximum effectiveness.

Appendix 1: D-ANP method

Step 1 Construct the measure scales of the direct relation matrix.

Decision-makers evaluate the relationship between the sets of paired criteria to indicate the direct influence that each ith criterion exerts on each jth criterion. The initial decision table is developed taking into consideration the expert opinion and literature survey and can be called direct relation matrix where an integer scale (score) ranging from 0 to 4 for pairwise comparison of dimensions/criteria is used: representing no influence (0), low influence (1), middle influence (2), high influence (3) and extreme influence (4).

Step 2 Generation of the initial influence matrix $A = \left[a_{ij}\right]_{n\times n}$.

The matrix A is obtained from the convergence of expert opinion with a direct relation matrix that was developed in Step 1. Then, as a result of these evaluations, the initial data are obtained in the form of $n \times n$ matrix, in which the individual element (a_{ij}) denotes the degree to which ith criterion affects jth criterion, and n denotes the total number of criteria.

$$A = \begin{bmatrix} a_{11} & \dots & a_{1j} & \dots & a_{1n} \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ a_{i1} & \dots & a_{ij} & \dots & a_{in} \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ a_{n1} & \dots & a_{nj} & \dots & a_{nn} \end{bmatrix} \tag{1}$$

Step 3 Determine the normalized direct influence matrix (N). This matrix has derived from the normalizing matrix A using Eqs. (2, 3):

$$N = A/s \tag{2}$$

$$s = \max\left[\max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}, \max_{1\le i\le n}\sum_{i=1}^{n} a_{ij}\right]. \tag{3}$$

Step 4 Build the total influence matrix T. T is produced using Eq. (4), where I is the identity matrix, and $\lim_{h\to\infty} N^h = [0]_{n\times n}$

$$\begin{aligned} T &= N + N^2 + N^3 + \cdots + N^h \\ &= N(I + N + N^2 + \cdots + N^{h-1})[(I-N)((I-N)^{-1}] \\ &= N(I - N^h)(I-N)^{-1}. \end{aligned}$$

Then,

$$T = N(I-N)^{-1}, \text{ when } \lim_{h\to\infty} N^h = [0]_{n\times n} \tag{4}$$

$$T = \left[t_{ij}\right]_{n\times n}, i,j = 1,2,\dots,n. \tag{5}$$

Step 5 Construct the influential network relation map (INRM). According to Eqs. (6, 7), the sum of each row and column for T can be obtained, where vector r (any criterion i influences all other criteria) denotes the sum of all vector rows $r = (r_1, r_2, \dots, r_n)$, and vector y (any criterion j is influenced by all other criteria) denotes the sum of all vector columns $y = (y_1, y_2, \dots, y_n)$. Further on, the sums of rows and columns of matrix T are calculated. At the total-relation matrix T, the sum of rows and sum of columns are represented by vectors r and y, which are derived using Eqs. (6) and (7). When i equals j, $i,j \in \{1,2,\dots,n\}$, then $(r_i + y_i)$ represents the total degree of influence among criteria, and the higher is its value, the closer is the criterion to the object's central point, and $(r_i - y_i)$ interprets the degree of causality among the criteria. The degrees of influence and causality can provide important reference information to inform decision-making by plotting the INRM:

$$r = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = \left[t_i\right]_{n\times 1}, i = 1,2,\dots,n \tag{6}$$

$$y = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n} = \left[t_j\right]_{n\times 1}, j = 1,2,\dots,n. \tag{7}$$

Now, the total influence matrix of criteria as $T = \left[t_{ij}\right]_{n\times n}, i,j = 1,2,\dots,n$ is considered, and the total influence matrix of dimensions (or clusters) as $T = \left[t_{ij}^{D}\right]_{m\times m}$ is regarded. Therefore, in order to obtain the dynamic degree of influence of weights, the weights and their influences in the super-matrix of the ANP need to be determined by normalizing T_c by dimension/cluster.

Step 6 Obtain the un-weighted super-matrix W by transposing the normalized total influence matrix T_c^{β} with the DEMATEL technique. This step uses the basic concepts of the ANP to build the un-weighted super-matrix W as follows:

In order to normalize the total influence matrix T_c using dimensions, the following relations must be done; thus, the normalized matrix T_c^{β} by dimensions can be obtained as shown in Eq. (9). For example, $T_c^{\beta 11}$ can be normalized similarly to obtain $T_c^{\beta nn}$ as shown in Eqs. (10, 11). Next, using Eq. (12), the normalized influence matrix T_c^{β} is transposed to obtain the un-weighted super-matrix W.

$$T_c = \begin{bmatrix} T_c^{11} & \dots & T_c^{1j} & \dots & T_c^{1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{i1} & \dots & T_c^{ij} & \dots & T_c^{in} \\ \vdots & & \vdots & & \vdots \\ T_c^{n1} & \dots & T_c^{nj} & \dots & T_c^{nn} \end{bmatrix} \tag{8}$$

$$T_c = \begin{bmatrix} T_c^{\beta 11} & \dots & T_c^{\beta 1j} & \dots & T_c^{\beta 1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{\beta i1} & \dots & T_c^{\beta ij} & \dots & T_c^{\beta in} \\ \vdots & & \vdots & & \vdots \\ T_c^{\beta n1} & \dots & T_c^{\beta nj} & \dots & T_c^{\beta nn} \end{bmatrix} \tag{9}$$

$$d_i^{11} = \sum_{j=1}^{m_1} t_{cij}^{11}\ i = 1,2,\dots,m_1 \tag{10}$$

$$T_c = \begin{bmatrix} t^{11}_{c^{11}}/d^{11}_1 & \dots & t^{11}_{c^{1j}}/d^{11}_1 & \dots & t^{11}_{c^{1m_1}}/d^{11}_1 \\ \vdots & & \vdots & & \vdots \\ t^{11}_{c^{i1}}/d^{11}_i & \dots & t^{11}_{c^{ij}}/d^{11}_i & \dots & t^{11}_{c^{im_1}}/d^{11}_i \\ \vdots & & \vdots & & \vdots \\ t^{11}_{c^{m_1 1}}/d^{11}_{m_1} & \dots & t^{11}_{c^{m_1 j}}/d^{11}_{m_1} & \dots & t^{11}_{c^{m_1 m_1}}/d^{11}_{m_1} \end{bmatrix} = \begin{bmatrix} t^{\beta 11}_{c^1_1} & \dots & t^{\beta 11}_{c^{1j}} & \dots & t^{\beta 11}_{c^{1m_1}} \\ \vdots & & \vdots & & \vdots \\ t^{\beta 11}_{c^{i1}} & \dots & T^{\beta 11}_{c^{ij}} & \dots & T^{\beta 11}_{c^{im_1}} \\ \vdots & & \vdots & & \vdots \\ t^{\beta 11}_{c^{m_1 1}} & \dots & t^{\beta 11}_{c^{m_1 1}} & \dots & t^{\beta 11}_{c^{m_1 m_1}} \end{bmatrix} \tag{11}$$

$$W = (T^{\beta}_c)' = \begin{bmatrix} W_{11} & \dots & W_{i1} & \dots & W_{n1} \\ \vdots & & \vdots & & \vdots \\ W_{1j} & \dots & W_{i1} & \dots & W_{nj} \\ \vdots & & \vdots & & \vdots \\ W_{1n} & \dots & W_{in} & \dots & W_{nn} \end{bmatrix}. \tag{12}$$

In this approach, D_n shows the nth dimension.

Step 7 Compute the weighted super-matrix W^{β}. In this case, $T_D = \left[t^D_{ij}\right]_{m\times m}$ is shown in Eq. (13) and should be normalized by Eq. (14):

$$T_D = \begin{bmatrix} t^{D_{11}}_{11} & \dots & t^{D_{1j}}_{1j} & \dots & t^{D_{1m}}_{1m} \\ \vdots & & \vdots & & \vdots \\ t^{D_{i1}}_{i1} & \dots & t^{D_{ij}}_{ij} & \dots & t^{D_{im}}_{im} \\ \vdots & & \vdots & & \vdots \\ t^{D_{m1}}_{m1} & \dots & t^{D_{mj}}_{m} & \dots & t^{D_{mm}}_{mm} \end{bmatrix} \tag{13}$$

$$d_i = \sum_{j=1}^{m} t^{D_{ij}}_{ij} \; i = 1, 2, \dots, m. \tag{14}$$

Therefore, T^{β}_D can be determined after normalizing T_D as shown in Eq. (15):

$$T^{\beta}_D = \begin{bmatrix} t^{D_{11}}_{11}/d_1 & \dots & t^{D_{1j}}_{1j}/d_1 & \dots & t^{D_{1m}}_{1m}/d_1 \\ \vdots & & \vdots & & \vdots \\ t^{D_{i1}}_{i1}/d_i & \dots & t^{D_{ij}}_{ij}/d_i & \dots & t^{D_{im}}_{im}/d_i \\ \vdots & & \vdots & & \vdots \\ t^{D_{m1}}_{m1}/d_m & \dots & t^{D_{mj}}_{m}/d_m & \dots & t^{D_{mm}}_{mm}/d_m \end{bmatrix} = \begin{bmatrix} t^{\beta_{11}}_{11} & \dots & t^{\beta_{1j}}_{1j} & \dots & t^{\beta_{1m}}_{1m} \\ \vdots & & \vdots & & \vdots \\ t^{\beta_{i1}}_{i1} & \dots & t^{\beta_{ij}}_{ij} & \dots & t^{\beta_{im}}_{im} \\ \vdots & & \vdots & & \vdots \\ t^{\beta_{m1}}_{m1} & \dots & t^{\beta_{mj}}_{m} & \dots & t^{\beta_{mm}}_{mm} \end{bmatrix} \tag{15}$$

T^{β}_D and W attempts to arrive at weights with different degrees of influence in order to obtain the weighted super-matrix W^{β}, as shown in Eq. (16):

$$W^{\beta} = T^{\beta}_D W = \begin{bmatrix} t^{\beta_{11}}_{11} \times W_{11} & \dots & t^{\beta_{1j}}_{1j} \times W_{i1} & \dots & t^{\beta_{1m}}_{1m} \times W_{n1} \\ \vdots & & \vdots & & \vdots \\ t^{\beta_{i1}}_{i1} \times W_{1j} & \dots & t^{\beta_{ij}}_{ij} \times W_{ij} & \dots & t^{\beta_{im}}_{im} \times W_{nj} \\ \vdots & & \vdots & & \vdots \\ t^{\beta_{m1}}_{m1} \times W_{1n} & \dots & t^{\beta_{mj}}_{m} \times W_{in} & \dots & t^{\beta_{mm}}_{mm} \times W_{nn} \end{bmatrix}. \tag{16}$$

Step 8 Clear the influential weights of the D-ANP with the limit super-matrix $\lim_{g\to\infty}(W^{\beta})^g$. The super-matrix W^{β} is multiplied by itself several times to obtain the limit weighted super-matrix (a concept based on the Markov chain) to a fixed convergence value. Then, the influential weights of the D-ANP can be obtained with $\lim_{g\to\infty}(W^{\beta})^g$, where g represents a positive integer number. This process is recognized as a D-ANP, which stands for DEMATEL-based ANP.

Appendix 2: WASPAS method

Among new MCDM tools, WASPAS is called a unique mixture of two well-known MCDM approaches, i.e. weighted sum model (WSM) and weighted product model (WPM) that starts with the following matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{17}$$

where m is the number of alternative solutions, and n is the number of evaluation criteria, and in this sense, x_{mn} is the performance rating of each alternative for the decision criteria. Thus, the first step is to normalize the decision matrix using the following equations, where the normalized value is denoted by $\bar{x}_{ij}$.

$$\text{For benefit attributes: } \bar{x}_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \tag{18}$$

$$\text{For non - benefit attributes: } \bar{x}_{ij} = \frac{\min_i x_{ij}}{x_{ij}}. \tag{19}$$

Algorithm of WASPAS is seeking a joint criterion of optimality based on two criteria of optimality. The first criterion of optimality, i.e. the criterion of a mean weighted success, is similar to WSM method. It is a popular and well-accepted MCDM approach applied for evaluating a number of alternatives in terms of a number of decision criteria. Based on WSM method, the total relative importance of ith alternative is calculated as follows (Triantaphyllou and Mann 1989):

$$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij} w_j \tag{20}$$

The model is based as well on the WPM method; the total relative importance of ith alternative is computed using the following expression:

$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j}. \tag{21}$$

A joint generalized criterion of weighted aggregation of additive and multiplicative methods is proposed as follows:

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)} = 0.5 \sum_{j=1}^{n} \bar{x}_{ij} w_j + 0.5 \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j}. \tag{22}$$

In order to have an increased ranking accuracy and effectiveness of the decision-making process of WASPAS method, a more generalized equation for determining the total relative importance of ith alternative is developed and provided below (Zavadskas et al. 2012, 2013; Hashemkhani Zolfani et al. 2013):

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)} = \lambda \sum_{j=1}^{n} \bar{x}_{ij} w_j + (1-\lambda) \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \tag{23}$$

Now, the candidate alternatives are ranked based on the Q values, i.e. the best alternative would be the one having the highest Q value. When the value of λ is 0, WASPAS method is transformed to WPM, and when λ is 1, it becomes WSM method.

Appendix 3: COPRAS method

The computational steps that are involved in COPRAS method-based analysis are now presented below (Chatterjee et al. 2011; Mulliner et al. 2013; Zavadskas et al. 2009; Bagocius et al. 2014):

Step 1 D is a decision matrix, containing the performance rating of m number of alternatives with respect to n number of criteria, as shown below.

$$D = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{24}$$

where x_{ij} is the rating of ith decision criteria on jth alternative, whereas m is the number of alternatives, and n is the number of criteria.

Step 2 Normalize the decision matrix using Eq. (24).

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}},\ j = 1, 2, \dots, m,\ i = 1, 2, \dots, n \tag{25}$$

Step 3 Calculate the weighted normalized decision matrix as follows, where w_i includes the weights of criteria and is given by $\sum_{i=1}^{n} w_i = 1$,

$$v_{ij} = w_i \times r_{ij},\ j = 1, 2, \dots, m,\ i = 1, 2, \dots, n. \tag{26}$$

The sum of dimensionless weighted normalized values of each criterion is always equal to the weight of that criterion.

$$\sum_{j=1}^{m} v_{ij} = w_i \tag{27}$$

Thus, it can be said that the weight, w_i of ith criterion, is proportionally distributed among all the alternatives according to their weighted normalized value v_{ij}.

Step 4 Calculate the sums of weighted normalized values for both beneficial (P_j) and non-beneficial attributes (R_j) using the following equations:

$$P_j = \sum_{i=1}^{k} v_{ij} \tag{28}$$

where k is the number of criteria to be maximized.

$$R_j = \sum_{i=1}^{n-k} v_{ij} \tag{29}$$

where $(n - k)$ is the number of criteria to be minimized.

Step 5 Determine the relative significances or priorities of the alternatives as follows:

$$Q_j = P_j + \frac{\sum_{j=1}^{m} R_j}{R_j \sum_{j=1}^{m} \frac{1}{R_j}}. \tag{30}$$

Step 6 Calculate the quantitative utility (N_j) for jth alternative. The degree of an alternative utility, which leads to a complete ranking of the candidate alternatives, is determined by comparing the priorities of all the alternatives with the most efficient one and can be denoted as it is shown below:

$$N_j = \frac{Q_j}{Q_{\max}} \times 100\% \tag{31}$$

where $Q_{\max}$ is the maximum relative significance value. These utility values of the alternatives range from 0 to 100%. Thus, this approach allows evaluating the direct and proportional dependence of the significance and utility degree of the considered alternatives in a decision-making problem having multiple criteria, their weights and performance values of the alternatives with respect to all the criteria.

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