Offshore Wind Farm Site Selection Using Interval Rough Numbers based Best Worst Method and MARCOS

Muhammet Deveci*[a], Ender Özcan[a], Robert John**, Dragan Pamucar[b], Himmet Karaman[c]

[a] *Computational Optimisation and Learning (COL) Lab, School of Computer Science, University of Nottingham, NG8 1BB, Nottingham, UK.*
[b] *Department of Logistics, University of Defence, 11000 Belgrade, Serbia*
[c] *Department of Geomatics Engineering, Faculty of Civil Engineering, University of Istanbul Technical, 34367 Maka, Istanbul, Turkey*

Abstract

Over the past 20 years, the development of offshore wind farms has become increasingly important across the world. One of the most crucial reasons for that is offshore wind turbines have higher average speeds than those onshore, producing more electricity. In this study, a new hybrid approach integrating Interval Rough Numbers (IRNs) into Best Worst Method (BWM) and Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) is introduced for multi-criteria intelligent decision support to choose the best offshore wind farm site in a Turkey's coastal area. Four alternatives in the Aegean Sea are considered based on a range of criteria. The results show the viability of the proposed approach which yields Bozcaada as the appropriate site, when compared to and validated using the other multi-criteria decision-making techniques from the literature, including IRN based MABAC, WASPAS, and MAIRCA.

Keywords: Renewable energy, Wind power, MARCOS, WASPAS, MAIRCA, MABAC.

*Corresponding author
**Prof. Robert John unfortunately passed away on the 17th of February 2020.
Email addresses: muhammet.deveci@nottingham.ac.uk (Muhammet Deveci*), ender.ozcan@nottingham.ac.uk (Ender Özcan), dpamucar@gmail.com (Dragan Pamucar), karamanhi@itu.edu.tr (Himmet Karaman)

1. Introduction

The importance of renewable energy resources has been increasing, as the energy demand across the world has been growing rapidly, not to mention the limitation of fossil fuel reserves, fossil fuel price instability, high restrictions on pollution levels, and global climate change [1, 2]. Renewable resources include wind, biomass, hydropower, sunlight, geothermal, wave, and tide. Wind energy is considered more advantageous for many aspects such as technology maturity, levelized cost of energy as compared to its counterparts [3]. As a result, there has been a continued interest and rapid growth in the wind energy sector over the past decade [4, 5], some of which has been formed in the offshore segment [6]. Recently, the technology development has moved towards offshore market thanks to increased capacity factor and less land contraints relative to onshore. Thousands of megawatt (MW) - capacity offshore wind farms have been installed for large-scale electricity generation [7]. The installed offshore wind capacity in Europe has risen from 3.6 GW in 2000 to 22 GW by 2019 [8].

New technologies are being investigated and developed to ensure the growth of low-cost, high-return establishment of offshore wind farms. For example, the sector are looking into the ways to install wind farms further away from the coastline [9]. Aligned with the global trend, Turkey has been also developing support schemes, regulatory and incentive policies to encourage the generation and use of renewable energy . Research has been conducting in offshore wind energy, particularly.

It is not trivial to determine an offshore site for constructing a wind farm. Many interacting criteria should be considered for such an investment with a high-cost and long-term return. Hence, offshore wind farm site selection is often formulated as a strategic multi-criteria decision-making problem. The average wind speed, total payback period, investment cost, infrastructure facilities, environmental impact, legal regulations, and financial incentives are the main criteria affecting the decisions on offshore site selection. In each case, a mutual compromise among the criteria is inevitable.

This study presents a novel interval rough numbers based Best Worst Method (BWM) and Measurement of alternatives and ranking according to Compromise Solution (MARCOS) approach for determining the best offshore site in Turkey's coastal area based on 6 main and 23 sub-criteria considering four alternatives.

1.1. Approaches to Offshore Wind Farm Site Selection

The majority of the wind farm location selection studies in the scientific literature were conducted considering onshore wind farm sites. Table 1 presents an overview of previous work on onshore wind farm location selection considering the approaches, number of sites, main and sub-criteria, and country of origin for the data. As a relatively new area of research, the studies on offshore wind farm (OWF) site selection has been growing slowly, which is the focus of this work. A summary of previous studies to date are provided in Table 2. Both tables show that various approaches, including Analytic Hierarchy Process (AHP), fuzzy Analytic Network Process (ANP), fuzzy ELimination Et Choix Traduisant la REalitwas (ELECTRE), fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL), hybrid methods and others have been applied to wind farm site selection for solving particular problems considering particular regions and often for multiple criteria.

Fetanat and Khorasaninejad [10], Wu et al. [11] and Kim et al. [12] are the previous studies using a high number of criteria as close to this study for multi-criteria decision-making. The latter two proposed GIS-based approaches, while the first paper is one of the few studies using type-1 fuzzy which investigated ANP, ELECTRE, and DEMATEL based hybrid multi-criteria decision-making approaches to help select OWF. Argin et al. [13] explored the techno-economic feasibility of wind farms in 55 coastal regions of Turkey using Wind Atlas Analysis and Application Program (WAsP). This study examined five different locations based on techno-economic analysis for wind farm siting.

None of the previous studies in Table 2 considers interval rough numbers as an intelligent decision support system, although it is known that the main feature of the interval rough number is that they reflect the attitude of a decision-maker towards risk and express their preferences better than the other approaches. IRNs consider dilemmas when making decisions

In this study, we propose a new approach embedding interval rough numbers and Best Worst Method - MARCOS for multi-criteria intelligent decision support, which is applied to a particular real-world offshore wind farm site selection problem from Turkey.

1.2. The main contribution and motivation for using Interval Rough Numbers based BMW and MARCOS

The goal of the decision-making model is to enable decision-makers to express their preferences objectively while minimizing subjectivity and uncertainty in the decision-making process. Accordingly, a new approach has been developed in this paper that takes advantage of interval rough numbers (IRN), as well as extending Best Worst Method (BWM) and Measurement of alternatives and ranking according to Compromise Solution (MARCOS) method. IRNs extend the traditional rough numbers and consider dilemmas in multi-criteria decision-making (MCDM) which commonly arise when a group of participants are evaluating the significance of an alternative and/or criterion [44]. The preferences as indicator of significance can be converted into double rough intervals that are much more precise capturing the uncertainties introduced in such situations.

By integrating IRN into BWM and MARCOS models, subjectivity in expert judgment is exploited and assumptions are avoided, which is not the case when fuzzy theory is applied Song et al. [45]. Also, the results of the research conducted by Saaty [46] should be emphasized. Saaty [46] showed that the fuzzification of the AHP method does not produce good results and they further recommend the elimination of uncertainty using intermediate values. Based on those observations, we can conclude that the use of IRN for the development of IR-BWM-MARCOS model has a significant basis. In addition to the above advantages, the integrated approach also exploits the benefits of the MARCOS method [47]. The MARCOS method is a powerful and robust tool for opti-

Table 1: An overview of some previous studies on onshore wind farm site selection problems.

Author(s)	Year	Technical characteristics					MCDM methods					Other methods	
		Main-criteria	Sub-criteria	Sites	Case study	Fuzzy Sets	AHP	ANP	TOPSIS	DEMATEL	ELECTRE	GIS	Cloud Model
Hansen [14]	2005	-	17	-	Baltic Sea	Yes						x	
Lee et al. [15]	2009	12	29	5	China	No	x						
Van Haaren and Fthenakis [16]	2011	3	7	-	USA	No						x	
Gorsevski et al. [17]	2013	2	7	-	USA	Yes						x	
Kang et al. [18]	2013	3	16	4	Taiwan	Yes		x					
Azizi et al. [19]	2014	3	13	-	Iran	No		x		x		x	
Sanchez-Lozano et al. [20]	2014	-	10	12 and 15	Spain	No					x	x	
Latinopoulos and Kechagia [21]	2015	5	6	-	Greece	No	x					x	
Watson and Hudson [22]	2015	4	7	-	United Kingdom	No	x					x	
Hófer et al. [23]	2016	-	9	-	Germany	No	x					x	
Noorollahi et al. [24]	2016	2	15	-	Iran	No						x	
Sanchez-Lozano et al. [25]	2015	-	10	10	Spain	Yes		x	x			x	
Baseer et al. [26]	2017	3	7	29	Saudi Arabia	No	x					x	
Gigovic et al. [27]	2017	3	11	11	Serbia	No		x		x		x	
Wu et al. [28]	2017	4	14	4	China	Yes							x
Ali et al. [29]	2019	-	12	-	Thailand	No	x					x	
Dhiman and Deb [30]	2020	-	-	4	USA	Yes			x				
Moradi et al. [31]	2020	-	6	-	Iran	No	x					x	

Table 2: An overview of some previous studies on offshore wind farm (OWF) site selection problems.

Author(s)	Year	Technical characteristics			Case study	Fuzzy Sets	MCDM methods					Other methods		
		Main-criteria	Sub-criteria	Sites			AHP/ANP	TOPSIS	DEMATEL	ELECTRE	PROMETHEE	B/C Ratio	GIS	WAsP
Lee [32]	2010	4	16	5	Taiwan	Yes	x							
Vagiona and Karanikolas [33]	2012	-	5	10	Greece	No	x						x	
Kim et al. [34]	2013	5	9	-	South Korea	No						x		
Fetanat et al. [10]	2015	6	31	4	Iran	Yes	x		x	x				
Mekonnen and Gorsevski [35]	2015	-	8	3	United State	No							x	
Kim et al. [12]	2016	4	26		South Korea	No							x	
Wu et al. [11]	2016	6	22	5	China	Yes				x				
Chaouachi et al. [36]	2017	3	6	15	Baltic States	No	x							
Vasileiou et al. [37]	2017	3	8	12	Greece	No	x						x	
Kim et al. [38]	2018	3	-	-	South Korea	No							x	
Argin et al. [13]	2019	-	8	55	Turkey	No								x
Emeksiz and Demirci [39]	2019	-	10	20	Turkey	No	x							
Deveci et al. [40]	2020	4	15	3	Turkey	Yes		x						
Deveci et al. [41]	2020	3	24	5	Ireland	Yes		x						
Gao et al. [42]	2020	6	23	5	China	Yes								
Wu et al. [43]	2020	6	18	4	China	Yes	x				x			

mizing multiple goals. Also, the results obtained by the MARCOS method are more reasonable due to the fusion of the results of the ratio approach and the reference point sorting approach (see Section 3.3).

The main contribution of this study are as follow:

1. One of the contributions developed in this paper is the introduction of the interval rough numbers (IRN) based BWM and MARCOS model that provides more objective expert evaluation of criteria in a subjective environment.

2. The improved multi-criteria decision-making (MCDM) methodology suggested provides purchasing managers with another tool for offshore wind farm site selection.

3. The present methodology enable the evaluation of alternative solutions despite dilemmas in the decision making process and lack of quantitative information.

4. The proposed MCDM framework uses exclusively internal knowledge, i.e., operative data, and there is no need to rely on assumption models. In other words, in this model instead of different additional/external parameters, only the structure of the given data is used. This leads to the objective decision making process.

5. Proposed IRN methodology eliminate the shortcomings of the traditional fuzzy approach relating to the interval borders, since for every rating of the expert unique interval borders are formed.

The renewable energy policies of Turkey are presented in Section 2. Section 3 covers the background for the proposed method. The case study of site selection is described in Section 4. Finally, Section 5 provides conclusions.

2. Renewable Energy in Turkey

Turkey is expected to reach an installed wind energy capacity of 20 GW by 2023. Turkey is currently one of the largest markets in the world in the sector [48]. The installed wind energy capacity in Turkey, with a 55-fold growth, has reached to 8,056 MW in the last decade as recently reported by the Turkish

Wind Energy Association. The cumulative growth in the electricity production capacity in recent years is illustrated in Fig. 1. The incredible increase in the installed capacity is mainly due to the dedicated governmental support by the Turkish Ministry of Energy and Natural Resource for renewable energy.

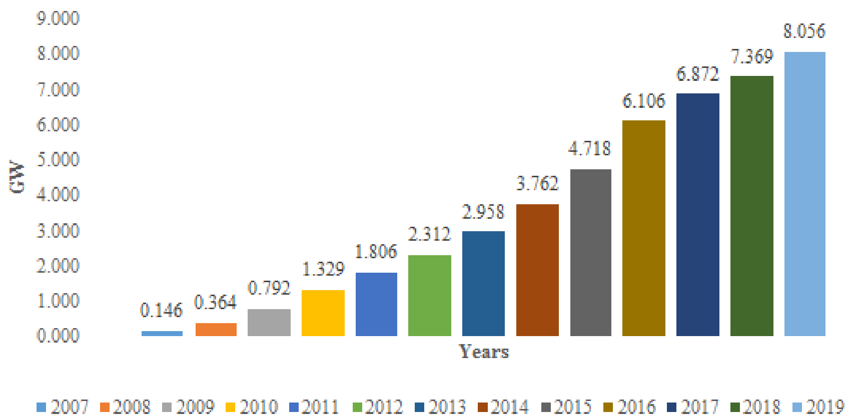


Figure 1: The cumulative electricity generation capacity at each year from 2007 to 2019 in Turkey in GW.

Turkey's long coastline, strong, consistent, and abundant wind profile can provide a sustainable renewable energy source. The total capacities of the operational wind power plants in the coastal cities of Turkey are illustrated in Fig. 2 [49]. Izmir takes the first place with a power generation capacity of 1,550 MW. Balikesir ranks the second and then comes Manisa with the capacity of 1,164 MW and 690 MW, respectively. Even though Turkey is still in the planning stages for offshore wind farm projects, there is a lot of potential because of the need to reduce greenhouse gas emissions across the country, which can diversify the supply of energy, as a renewable energy source that can produce affordable electricity reducing the high energy costs for homes and businesses [40].

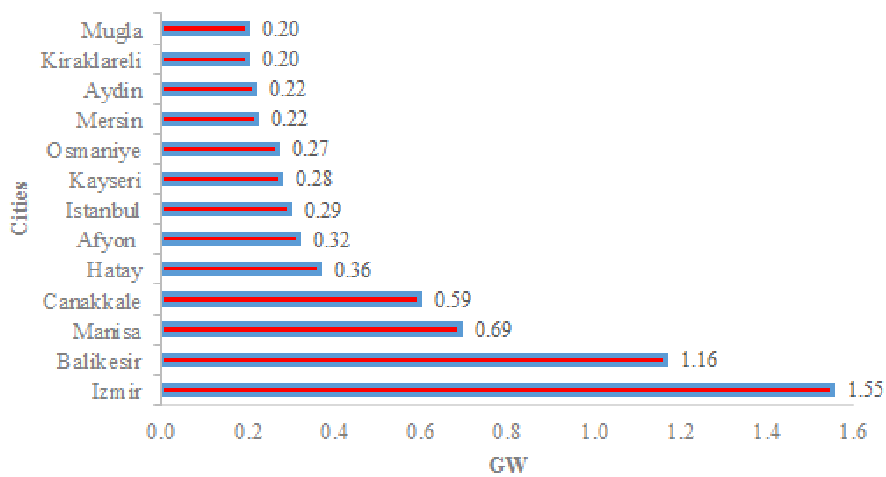


Figure 2: The total capacities of the operational wind power plants in the coastal cities of Turkey.

Having a wind energy capacity of 7 GW and with experience in the wind energy sector, Turkey went for the first offshore wind energy tender joining the 'league of wind industry'. Following the release of the first offshore wind tender, WindEurope, suggested that the most favourable wind energy source for Turkey would be the floating wind farms. Similarly, the report of the Totaro and Associates, a market research and innovation strategy consulting firm, also proposed floating wind farms [50]. The WindEurope CEO Dickson says

"The highway transport infrastructure investments in Turkey would be beneficial for Turkey to help utilize its offshore wind potential and contribute to the economic benefits.".

According to the report by Totaro and Associates [50], the territories within the continental scenery of the Bozcaada island, the Çanakkale region and the Black Sea coast of Saros Gulf and Trakya have considerable potential. The report also mentions that the region around Gökçeada especially the western part, as well as the northern part of Ayvalık has the greatest potential in the Aegean Sea. Our study focuses on offshore wind farm site selection in the Aegean Sea.

3. Proposed Methodology

3.1. MCDM methodology based on IRNs

Suppose there are k decision-makers who have expressed their preferences based on a scale in the initial decision matrix $X = [x_{ij}^k]_{m\times n}$, where m and n are the total numbers of alternatives and criteria, respectively, and x_{ij}^k represents the preference of the $k-$th decision-maker, for the $i-$th alternative considering the $j-$th criterion.

The preferences of the $k-$th decision maker is expressed in the form $x_{ij}^k = (x_{ij}^{k-}; x_{ij}^{k+})$. The expert correspondence matrix can be aggregated into another matrix representing all expert preferences as in Eq. (1).

$$X_k = \begin{bmatrix} (x_{11}^{e-}; x_{11}^{1e}) & (x_{12}^{e-}; x_{12}^{1e}) & ,\ldots, & (x_{1n}^{e-}; x_{1n}^{1e}) \\ (x_{21}^{e-}; x_{21}^{1e}) & (x_{22}^{e-}; x_{22}^{1e}) & ,\ldots, & (x_{2n}^{e-}; x_{2n}^{1e}) \\ \vdots & \vdots & \ddots & \vdots \\ (x_{m1}^{e-}; \ldots, x_{m1}^{1e}) & (x_{m2}^{e-}; x_{m2}^{1e}) & ,\ldots, & (x_{mn}^{e-}; x_{mn}^{1e}) \end{bmatrix}; 1 \leq e \leq k \quad (1)$$

In the matrix (1), we can distinguish a set of k classes of expert preferences $x^- = \{x_1^-, x_2^-, \ldots, x_k^-\}$ that satisfy the condition that $x_1^- \leq x_2^- \leq, \ldots, \leq x_k^-$. We can also distinguish another set of b classes of expert preferences $x^+ = \{x_1^+, x_2^+, \ldots, x_k^+\}$ that are described in the universe. An interval can be defined in each class $x_i^+ = [x_i^L, x_i^U]; x_i^L \leq x_i^U; 1 \leq i \leq b; x_i^L, x_i^U \in x^-$, where x_i^L and x_i^U represent the lower and upper boundary of the ith class, respectively. Suppose that X is a universe containing all objects and x is an arbitrary object in universe X. If the lower and upper classes of values are sequenced as follows $x_1^L < x_2^L <, \ldots, x_l^L, x_1^U < x_2^U <, \ldots, x_k^L (1 \leq l, k \leq b)$, then the above sequences can be we present as two sets: 1) a set of lower classes $x^L = \{x_1^L, x_2^L, \ldots, x_i^L\}$ and a set of upper classes $x^U = \{x_1^U, x_2^U, \ldots, x_i^U\}$. If $x_i^L \in x^L, 1 \leq i \leq l$ and $x_i^U \in x^U, 1 \leq i \leq k$, then lower and upper approximations of x_i^L and x_i^U are described as follows.

- Lower approximation:

$$\underline{Apr}(x_i^L) = \cup\Big\{x \in X / x^L(x) \le x_i^L\Big\} \tag{2}$$

$$\underline{Apr}(x_i^U) = \cup\Big\{x \in X / x^U(x) \le x_i^U\Big\} \tag{3}$$

- Upper approximation:

$$\overline{Apr}(x_i^L) = \cup\Big\{x \in X / x^L(x) \ge x_i^L\Big\} \tag{4}$$

$$\overline{Apr}(x_i^U) = \cup\Big\{x \in X / x^U(x) \ge x_i^U\Big\} \tag{5}$$

where $\underline{Apr}(x_i^L)$ and $\underline{Apr}(x_i^U)$ represents lower approximation, while $\overline{Apr}(x_i^L)$ and $\overline{Apr}(x_i^U)$ represents upper approximation, respectively. Then we can define lower and upper limit of x_i^L and x_i^U as follows.

- Lower limit:

$$\underline{Apr}(x_i^L) = \frac{1}{N_L}\sum_{b=1}^{N_L} x_i^{bL} | x_i^{bL} \in \underline{Apr}(x_i^L) \tag{6}$$

$$\underline{Apr}(x_i^L) = \frac{1}{N_L^*}\sum_{b=1}^{N_L^*} x_i^{bU} | x_i^{bU} \in \underline{Apr}(x_i^U) \tag{7}$$

- Upper limit:

$$\overline{Apr}(x_i^L) = \frac{1}{N_U}\sum_{b=1}^{N_U} x_i^{bL} | x_i^{bL} \in \underline{Apr}(x_i^L) \tag{8}$$

$$\overline{Apr}(x_i^U) = \frac{1}{N_U^*}\sum_{b=1}^{N_U^*} x_i^{bU} | x_i^{bU} \in \underline{Apr}(x_i^U) \tag{9}$$

where N_L, N_L^*, N_U and N_U^* respectively represent the number of objects that are contained in the upper approximation of the classes of objects x_i^L and x_i^U.

Then, we can then define the interval rough number (IRN) as in Eq. (10)

$$IRN(x)_i = \Big[\Big(\underline{Lim}(x_i^L), \overline{Lim}(x_i^L)\Big), \Big(\underline{Lim}(x_i^U), \overline{Lim}(x_i^U)\Big)\Big] = \Big[\Big(x_i^{L'}, x_i^{U'}\Big), \Big(x_i^L, x_i^U\Big)\Big] \tag{10}$$

IRNs introduce two separate groups of interval numbers representing uncertainty and imprecision. A detailed description of the arithmetic operations with

IRN and algorithm for IRN ranking can be found in Pamucar et al. [44]. The following example justifies and describes an implementation of IRN in a realistic circumstance.

Example 1: Suppose that one attribute was assigned to a value within a qualitative scale from 1 to 5. Also, suppose that three experts expressed their preferences for the attribute: Expert $E1$ considers the attribute to have values between 3 and 4; Expert $E2$ believes that the attribute should be assigned values between 4 and 5; while Expert $E3$ thinks the attribute should be assigned a value of 4.

Such dilemmas, where some experts are not certain with their judgement (e.g., $E1$ and $E2$), while some others are (e.g., $E3$) are very common in group decision-making. Then a compromise solution is commonly adopted in such cases eliminating the uncertainty (e.g., represented by $E1$ and $E2$) by converting the expert preferences into crisp values, for example, via computing the geometric mean. In such situations, fuzzy or grey techniques would be appropriate for capturing imprecision. However, both theories require subjective definitions of the interval limits to represent uncertainty.

The subjectivity at intervals, which is used to express uncertainty, can significantly influence the final decision for a given MCDM problem [44]. Therefore, it is necessary to eliminate the additional subjective influences in situations wherever there is already existing uncertainty, to make the decision-making process as objective as possible. On the other hand, an IRN-based approach exploits the uncertainties contained in the real data. As presented in the previous section, the attribute values are obtained taking the uncertainties in the judgement of each expert into account, while eliminating any subjective influence when defining the final expert preferences.

The expert preferences from the example can be represented as follows: $A(E1) = (3; 4)$, $A(E2) = (4; 5)$ and $A(E3) = (4; 4)$. Based on the defined IRN properties and expert preferences, we can define two rough sequences and form two classes of objects $x_i^{'}$ and x_i: $x_i^{'} = 3; 4; 4$ and $x_i = 4; 5; 4$. Applying Eqs. (2) to (9), for each class of objects $x_i^{'}$ and x_i, two rough sequences are formed

$\left(x_i^{L'}, x_i^{U'}\right)$ and $\left(x_i^{L}, x_i^{U}\right)$. For the first class of objects we get: $x_i^{L'}(3) = 3$, $x_i^{U'}(3) = \frac{1}{3}(3+4+4) = 3.67 \rightarrow x_i^{'}(3) = (3, 3.5); x_i^{L'}(4) = \frac{1}{3}(3+4+4) = 3.5, x_i^{U'}(4) = 4 \rightarrow x_i^{'}(4) = (3.5, 4)$. Similarly, for the second class of objects we get: $x_i^{L}(4) = 4 \rightarrow x_i(4) = (4, 4.33); x_i^{L}(5) = \frac{1}{3}(4+5+4) = 4.33, x_i^{U}(5) = 5 \rightarrow x_i(5) = (4.33, 5)$. Based on the presented sequences, we obtain interval rough numbers: $IRN(E1) = [(3, 3.5), (4, 4.33)], IRN(E2) = [(3.5, 4), (4.33, 5)]$ and $IRN(E3) = [(3.5, 4), (4, 4.33)]$.

3.2. Interval rough number based Best Worst Method (IRN-BMW)

To handle the uncertainty and subjectivity that exist in group decision-making, BWM is extended with IRN. The application of IRNs enables: (i) interval values of rough numbers are defined based on uncertainties and imprecision that exist in experts evaluations, and (ii) elimination of the need for additional subjectivity in defining intervals of numbers, which is the case for fuzzy numbers, grey numbers, and other theories of uncertainty. The use of IRN in BWM maintains the quality of existing data in group decision-making, through the objective representation of expert preferences in terms of two matrices; aggregated Best-to-Other (BO) and Other-to-Worst (OW).

There are variants of BWM applying different uncertainty theories in the scientific literature, such as fuzzy BWM [51], intuitionistic fuzzy multiplicative BWM [52], intuitionistic multiplicative preference BWM [53], intuitionistic preferences relation BWM [54], interval-valued fuzzy-rough BWM [55] and rough BWM [56, 57]. As a new IRN-based methodology, we propose the following eight-step algorithm.

Step 1:Defining a set of criteria for evaluating alternatives. Suppose there is a group of e experts for the decision-making process, who have defined a set of criteria $C = \{C_1, C_2, \ldots, C_n\}$, where n is the total number of criteria.

Step 2:Defining the best (B) and worst (W) criteria from the set C. The experts arbitrarily choose the B and W criteria.

Step 3: Defining the IRN BO vector. In BO matrices, experts represent their preferences and compare B criteria to the other criteria in the set

$C = \{C_1, C_2, \ldots, C_n\}$. The comparison of the criterion B with the other criteria in C is expressed through the advantage of the criterion B over the criterion j (where $j = 1, 2, \ldots, n$), i.e. $a^e_{Bj} = (a^{eL}_{Bj}, a^{e'U}_{Bj})(1 \leq e \leq k)$. As a result of the comparison, a vector is obtained $BO(A^e_B)$: $A^e_B = (a^{eL}_{B1}; a^{e'U}_{B1}, a^{eL}_{B2}; a^{e'U}_{B2}, \ldots, a^{eL}_{Bn}; a^{e'U}_{Bn}); (1 \leq e \leq k)$
where a^{eL}_{Bj} and $a^{e'U}_{Bj}$ represent the advantage of the criterion B over the criterion $j; a^{eL}_{BB} = 1$ and $a^{e'U}_{BB} = 1$. So, for each $e-$th $(1 \leq e \leq k)$ expert we get a BO matrix $A^1_B, A^2_B, \ldots, A^e_B, \ldots, A^k_B$. The individual expert BO matrices are used to obtain an averaged IRN BO matrix (Step 5).

Step 4:Defining the IRN OW vector. Each expert compares the j criteria to the W criterion, whereby the advantage of the criterion j (j =1,2,...,n) over the criterion W is represented as $a^e_{jW} = (a^{eL}_{jW}, a^{e'U}_{jW})(1 \leq e \leq k)$. As a result, we get the $OW(a^e_W)$ vector for each expert:

$$A^e_W = (a^{eL}_{1W}; a^{e'U}_{1W}, a^{eL}_{2W}; a^{e'U}_{2W}, \ldots, a^{eL}_{nW}; a^{e'U}_{nW}); (1 \leq e \leq k) \tag{11}$$

where a^{eL}_{jW} and $a^{e'U}_{jW}$ represent an advantage of criterion j over criterion $W; a^e_{WW} = 1$ and $a^{e'}_{WW} = 1$. So, for each $e-$th $(1 \leq e \leq k)$ expert we obtain an OW matrix $A^1_W, A^2_W, \ldots, A^e_W, \ldots, A^k_W$. Similar to the previous step, the individual expert OW matrices are used to obtain an averaged IRN OW matrix (Step 6).

Step 5: Definition IRN BO matrix of average expert's answers. Based on individual expert BO matrices $A^e_B = \left[a^{eL}_{Bj}; a^{e'U}_{Bj}\right]_{1xn}$, two separate matrices A^{*eL}_B and $A^{*e'U}_B$ are formed in which the expert decisions are aggregated:

$$A^{*eL}_B = \left[a^{1L}_{B1}, a^{2L}_{B1}, \ldots a^{kL}_{B1}; a^{1L}_{B2}, a^{2L}_{B2}, \ldots a^{kL}_{B2}; \ldots, a^{1L}_{Bn}, a^{2L}_{Bn}, \ldots a^{kL}_{Bn}\right]_{1xn} \tag{12}$$

$$A^{*e'U}_B = \left[a^{1'U}_{B1}, a^{2'U}_{B1}, \ldots a^{k'U}_{B1}; a^{1'U}_{B2}, a^{2'U}_{B2}, \ldots a^{k'U}_{B2}; \ldots, a^{1'U}_{Bn}, a^{2'U}_{Bn}, \ldots a^{k'U}_{Bn}\right]_{1xn} \tag{13}$$

where $a^{eL}_{Bj} = \left\{a^{1L}_{Bj}, a^{2L}_{Bj}, \ldots a^{kL}_{Bn}\right\}$ and $a^{e'U}_{Bj} = \left\{a^{1'U}_{Bj}, a^{2'U}_{Bj}, \ldots a^{k'U}_{Bn}\right\}$ represent the advantage of criterion B over criterion C_j.

After forming the A_B^{*eL} and $A_B^{*e'U}$ matrices, using Eqs. (2)(9), each pair of sequences a_{Bj}^{eL} and $a_{Bj}^{e'U}$ is transformed into $IRN(a_{Bj}^{e}) = \left[\left(\underline{Lim}(a_{Bj}^{eL-}), \overline{Lim}(a_{Bj}^{eU-})\right), \left(\underline{Lim}(a_{Bj}^{eL+}), \overline{Lim}(a_{Bj}^{eU+})\right)\right]$ sequence, where $\underline{Lim}(a_{Bj}^{eL-})$ and $\overline{Lim}(a_{Bj}^{eL+})$ represent lower limits, while $\underline{Lim}(a_{Bj}^{eU-})$ and $\overline{Lim}(a_{Bj}^{eU+})$ represent upper limits of $IRN(a_{Bj}^{e})$ sequence, respectively. So for each sequence $IRN(a_{Bj}^{e})$ we get BO matrices $A_B^1, A_B^2, \ldots, A_B^e, \ldots, A_B^k (1 \leq e \leq k)$. By applying the interval rough Dombi weighted geometric averaging (IRNDWGA) operator, we obtain the average IRN sequences, the expression (Appendix A-6). So, we obtain the aggregated IRN BO matrix as given in Eq. (14).

$$\overline{A}_B = \left[IRN(\overline{a}_{B1}), IRN(\overline{a}_{B2}, \ldots, IRN(\overline{a}_{Bn})\right]_{1xn} \tag{14}$$

where $IRN(\overline{a}_{Bj}) = \left\langle \left[\overline{a}_{Bj}^{L-}, \overline{a}_{Bj}^{U-}\right], \left[\overline{a}_{Bj}^{L+}, \overline{a}_{Bj}^{U+}\right] \right\rangle$ presents average IRNs obtained by applying the expression (Appendix A-6).

Step 6: Averaged IRN OW matrix over expert's preferences. Similar to *Step 5*, two separate matrices a_W^{*eL} and $a_W^{e'U}$ are formed on the basis of individual expert's OW matrices $A_W^e = \left[a_{jW}^{eL}; a_{jW}^{'eU}\right]_{1xn}$:

$$A_W^{*eL} = \left[a_{1W}^{1L}, a_{1W}^{2L}, \ldots, a_{1W}^{mL}; a_{2W}^{1L}, a_{2W}^{2L}, \ldots, a_{2W}^{mL}, \ldots, a_{nW}^{1L}, a_{nW}^{2L}, \ldots, a_{nW}^{mL}\right]_{1xn} \tag{15}$$

$$A_W^{*'U} = \left[a_{1W}^{1'U}, a_{1W}^{2'U}, \ldots, a_{1W}^{m'U}; a_{2W}^{1'U}, a_{2W}^{2'U}, \ldots, a_{2W}^{m'U}, \ldots, a_{nW}^{1'U}, a_{nW}^{2'U}, \ldots, a_{nW}^{m'U}\right]_{1xn} \tag{16}$$

where $a_{jW}^{eL} = \left\{a_{jW}^{1L}, a_{jW}^{2L}, \ldots, a_{nW}^{mL}\right\}$ and $a_{jW}^{e'U} = \left\{a_{jW}^{1'U}, a_{jW}^{2'U}, \ldots, a_{nW}^{m'U}\right\}$ represent sequences expressing the advantage of the criterion j over the criterion W. By applying Eqs. (2)(9), each pair of sequences a_{jW}^{eL} and $a_{jW}^{e'U}$ is transformed into $IRN(a_{jW}^{e}) = \left[\left(\underline{Lim}(a_{jW}^{eL-}), \overline{Lim}(a_{jW}^{eU-})\right), \left(\underline{Lim}(a_{jW}^{eL+}), \overline{Lim}(a_{jW}^{eU+})\right)\right]$ sequence, where $\underline{Lim}(a_{jW}^{eL-})$ and $\overline{Lim}(a_{jW}^{eL+})$ represent lower limits, while $\underline{Lim}(a_{jW}^{eU-})$ and $\overline{Lim}(a_{jW}^{eU+})$ represent upper limits of $IRN(a_{jW}^{e})$ sequence, respectively. So, for each $IRN(a_{jW}^{e})$ sequence, we have the BO matrices

$A_W^1, A_W^2, \ldots, A_W^e, \ldots, A_W^k (1 \leq e \leq k)$. As in the previous step, applying the IRNDWGA operator, we end up with the average IRN sequences, as per expression (Eq. 17)

$$\overline{A}_W = \left[IRN(\overline{a}_{1W}), IRN(\overline{a}_{2W}, \ldots, IRN(\overline{a}_{nW}) \right]_{1xn} \tag{17}$$

where $IRN(\overline{a}_{jW}) = \left\langle \left[\overline{a}_{jW}^{L-}, \overline{a}_{jW}^{U-} \right], \left[\overline{a}_{jW}^{L+}, \overline{a}_{jW}^{U+} \right] \right\rangle$ is the average IRNs obtained using the IRNDWGA operator.

Based on the obtained aggregate values of IRN BO matrix (14) and IRN OW matrix (17), a nonlinear model for calculating the optimal values of the weight coefficients is formed, as presented in Step 7.

Step 7: Calculation of optimal values of criteria weights. By solving model (18), we obtain the IRN values of the criterion weights.

min ξ

s.t.

$$\begin{aligned}
\left| \frac{w_B^{L-}}{w_j^{U+}} - a_{Bj}^{-U+} \right| \leq \xi; \left| \frac{w_B^{U-}}{w_j^{L+}} - a_{Bj}^{-L+} \right| \leq \xi \\
\left| \frac{w_B^{L+}}{w_j^{U+}} - a_{Bj}^{-U-} \right| \leq \xi; \left| \frac{w_B^{U+}}{w_j^{L-}} - a_{Bj}^{-L-} \right| \leq \xi \\
\left| \frac{w_j^{L-}}{w_W^{U+}} - a_{jW}^{-U+} \right| \leq \xi; \left| \frac{w_j^{U-}}{w_W^{L+}} - a_{jW}^{-L+} \right| \leq \xi \\
\left| \frac{w_j^{L+}}{w_W^{U-}} - a_{jW}^{-U-} \right| \leq \xi; \left| \frac{w_j^{U+}}{w_W^{L-}} - a_{jW}^{-L-} \right| \leq \xi \\
\sum_{j=1}^{n} w_j^{L-}, \sum_{j=1}^{n} w_j^{L+} \leq 1; \\
\sum_{j=1}^{n} w_j^{U-}, \sum_{j=1}^{n} w_j^{U+} \geq 1; \\
w_j^{L-} \leq w_j^{L+} \leq w_j^{U-} \leq w_j^{U+}, \quad \forall j = 1, 2, , \ldots, n \\
w_j^{L-}, w_j^{L+}, w_j^{U-}, w_j^{U+} \geq 0, \quad \forall j = 1, 2, , \ldots, n
\end{aligned} \tag{18}$$

where $IRN(w_j) = \left[\left(w_j^{L-}, w_j^{U-} \right), \left(w_j^{L+}, w_j^{U+} \right) \right]$ represents the optimal value of the weight coefficient, while $IRN(\overline{a}_{jW}) = \left\langle \left[\overline{a}_j^{-L-}, \overline{a}_j^{-U-} \right], \left[\overline{a}_j^{-L+}, \overline{a}_j^{-U+} \right] \right\rangle$

and $IRN(\overline{a}_{Bj}) = \left\langle \left[\overline{a}_{Bj}^{-L-}, \overline{a}_{Bj}^{-U-} \right], \left[\overline{a}_{Bj}^{-L+}, \overline{a}_{Bj}^{-U+} \right] \right\rangle$ represent the values from the IRN OW and BO matrices, respectively.

By solving the model (18), we obtain the optimal values of the weight coefficients of the criteria. Since the expert comparisons captured by the IRN BO and IRN OW matrices are used to define the model, a check is required for the consistency of the comparisons. This consistency check also represents somewhat the validation of the values of the weight coefficients of the criteria. The next step provides the procedure for checking the consistency of the solution.

Step 8: Level of consistency for IRN-BWM. Based on the condition defined in [58], we can define an expression that represents the minimum consistency in the IRN BWM model. Since there is a requirement that $a_{BW}^{-L-} \leq a_{BW}^{-L+} \leq a_{BW}^{-U-} \leq a_{BW}^{-U+} \leq$, the advantage of the best criteria over the worst criteria cannot be bigger than a_{BW}^{-U+}. In that case, we can use the upper limit a_{BW}^{-U+} to fix the value of the *consistency index* CI, then all the variables connected to $IRN(\overline{a}_{BW})$ can use CI to calculate the *consistency ratio* CR. We can make this conclusion based on fact that the consistency index which corresponds to a_{BW}^{-U+} has the biggest value in the interval $\left[a_{BW}^{-L-}, a_{BW}^{-U+} \right]$. Based on that assumption, we can define in Eq. (19) for determining CI.

$$\xi - \left(1 + 2a_{BW}^{-U+}\right)\xi + \left(a_{BW}^{-U+2} - a_{BW}^{-U+}\right) = 0 \tag{19}$$

Then we get the consistency ratio (CR).

$$CR = \frac{\xi^*}{CI} \tag{20}$$

where CR is in $[0, 1]$.

3.3. Interval rough number based MARCOS method

This subsection explains how the MARCOS model is extended using IRN. The MARCOS method was presented in Stevic et al. [47] and is based on the integration of three well-known concepts in the MCDM field, which enable the provision of a robust decision-making, defining the (i) ideal and anti-ideal reference points, (ii) relationships between the reference points and a set of alternatives, and (iii) utility degrees of an alternative measuring its distance to the ideal and anti-ideal reference. Since this is a new MCDM technique, there are only a few applications of the MARCOS methods in the scientific literature [59, 60]. To the best of our knowledge, there is no study on the extension of the MARCOS model applying uncertainty theories. The methodology combining IRN and MARCOS model is summarized in the following algorithmic steps.

Step 1: Formation of the aggregated IRN initial decision matrix. Based on the expert evaluation of alternatives, the expert correspondent matrices are formed as an aggregated matrix as given in Eq. (1). Based on $\left[x_{ij}^e\right]_{mxn}(1 \leq e \leq k)$, we get two aggregated sequences of matrices x^{*L} and $x^{*'U}$, respectively, for k experts:

$$X^{*L} = \begin{bmatrix} x_{11}^{1L}, x_{11}^{2L}, \ldots, x_{11}^{kL} & x_{12}^{1L}; x_{12}^{2L}; \ldots, x_{12}^{kL} & ,\ldots, & x_{1n}^{1L}; x_{1n}^{2L}; \ldots, x_{1n}^{kL} \\ x_{21}^{1L}, x_{21}^{2L}, \ldots, x_{21}^{kL} & x_{22}^{1L}; x_{22}^{2L}; \ldots, x_{22}^{kL} & ,\ldots, & x_{2n}^{1L}; x_{2n}^{2L}; \ldots, x_{2n}^{kL} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1}^{1L}, x_{m1}^{2L}, \ldots, x_{m1}^{kL} & x_{m2}^{1L}; x_{m2}^{2L}; \ldots, x_{m2}^{kL} & ,\ldots, & x_{mn}^{1L}; x_{mn}^{2L}; \ldots, x_{mn}^{kL} \end{bmatrix} \tag{21}$$

$$X^{*'U} = \begin{bmatrix} x_{11}^{1'U}, x_{11}^{2'U}, \ldots, x_{11}^{k'U} & x_{12}^{1'U}; x_{12}^{2'U}; \ldots, x_{12}^{k'U} & ,\ldots, & x_{1n}^{1'U}; x_{1n}^{2'U}; \ldots, x_{1n}^{k'U} \\ x_{21}^{1'U}, x_{21}^{2'U}, \ldots, x_{21}^{k'U} & x_{22}^{1'U}; x_{22}^{2'U}; \ldots, x_{22}^{k'U} & ,\ldots, & x_{2n}^{1L}; x_{2n}^{2L}; \ldots, x_{2n}^{k'U} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1}^{1'U}, x_{m1}^{2'U}, \ldots, x_{m1}^{k'U} & x_{m2}^{1'U}; x_{m2}^{2'U}; \ldots, x_{m2}^{k'U} & ,\ldots, & x_{mn}^{1'U}; x_{mn}^{2'U}; \ldots, x_{mn}^{k'U} \end{bmatrix} \tag{22}$$

where $x_{ij}^L = \left\{x_{ij}^{1L}, x_{ij}^{2L}, \ldots, x_{ij}^{kL}\right\}$ and $x_{ij}^{'U} = \left\{x_{ij}^{1'U}, x_{ij}^{2'U}, \ldots, x_{ij}^{k'U}\right\}$ represent sequences that describe the relative meaning of criteria i over the alternative j. By applying Eqs. (2)-(9), the sequences x_{ij}^e and $x_{ij}^{e'}$ $1 \leq e \leq k$ are transformed into $IRN(x_{ij}^e), 1 \leq e \leq k$. Thus, we obtain k intervals of rough correspondence matrices $X_1, X_2, \ldots, X_k$. Using the IRNDWGA operator (Appendix A-6), we obtain the averaged initial decision matrix $X = \left[IRN(x_{ij})\right]_{mxn}$ (see Eq. (23)), where each $IRN(x_{ij}) = \left[\left(x_{ij}^{L'}, x_{ij}^{U'}\right), \left(x_{ij}^L, x_{ij}^U\right)\right], \quad (i = 1, 2, \ldots, m; j =$

$1, 2, \ldots, n$) represents elements of the matrix X.

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} IRN(x_{11}) & IRN(x_{12}) & \cdots & IRN(x_{1n}) \\ IRN(x_{21}) & IRN(x_{22}) & \cdots & IRN(x_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ IRN(x_{m1}) & IRN(x_{m2}) & \cdots & IRN(x_{mn}) \end{pmatrix}_{mxn} \end{array} \tag{23}$$

After forming the initial decision matrix, the ideal and anti-ideal values of the alternatives for each criterion are identified.

Step 2: Formation of an extended initial matrix (X). In this step, the extension of the initial matrix is performed by defining the ideal (AI) and anti-ideal (AAI) solution.

$$X' = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} IRN(x_{aa1}) & IRN(x_{aa2}) & \cdots & IRN(x_{aan}) \\ IRN(x_{11}) & IRN(x_{12}) & \cdots & IRN(x_{1n}) \\ IRN(x_{21}) & IRN(x_{22}) & \cdots & IRN(x_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ IRN(x_{m1}) & IRN(x_{m2}) & \cdots & IRN(x_{mn}) \\ IRN(x_{ai1}) & IRN(x_{ai2}) & \cdots & IRN(x_{ain}) \end{pmatrix} \end{array} \tag{24}$$

The anti-ideal solution (AAI) is the worst alternative while the ideal solution (AI) is the alternative with the best characteristic. Depending on the nature of the criteria, AAI and AI are defined by applying Eqs. (25) and (26):

$$AAI = \begin{cases} min\left\{x_{ij}^{L'}; x_{ij}^{L}\right\} & \forall i \quad \text{if } j \in B \\ max\left\{x_{ij}^{U'}; x_{ij}^{U}\right\} & \forall i \quad \text{if } j \in C \end{cases} \tag{25}$$

$$AI = \begin{cases} max\left\{x_{ij}^{U'}; x_{ij}^{U}\right\} & \forall i \quad \text{if } j \in B \\ max\left\{x_{ij}^{L'}; x_{ij}^{L}\right\} & \forall i \quad \text{if } j \in C \end{cases} \tag{26}$$

where B represents all *benefit* type of criteria, while C represents all *cost* type of criteria.

Step 3: Normalization of the extended initial matrix $X^{'}$. Elements of the normalised matrix $Y = \Big[IRN(\hat{y}_{ij})\Big]_{mxn}$ are defined by setting the expression as follows for the different types of criteria.

- *Benefit* type criteria (higher values for such criteria are desirable)

$$IRN(\hat{y}_{ij}) = \frac{IRN(x_{ij})}{max\ x_{ij}^{U}} = \left(\left[\frac{x_{ij}^{L'}}{max\ x_{ij}^{U}}, \frac{x_{ij}^{U'}}{max\ x_{ij}^{U}}\right], \left[\frac{x_{ij}^{L}}{max\ x_{ij}^{U}}, \frac{x_{ij}^{U}}{max\ x_{ij}^{U}}\right]\right) \tag{27}$$

- *Cost* type criteria (lower values for such criteria are desirable)

$$IRN(\hat{y}_{ij}) = \frac{min\ x_{ij}^{L}}{IRN(x_{ij})} = \left(\left[\frac{min\ x_{ij}^{L'}}{y_{ij}^{U}}, \frac{min\ x_{ij}^{U}}{y_{ij}^{L}}\right], \left[\frac{min\ x_{ij}^{L'}}{y_{ij}^{U'}}, \frac{min\ x_{ij}^{L'}}{y_{ij}^{L'}}\right]\right) \tag{28}$$

where $IRN(y_{ij})$ represents the normalised elements of the extended initial matrix $X^{'}$.

Step 4: Determination of the IRN weighted matrix $V = \Big[IRN(v_{ij})\Big]_{mxn}$. The weighted matrix V is obtained by multiplying the normalized matrix Y with the IRN weight coefficients of the criterion $IRN(w_j)$. The elements of the V matrix are used in the next step to determine the utility degree of alternatives.

Step 5: Calculation of the utility degree of alternatives $IRN(K_i)$. By applying Eqs. (29) and (30), the utility degrees of an alternative concerning the anti-ideal and ideal solutions are calculated.

$$IRN(K_i^{-}) = \frac{IRN(S_i)}{IRN(S_{aai})} \tag{29}$$

$$IRN(K_i^{+}) = \frac{IRN(S_i)}{IRN(S_{ai})} \tag{30}$$

where $S_i(i = 1, 2, \ldots, m)$ represents the sum of the elements of the weighted matrix V:

$$IRN(S_i) = \sum_{i=1}^{n} IRN(v_{ij}) = \left[\left(\sum_{i=1}^{n} v_{ij}^{L'}, \sum_{i=1}^{n} v_{ij}^{U'}\right), \left(\sum_{i=1}^{n} v_{ij}^{L}, \sum_{i=1}^{n} v_{ij}^{U}\right)\right] \tag{31}$$

Step 6: Determination of the IRN utility function of alternatives $IRN(K_i)$. The utility function is the compromise for the observed alternative in relation to the ideal and anti-ideal solutions. The utility function of alternatives is defined by Eq. (32).

$$IRN\Big(K_i\Big) = \frac{IRN(K_i^+) + IRN(K_i^-)}{1 + \frac{1-IRN\left(f(K_i^+)\right)}{IRN\left(f(K_i^+)\right)} + \frac{1-IRN\left(f(K_i^-)\right)}{IRN\left(f(K_i^-)\right)}}; \tag{32}$$

where $IRN\Big(f(K_i^-)\Big)$ and $IRN\Big(f(K_i^+)\Big)$ represent the utility function in relation to the anti-ideal and ideal solutions, respectively, as formulated in Eqs. (33) and (34).

$$IRN\Big(f(K_i^-)\Big) = \frac{IRN(K_i^+)}{IRN(K_i^+)+IRN(K_i^-)} = \left[\left(\frac{K_i^{+L'}}{K_i^{+U}+K_i^{-U}}, \frac{K_i^{+U'}}{K_i^{+U}+K_i^{-U}}\right), \left(\frac{K_i^{+L}}{K_i^{+U}+K_i^{-U}}, \frac{K_i^{+U}}{K_i^{+U}+K_i^{-U}}\right)\right] \tag{33}$$

$$IRN\Big(f(K_i^+)\Big) = \frac{IRN(K_i^-)}{IRN(K_i^+)+IRN(K_i^-)} = \left[\left(\frac{K_i^{-L'}}{K_i^{+U}+K_i^{-U}}, \frac{K_i^{-U'}}{K_i^{+U}+K_i^{-U}}\right), \left(\frac{K_i^{-L}}{K_i^{+U}+K_i^{-U}}, \frac{K_i^{-U}}{K_i^{+U}+K_i^{-U}}\right)\right] \tag{34}$$

Eqs. (33) and (34) represent an additive normalization of the utility degree of alternatives, which are defined in Step 5 through Eqs. (29) and (30).

Step 7: Ranking the alternatives. Ranking of the alternatives is based on the final values of utility functions. It is desirable that an alternative has the highest possible value of the utility function. The ranking of alternatives is performed by transformation of the interval rough numbers $IRN(S_i) = \Big[\Big(S_i^{L'}, S_i^{U'}\Big), \Big(S_i^L, S_i^U\Big)\Big]$ into crisp numbers $S_i = (i = 1, 2, \ldots, m)$, applying Eqs. (35) and (36).

$$\mu_i = \left[\frac{RB(S)_{ui}}{RB(S)_{ui}+RB(S)_{li}}\right], 0 \leq \mu_i \leq 1; RB(S)_{ui} = \Big[S_i^U - S_i^L\Big]; \quad RB(S)_{li} = \Big[S_i^{U'} - S_i^{L'}\Big] \tag{35}$$

$$S_i = \Big(\Big[\mu_i.S_i^{L'}\Big] + \Big[(1-\mu_i).S_i^U\Big]\Big) \tag{36}$$

where $RB(S)_{ui}$ and $RB(S)_{li}$ represent the rough boundary intervals of $IRN(S)_i$.

By applying Eqs. (35) and (36), we obtain the crisp values for the alternatives based on the criterion functions. Then those values are used for the final ranking of alternatives. The higher the value of S_i, the higher the rank of an alternative is.

4. Case Study

To select the offshore wind farm site for a given case study, we put forward an interval rough numbers environment based on Best Worst Method and MARCOS method for solving OWF selection problems. The criteria and alternatives required for the MCDM problem were determined. For this, we identified 6 main criteria and 23 sub-criteria that is selected among 51 criteria for this fuzzy decision-making problem, drawn from both the scientific literature and expert opinions (see Section 4.3).

Four offshore wind farm site alternatives were determined based on the expert opinions, meteorological data, and wind power data from the Turkey Atlas Report [1] and other criteria. The alternative sites are (1) Gokçeada, (2) Bozcaada, (3) Ayvalık, and (4) Saros Gulf. Fig. 3 shows the study region as a whole highlighted in grey. Four expert decision makers (DMs) are selected from the energy companies and academy to evaluate offshore wind farm sites for the MCDM problem.

[1] Turkish state Meteorological Service: https://www.mgm.gov.tr/genel/ruzgar-atlasi.aspx

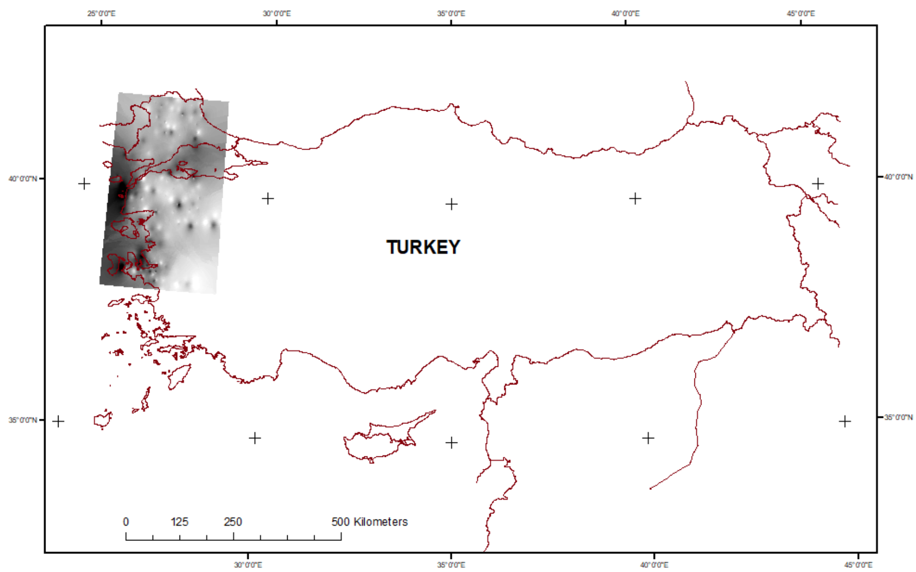


Figure 3: Study region in the Aegean Sea highlighted in grey.

4.1. Data Collection

Some of the essential statistical and geographical information from the Government Agencies of State of the Republic of Turkey for offshore wind farm location selection problem were collected. One of them is the General Directorate of Meteorology in Turkey. The data obtained from this institution are given in Table 3 which includes the mean wind speed (m/s), max wind speed (m/s), dominant wind direction, height of anemometer (m), pressure (hPa), mean temperature (C) and some information about the sea. The data is taken monthly for some regions of high power generation potential, including Tekirdağ, Edirne, Kırıklareli, Balıkesir, Izmir, and Çanakkale in Turkey.

Table 3: Meteorological data for the study area.

Weather conditions (Monthly/mean)	Alternative locations					
	Balıkesir	Çanakkale	Edirne	Izmir	Kırıklareli	Tekirdağ
Mean wind speed (m/s)	2.63	3.62	2.81	2.82	2.08	2.96
Max wind speed (m/s)	24.58	29.3	24.01	24.83	23.82	24.36
Wave height (m)	2.5 - 4	2.5 - 4	-	2.5 - 4	0.1 - 0.5	2.5 - 4
Other parameters						
Dominant wind direction *	N	NE	N	N	NE	NE
Height of anemometer (m)	10	10	10	10	10	10
Numbers of station	48	41	23	67	23	20
Date range (years)	1950-2017	1929-2018	1962-2018	1938-2018	1928-2018	1940-2018

* N: North, NE: Northeast

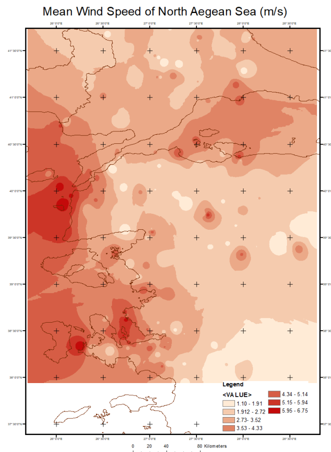
The geographical information consisting of national parks, natural parks, specially protected environments, waterfowl/wetlands habitats for improving the decision-making process with enriched information to detect the best offshore wind farm site were collected from the Ministry of Forestry and Water Affairs, and Ministry of Environment and Urbanization in Turkey (see Fig. 4(c) and 4(d)). All energy technologies have some adverse effects on the natural environment. Those adverse effects should be considered when there are developing and existing areas of national importance in the environment while deciding on the best OWF site.

The latitude and longitude of the electric distribution substations as geographic locations were obtained for Edirne, Kırıklareli, Tekirdağ, and Izmir from the TREDAS and TEIAS electricity distribution companies in Turkey. The electricity obtained from the OWF can only have economic value, once it is delivered to the offshore substation and final consumers. OWFs should be closer to the local electricity/power distribution networks. Fig 4(e) shows some of the substations within the study region.

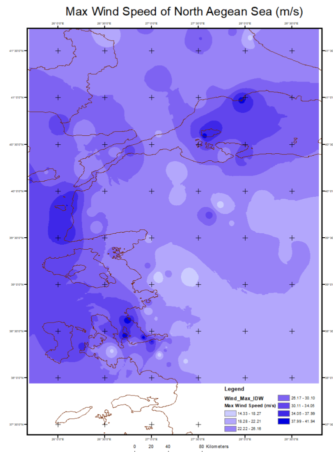
4.2. Geographic Information System Analysis

A geographic information system (GIS) tool collects, displays, manages and analyzes geographic information. The inverse-distance weighting (IDW) method based on the deterministic models in spatial interpolation is one of the popular methods, commonly used by the geoscientists and geographers, and so included in many GIS tools [61].

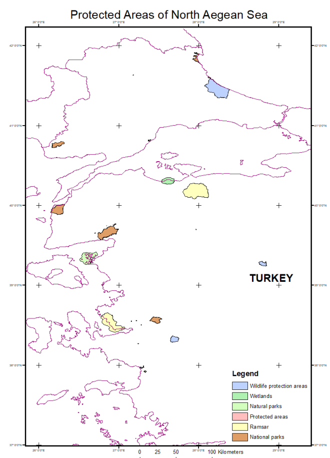
This stage of the methodology aims to restrict the sites within a reasonable region, with respect to the pre-determined factors, using a geographic information system based inverse-distance weighting method to classify some alternatives through geographical information data and some relevant criteria, such as mean and maximum wind speed. The mean and maximum wind speed distributions are shown in Fig. 4(a) and Fig. 4(b) for 90 years (range of 1928 - 2018) at 10m above sea level. Looking into the regional differences in offshore wind velocity distribution, the wind speed in the Saros Gulf and the Aegean Sea coasts is higher than the Western Black Sea, and especially in the areas around Bozcaada and Gokçeada.



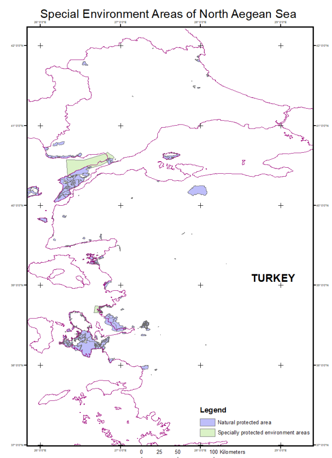
(a) mean wind speed



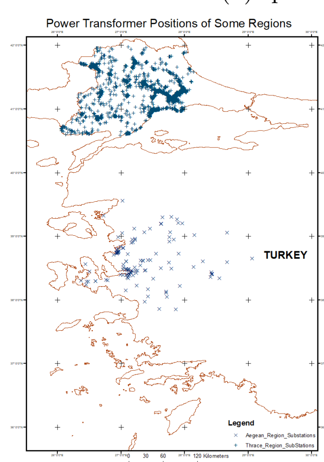
(b) max wind speed



(c) protected areas



(d) special environment areas



(e) grid substations

Figure 4: Some selected GIS-based evaluation criteria for the study region (a) mean wind speed, (b) max wind speed, (c) protected area, (d) special environment areas, (e) grid substation positions

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4.3. Criteria for Offshore Wind Farm

Offshore wind farm site selection criteria were collected by examining the wind farm site studies in the literature. Firstly, 82 criteria were found from the literature and experts, and then the criteria which have similar characteristic were merged reducing the number of criteria to 51.

We identified 6 main criteria and 23 sub-criteria that are selected among 51 criteria for this fuzzy decision-making problem, drawing from both extant literature and expert opinion (energy company employees). A summary of the literature related to criteria is given in Table 4.

4.3.1. Weather conditions

(1) *Wind speed:* Wind speed is the most important criterion in economic feasibility [16]. The economic feasibility of a project is largely dependent on the wind source. For the installation of OWFs, there must be strong and constant winds [69]. Sea areas with an average wind speed of less than 6 m/s are not suitable for the location of offshore wind farms [33, 62, 37].

(2) *Wave height and period:* Wave height and period (5 to 10 m wave heights) are a criterion to be considered in OWF design [70, 10]. Leontaris et al. [71] noted some uncertainties (variables) affecting the offshore operations, such as wavelength and wind speed. These variables can influence the cost of installation and operation maintenance as well as potential delays and financial consequences.

(3) *Extreme weather conditions:* This sub-criterion is also important for offshore wind farm site selection. It can damage a wind turbine.

    Just as for onshore wind farms, extreme weather conditions can also damage offshore farms. Wind turbines are designed to output power within a predefined range of wind speeds.

4.3.2. Operation/Profitability and Costs

(4) *Total project payback period:* Investors' initial investment is needed to recover from the cash flow of the offshore wind farm [72]. The return on

Table 4: A summary of literature about related to selecting a site for OWF.

Main-criteria		Sub-criteria	Litrature (Authors)
Weather condition			
	C1	Wind speed	Vasileiou et al. [37], Wu et al. [11], Kim et al. [34], Vagiona and Karanikolas [33] Lynch et al. [62], Schillings et al. [63], Deveci et al. [64]
	C2	Wave height and period	Fetanat and Khorasaninejad [10], Kim et al. [34], Ho et al. [65], Schillings et al. [63], Deveci et al. [64]
	C3	Extreme weather conditions	Kim et al. [34], Deveci et al. [64]
Operation/Profitability and Cost			
	C4	Total project pay back period	Wu et al. [11], Deveci et al. [64]
	C5	Expected benefit to cost ratio	Wu et al. [11], Fetanat and Khorasaninejad [10], Deveci et al. [64]
	C6	Investment cost	Wu et al. [11], Chaouachi et al. [36], Fetanat and Khorasaninejad [10], Kim et al. [38], Móller [66], Punt et al. [67], Deveci et al. [64]
	C7	Operation and maintenance costs	Wu et al. [11], Kim et al. [38], Móller [66], Punt et al. [67], Deveci et al. [64]
Characteristics of the region			
	C8	Water depth	Vasileiou et al. [37], Wu et al. [11], Kim et al. [34], Kim et al. [12], Lynch et al. [62], Schillings et al. [63], Deveci et al. [64]
	C9	Soil conditions	Kim et al. [34], Schillings et al. [63], Deveci et al. [64]
	C10	Typhoon and earthquakes	Kim et al. [34], Deveci et al. [64]
	C11	Proximity to shore	Vasileiou et al. [37], Wu et al. [11], Kim et al. [34], Kim et al. [12], Mekonnen et al. [35], Vagiona and Karanikolas [33], Ho et al. [65], Lynch et al. [62], Schillings et al. [63], Deveci et al. [64]
	C12	Proximity to power transmission grid	Vasileiou et al. [37], Wu et al. [11], Fetanat and Khorasaninejad [10], Kim et al. [34], Kim et al. [12], Vagiona and Karanikolas [33], Ho et al. [65], Lynch et al. [62], Schillings et al. [63], Deveci et al. [64]
	C13	Proximity to hydrocarbon oil/gas reserves	Kim et al. [12], Ho et al. [65], Schillings et al. [63], Deveci et al. [64]
	C14	Shipping density /congestion	Vasileiou et al. [37], Wu et al. [11], Lynch et al. [62], Móller [66], Schillings et al. [63], Deveci et al. [64]
	C15	Proximity to military operation area	Vasileiou et al. [37], Wu et al. [11], Kim et al. [34], Kim et al. [12], Ho et al. [65], Móller [66], Schillings et al. [63], Deveci et al. [64]
	C16	Wind farm size (in terms of capacity in MW)	Kim et al. [34], Deveci et al. [64]
Environmental impact			
	C17	Proximity to natural environment conservation area	Kim et al. [34], Vagiona and Karanikolas [33], Móller [66], Schillings et al. [63], Deveci et al. [64]
	C18	Noise impact	Fetanat and Khorasaninejad [10], Ho et al. [65], Bailey et al. [68], Deveci et al. [64]
	C19	Effect on marine life	Fetanat and Khorasaninejad [10], Bailey et al. [68], Deveci et al. [64]
Economic and social factors			
	C20	Economic externalities	Fetanat and Khorasaninejad [10], Deveci et al. [64]
	C21	Community/local acceptance	Fetanat and Khorasaninejad [10], Ho et al. [65], Deveci et al. [64]
Incentives			
	C22	Investment incentives	Ho et al. [65], Lynch et al. [62], Deveci et al. [64]
	C23	Feed-in-tariff for offshore wind energy	Ho et al. [65], Deveci et al. [64]

investment of the wind turbine, the cost of electricity generated by the project payback period, and wind energy, are some of the factors that determine whether a particular installation is worthwhile [11].

(5) *Expected benefit to cost ratio:* This method can be used to economically evaluate large-scale infrastructure structures using one of the engineering economy techniques [10].

(6) *Investment cost:* It is the construction cost required for the installation of the offshore wind power plant [11]. The total cost of a project is not limited to construction costs alone. In addition to the construction costs, many other factors should to be taken into account to calculate the total investment. As an example, these are setup costs, equipment costs, auxiliary costs, and so on.

(7) *Operation and maintenance costs:* Operation and Maintenance (O & M) costs can contribute to a quarter of life cycle costs, making it one of the biggest cost components of the offshore wind power plant [6, 73]. Sea vessels and a helicopter fleet are required to support maintenance work on the coast wind turbines. The ships and helicopters needed to deliver personnel and spare parts to wind turbines are expensive sources that consist of a large part of the total cost of operation [9].

4.3.3. Characteristics of the region

(8) *Water depth:* The type of offshore wind turbines (OWT) and choice of the technology depend on the water depth and soil structure. Larger the depth gets, the more costly the wind energy project becomes [11].

(9) *Soil conditions:* Although OWTs are typically designed for a lifetime of 20 years, the long-term variability of the environment is not considered. Particularly, changes in the soil conditions play a crucial role in the type of OWT that should be used within the farm [74].

(10) *Typhoon and earthquakes:* Typhoons damage the wind turbines because they are very strong wind waves. Normally, wind and wave loads are two of the most important environmental loads that affect the structures sup-

porting offshore wind turbines [75]. However, seismic movements in the sea (from offshore to coast) are devastating to the safety of offshore wind turbines in active seismic areas [76]. Thus, OWFs have been built to a large extent in areas where seismic risk is low [77].

(11) *Proximity to shore:* Proximity to shore is a critical factor in the OWF site selection. The location of OWFs near the shore can lead to adverse environmental impacts such as visual, noise, aesthetic, and electric shock. There has been no legal regulation for the visual impact of offshore wind turbines, however, it is likely to lead to civil complaints [37, 34].

(12) *Proximity to power transmission grid:* Large OWFs are often located far from highly populated areas where the electricity consumption is also high. For this reason, the transmission networks should be designed to carry the power from OWFs at long distances [78]. The electricity obtained from the OWF can only have economic value once it has been delivered to the offshore substation and final consumers. Hence, OWFs should be close to the local electricity / power transmission networks [38].

(13) *Proximity to hydrocarbon oil/gas reserves:* The rich natural hydrocarbon energy sources, such as, methane gas in the seabed are important energy reserves for all countries. Any area for which the exploration and exploitation of hydrocarbons have been licensed is not suitable for an offshore wind power plant site [37].

(14) *Shipping density/congestion:* Building large offshore wind farms around the coastline can create a security risk for shipping and other marine users. It is recommended that OWFs be installed in areas with lower shipping densities. Otherwise, the offshore renewable energy facilities could introduce additional hazards to transportation safety on the waterways where a good plan is already in place [79].

(15) *Proximity to military operation area:* OWFs may conflict with the use of naval forces' military operations (e.g. maneuvers and exercises) and the passage of submarines [11]. When those areas are used for the application of periodic and / or special military operations, these maritime areas are

not suitable for OFW settlement [37].

(16) *Wind farm size (in terms of capacity in MW)* Typically, turbines in a wind farm are spaced 500-1000 m apart and have blades at least 20 m above sea level at their lowest point [6]. For this reason, OWFs should be placed into a sufficiently large area for reasonable capacity and allowing capacity growth in the future.

4.3.4. Environmental impact

(17) *Proximity to the natural environment conservation area:* All energy technologies have some negative effects on the natural environments [80], including special protection zones, nature parks, national parks, and wetlands. OWFs should not adversely affect their development and areas of national importance.

(18) *Effect on marine life:* The environmental impact of an OWF can be divided into two classes: during the construction and longer operational periods [81, 82]. The negative influences include alteration of water flow and altered habitat quality (social reef effect) [83].

(19) *Noise impact:* Different parts of the turbines generate noise propagating along the water. For example, the noise has an effect on benthic fauna, fish, and sea mammals near the bases of the wind turbines. Wind turbines cause a certain increase in boat traffic in the farm area during maintenance work. The response of fish to noise from turbines and boat engines varies [84].

4.4. Economic and social factors

(20) *Economic externalities:* This criterion can be considered as a variable that can affect the economic processes and developments of the activities both positively and negatively [10] in the region. OWFs indirectly contribute to the local economy, for example, through the establishment of local maintenance facilities/shops, creating new jobs.

(21) *Community/local acceptance:* The community may have several reasons for supporting or opposing wind energy projects. Indeed, the scope of wind energy development is much more of a social, regulatory, and political issue than a technological one [85]. The local communities often want to know how a wind farm can affect their environment and property values. Also, they may be concerned about noise, visual impact, or the effects on birds and other wildlife [86].

(22) *Investment incentives:* The tax and investment incentives for offshore wind energy attract energy companies, investors and others relevant parties. Hence, it is important for that the government policies and programs that support renewable energy are in place [87].

(23) *Feed-in-tariff for offshore wind energy:* Feed-in tariffs (FITs) are a production-backed incentive that is required to purchase all of the renewable energy produced by qualified generators in the service area for a certain guaranteed period [87].

4.5. Experimental Results

This section presents the application of the IRN BWM methodology for determining the weights of criteria and sub-criteria. The flowchart of the proposed framework is shown in Fig. 5.

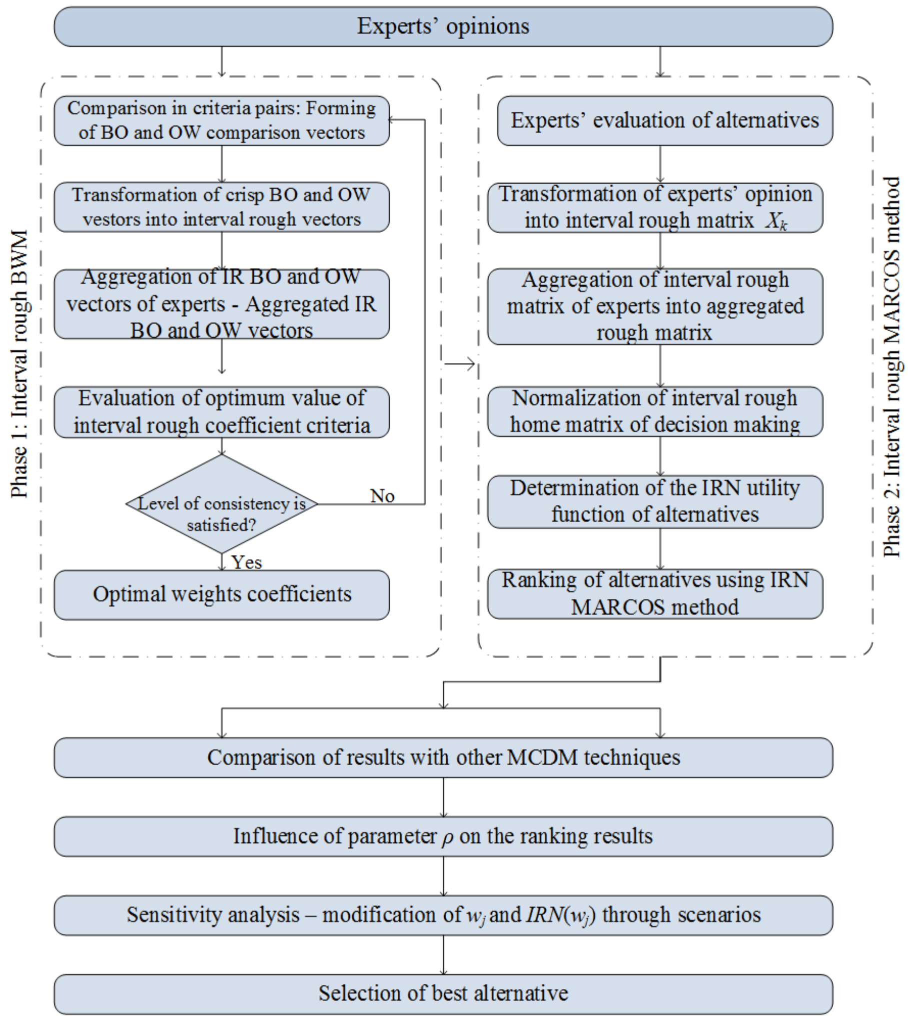


Figure 5: Flowchart of the proposed model.

Steps 1 and 2: After defining the criteria and sub-criteria, the experts $E_e(1 \leq e \leq 4)$ determined the *best (B)* and *worst (W)* criteria/sub-criteria, respectively.

Within the group of criteria, a total of six criteria (clusters) were defined, while a total of 23 sub-criteria were defined as given in Table 4.

Steps 3 and 4: Based on the defined set of criteria and sub-criteria, the experts determined the BO and OW vectors for the criteria and sub-criteria, as presented in Table 5. In the BO and OW vectors, the experts $E_e(1 \leq e \leq 4)$ expressed their preferences of the B and W over all the criteria/sub-criteria from the considered set of criteria/sub-criteria. The experts were assigned the weight coefficients of $w_{E1} = 0.182$, $w_{E2} = 0.273$, $w_{E3} = 0.227$ and $w_{E4} = 0.318$. The experts returned a score based on the scale from 1-9 to express their preferences.

Steps 5 and 6: Using Eqs. (2)-(9), the vectors BO and OW (see Table 5) were transformed into IRNs respectively. Using the IRNDWGA operator (A6), the IRN BO and OW vectors are aggregated into unique IRN vectors, which are shown in Table 6.

Table 5: BO and OW vectors.

Criteria evaluation			
Best: MC1	Expert evaluation (E1, E2, ..., E4)	Worst: MC5	Expert evaluation (E1, E2, ..., E4)
MC2	(3, 4); (3, 3); (2, 3); (2, 3)	MC1	(9, 9); (8, 9); (8, 9); (7, 8)
MC3	(5, 5); (4, 5); (5, 6); (7, 7)	MC2	(7, 7); (7, 8); (6, 7); (8, 8)
MC4	(6, 7); (5, 6); (6, 6); (6, 7)	MC3	(6, 7); (5, 6); (6, 7); (6, 7)
MC5	(9, 9); (8, 9); (9, 9); (8, 8)	MC4	(4, 5); (5, 6); (4, 4); (6, 7)
MC6	(7, 8); (5, 6); (6, 7); (7, 8)	MC6	(2, 3); (3, 4); (3, 4); (4, 5)
Sub-criteria evaluation - MC1			
Best: C1	Expert evaluation (E1, E2, ..., E4)	Worst: C2	Expert evaluation (E1, E2, ..., E4)
C2	(2, 3); (4, 5); (3, 4); (3, 4)	C1	(5, 6); (6, 6); (6, 7); (5, 6)
C3	(3, 4); (5, 6); (4, 5); (3, 4)	C3	(3, 4); (4, 5); (4, 5); (5, 6)
Sub-criteria evaluation - MC2			
Best: C6	Expert evaluation (E1, E2, ..., E4)	Worst: C7	Expert evaluation (E1, E2, ..., E4)
C4	(3, 4); (2, 3); (3, 4); (3, 4)	C4	(2, 3); (4, 5); (6, 6); (3, 4)
C5	(2, 3); (4, 5); (3, 4); (2, 3)	C5	(3, 4); (2, 3); (3, 4); (4, 5)
C7	(5, 6); (5, 6); (4, 5); (5, 6)	C6	(5, 6); (6, 7); (5, 6); (6, 7)
Sub-criteria evaluation - MC3			
Best: C9	Expert evaluation (E1, E2, ..., E4)	Worst: C15	Expert evaluation (E1, E2, ..., E4)
C8	(2, 3); (3, 4); (2, 3); (2, 3)	C8	(8, 9); (8, 8); (8, 9); (9, 9)
C10	(6, 7); (5, 6); (6, 7); (6, 6)	C9	(9, 9); (9, 9); (8, 8); (9, 9)
C11	(5, 6); (4, 5); (5, 6); (5, 6)	C10	(4, 5); (4, 5); (4, 5); (3, 4)
C12	(3, 4); (2, 3); (3, 4); (3, 4)	C11	(5, 6); (4, 5); (5, 6); (5, 6)
C13	(7, 7); (6, 7); (7, 8); (7, 8)	C12	(7, 8); (7, 7); (6, 7); (7, 8)
C14	(4, 5); (3, 4); (4, 5); (4, 5)	C13	(3, 4); (4, 4); (3, 4); (3, 4)
C15	(8, 9); (9, 9); (8, 9); (9, 9)	C14	(6, 7); (6, 7); (5, 6); (6, 7)
C16	(8, 9); (8, 8); (8, 8); (8, 8)	C16	(2, 3); (2, 3); (3, 4); (2, 3)
Sub-criteria evaluation - MC4			
Best: C19	Expert evaluation (E1, E2, ..., E4)	Worst: C18	Expert evaluation (E1, E2, ..., E4)
C17	(2, 3); (3, 4); (2, 3); (4, 5)	C17	(2, 3); (4, 5); (3, 4); (3, 4)
C18	(4, 5); (5, 6); (4, 5); (5, 6)	C19	(6, 7); (5, 6); (5, 6); (6, 7)
Sub-criteria evaluation - MC5			
Best: C20	Expert evaluation (E1, E2, ..., E4)	Worst: C21	Expert evaluation (E1, E2, ..., E4)
C21	(4, 5); (3, 4); (5, 6); (4, 5)	C20	(5, 6); (4, 5); (5, 5); (4, 5)
Sub-criteria evaluation - MC6			
Best: C22	Expert evaluation (E1, E2, ..., E4)	Worst: C23	Expert evaluation (E1, E2, ..., E4)
C22	(5, 6); (3, 4); (4, 5); (4, 5)	C23	(4, 5); (5, 5); (5, 5); (4, 5)

Table 6: Aggregated IRN BO and NOW vectors of criteria/sub-criteria.

Criteria evaluation			
Best: MC1	Aggregated IRN value	Worst: MC5	Aggregated IRN value
MC2	[(2.25, 2.75), (3.06, 3.44]	MC1	[(7.59, 8.42), (8.56, 8.94]
MC3	[(4.65, 5.9), (5.27, 6.25]	MC2	[(6.59, 7.42), (7.25, 7.75]
MC4	[(5.56, 5.94), (6.25, 6.75]	MC3	[(5.56, 5.94), (6.56, 6.94]
MC5	[(8.25, 8.75), (8.56, 8.94]	MC4	[(4.27, 5.25), (4.75, 6.25]
MC6	[(5.75, 6.73), (6.75, 7.73]	MC6	[(2.59, 3.42), (3.59, 4.42]
Sub-criteria evaluation - MC1			
Best: C1	Aggregated IRN value	Worst: C2	Aggregated IRN value
C2	[(2.59, 3.42), (3.59, 4.42]	C1	[(5.25, 5.75), (6.06, 6.44]
C3	[(3.27, 4.25), (4.27, 5.25]	C3	[(3.59, 4.42), (4.59, 5.42]
Sub-criteria evaluation - MC2			
Best: C6	Aggregated IRN value	Worst: C7	Aggregated IRN value
C4	[(2.56, 2.94), (3.56, 3.94)]	C4	[(2.81, 4.77), (3.75, 5.25)]
C5	[(2.27, 3.25), (3.27, 4.25)]	C5	[(2.59, 3.42), (3.59, 4.42)]
C7	[(4.56, 4.94), (5.56, 5.94)]	C6	[(5.25, 5.75), (6.25, 6.75)]
Sub-criteria evaluation - MC3			
Best: C9	Aggregated IRN value	Worst: C15	Aggregated IRN value
C8	[(2.06, 2.44), (3.06, 3.44)]	C8	[(8.06, 8.44), (8.56, 8.94)]
C10	[(5.56, 5.94), (6.25, 6.75)]	C9	[(8.56, 8.94), (8.56, 8.94)]
C11	[(4.56, 4.94), (5.56, 5.94)]	C10	[(3.56, 3.94), (4.56, 4.94)]
C12	[(2.56, 2.94), (3.56, 3.94)]	C11	[(4.56, 4.94), (5.56, 5.94)]
C13	[(6.56, 6.94), (7.25, 7.75)]	C12	[(6.56, 6.94), (7.25, 7.75)]
C14	[(3.56, 3.94), (4.56, 4.94)]	C13	[(3.06, 3.44), (4, 4)]
C15	[(8.25, 8.75), (9, 9)]	C14	[(5.56, 5.94), (6.56, 6.94)]
C16	[(8, 8), (8.06, 8.44)]	C16	[(2.06, 2.44), (3.06, 3.44)]
Sub-criteria evaluation - MC4			
Best: C19	Aggregated IRN value	Worst: C18	Aggregated IRN value
C17	[(2.27, 3.25), (3.27, 4.25]	C17	[(2.59, 3.42), (3.59, 4.42)]
C18	[(4.25, 4.75), (5.25, 5.75)]	C19	[(5.25, 5.75), (6.25, 6.75)]
Sub-criteria evaluation - MC5			
Best: C20	Aggregated IRN value	Worst: C21	Aggregated IRN value
C21	[(3.59, 4.42), (4.59, 5.42)]	C20	[(4.25, 4.75), (5.06, 5.44)]
Sub-criteria evaluation - MC6			
Best: C22	Aggregated IRN value	Worst: C23	Aggregated IRN value
C22	[(3.59, 4.42), (4.59, 5.42)]	C23	[(4.25, 4.75), (5, 5)]

As noted above, the IRNDWGA operator was used to aggregate the elements of the IRN BO and IRN OW vectors (Appendix A-6).

Steps 7 and 8: The aggregated IRN BO and OW vectors were used to solve the model (see Eq. 18). A separate model was formed for each group of criteria/sub-criteria. Thus, seven models were obtained for determining the local IRN values of the criterion/sub-criterion as given in Table 7.

$Model1(Criteria) - C$

$min \xi$

$s.t.$

$$\left|\frac{w_B^{L'}}{w_2^U} - 3.44\right| \leq \xi; \left|\frac{w_B^{U'}}{w_2^L} - 3.06\right| \leq \xi; \left|\frac{w_B^L}{w_2^{U'}} - 2.75\right| \leq \xi; \left|\frac{w_B^U}{w_2^{L'}} - 2.25\right| \leq \xi;$$

$$\left|\frac{w_B^{L'}}{w_3^U} - 6.25\right| \leq \xi; \left|\frac{w_B^{U'}}{w_3^L} - 5.27\right| \leq \xi; \left|\frac{w_B^L}{w_3^{U'}} - 5.90\right| \leq \xi; \left|\frac{w_B^U}{w_3^{L'}} - 4.65\right| \leq \xi;$$

$$\left|\frac{w_B^{L'}}{w_4^U} - 6.75\right| \leq \xi; \left|\frac{w_B^{U'}}{w_4^L} - 6.25\right| \leq \xi; \left|\frac{w_B^L}{w_4^{U'}} - 5.94\right| \leq \xi; \left|\frac{w_B^U}{w_4^{L'}} - 5.56\right| \leq \xi;$$

$$\left|\frac{w_B^{L'}}{w_W^U} - 8.94\right| \leq \xi; \left|\frac{w_B^{U'}}{w_W^L} - 8.56\right| \leq \xi; \left|\frac{w_B^L}{w_W^{U'}} - 8.75\right| \leq \xi; \left|\frac{w_B^U}{w_W^{L'}} - 8.25\right| \leq \xi;$$

$$\left|\frac{w_B^{L'}}{w_6^U} - 7.73\right| \leq \xi; \left|\frac{w_B^{U'}}{w_6^L} - 6.75\right| \leq \xi; \left|\frac{w_B^L}{w_6^{U'}} - 6.73\right| \leq \xi; \left|\frac{w_B^U}{w_6^{L'}} - 5.75\right| \leq \xi;$$

$$\left|\frac{w_2^{L'}}{w_W^U} - 7.75\right| \leq \xi; \left|\frac{w_2^{U'}}{w_W^L} - 7.25\right| \leq \xi; \left|\frac{w_2^L}{w_W^{U'}} - 7.42\right| \leq \xi; \left|\frac{w_2^U}{w_W^{L'}} - 6.59\right| \leq \xi;$$

$$\left|\frac{w_3^{L'}}{w_W^U} - 6.94\right| \leq \xi; \left|\frac{w_3^{U'}}{w_W^L} - 6.56\right| \leq \xi; \left|\frac{w_3^L}{w_W^{U'}} - 5.94\right| \leq \xi; \left|\frac{w_3^U}{w_W^{L'}} - 4.27\right| \leq \xi;$$

$$\left|\frac{w_4^{L'}}{w_W^U} - 6.25\right| \leq \xi; \left|\frac{w_4^{U'}}{w_W^L} - 4.75\right| \leq \xi; \left|\frac{w_4^L}{w_W^{U'}} - 5.25\right| \leq \xi; \left|\frac{w_4^U}{w_W^{L'}} - 4.27\right| \leq \xi;$$

$$\left|\frac{w_6^{L'}}{w_W^U} - 4.42\right| \leq \xi; \left|\frac{w_6^{U'}}{w_W^L} - 3.59\right| \leq \xi; \left|\frac{w_6^L}{w_W^{U'}} - 3.42\right| \leq \xi; \left|\frac{w_6^U}{w_W^{L'}} - 2.59\right| \leq \xi;$$

$\sum_{j=1}^{6} w_j^{L'}, \sum_{j=1}^{6} w_j^L \leq 1;$

$\sum_{j=1}^{6} w_j^{U'}, \sum_{j=1}^{6} w_j^U \geq 1;$

$w_j^{L'} \leq w_j^L \leq w_j^{U'} \leq w_j^U, \quad \forall j = 1, 2, , \ldots, 6$

$w_j^{L'}, w_j^L, w_j^{U'}, w_j^U \geq 0, \quad \forall j = 1, 2, , \ldots, 6$

Similarly, we obtained the six nonlinear constrained optimization problems for sub-criteria. LINGO 17.0 software was used to solve model (see Eq. 18).

Multiplying the local values of the criteria weights with the corresponding values of the weight coefficients of the sub-criterion, gives the global values for the sub-criterion, Table 7. Then those global values were used to evaluate the alternatives in the IRN MARCOS model.

Table 7: Optimal IRN values of criteria/sub-criteria.

Criteria/subcriteria	IRN local weights	IRN global weights
CM1	[(0.217, 0.389), (0.224, 0.456)]	-
C1	[(0.518, 0.576), (0.56, 0.618)]	[(0.112, 0.224), (0.125, 0.282)]
C2	[(0.099, 0.111), (0.1, 0.111)]	[(0.021, 0.043), (0.022, 0.051)]
C3	[(0.214, 0.265), (0.224, 0.271)]	[(0.046, 0.103), (0.05, 0.124)]
CM2	[(0.111, 0.17), (0.12, 0.186)]	-
C4	[(0.128, 0.215), (0.141, 0.248)]	[(0.014, 0.036), (0.017, 0.046)]
C5	[(0.17, 0.202), (0.185, 0.214)]	[(0.019, 0.034), (0.022, 0.04)]
C6	[(0.382, 0.441), (0.391, 0.491)]	[(0.042, 0.075), (0.047, 0.091)]
C7	[(0.052, 0.068), (0.062, 0.075)]	[(0.006, 0.011), (0.007, 0.014)]
CM3	[(0.113, 0.134), (0.117, 0.149)]	-
C8	[(0.163, 0.23), (0.23, 0.276)]	[(0.018, 0.031), (0.027, 0.041)]
C9	[(0.21, 0.262), (0.257, 0.281)]	[(0.024, 0.035), (0.03, 0.042)]
C10	[(0.044, 0.049), (0.045, 0.059)]	[(0.005, 0.007), (0.005, 0.009)]
C11	[(0.07, 0.08), (0.071, 0.085)]	[(0.008, 0.011), (0.008, 0.013)]
C12	[(0.112, 0.132), (0.132, 0.216)]	[(0.013, 0.018), (0.015, 0.032)]
C13	[(0.041, 0.049), (0.049, 0.055)]	[(0.005, 0.007), (0.006, 0.008)]
C14	[(0.107, 0.12), (0.111, 0.122)]	[(0.012, 0.016), (0.013, 0.018)]
C15	[(0.01, 0.018), (0.017, 0.026)]	[(0.001, 0.002), (0.002, 0.004)]
C16	[(0.021, 0.025), (0.023, 0.046)]	[(0.002, 0.003), (0.003, 0.007)]
CM4	[(0.112, 0.121), (0.114, 0.122)]	-
C17	[(0.2, 0.259), (0.239, 0.265)]	[(0.022, 0.031), (0.027, 0.032)]
C18	[(0.089, 0.103), (0.097, 0.983]	[(0.01, 0.012), (0.011, 0.12)]
C19	[(0.518, 0.608), (0.561, 0.632)]	[(0.058, 0.073), (0.064, 0.077)]
CM5	[(0.011, 0.029), (0.019, 0.04)]	-
C20	[(0.681, 0.783), (0.69, 0.819)]	[(0.008, 0.023), (0.013, 0.033)]
C21	[(0.17, 0.179), (0.177, 0.181)]	[(0.002, 0.005), (0.003, 0.007)]
CM6	[(0.035, 0.046), (0.038, 0.051)]	-
C22	[(0.751, 0.805), (0.781, 0.818)]	[(0.026, 0.037), (0.03, 0.042)]
C23	[(0.161, 0.179), (0.171, 0.182)]	[(0.006, 0.008), (0.006, 0.009)]

By solving the nonlinear models that were used to determine the weights of the criteria/sub-criteria, the values of ξ^* are obtained as follows: $\xi^*_C = 1.454$, $\xi^*_{C1} = 0.974$, $\xi^*_{C2} = 0.959$, $\xi^*_{C3} = 0.640$, $\xi^*_{C4} = 0.861$, $\xi^*_{C5} = 0.525$ and $\xi^*_{C6} = 0.414$. The ξ^* values are plugged into Eq. 20 to calculate CR for each level of criteria as illustrated in Table 8. Similarly, using Eq. (19), the values of the consistency index are computed as ξ. Since the CR values (see Table 8) are lower than 0.30, we can conclude that the observed criteria weights are determined based on consistent expert preferences as suggested in [58].

Table 8: CR values.

Level of the criteria	C (Main Group)	MC1	MC2	MC3	MC4	MC5	MC6
a^{-U+}_{BW}	8.94	6.44	6.75	9.0	6.75	5.44	5.42
CI (max ξ)	5.18	3.32	3.54	5.23	3.54	2.60	2.59
CR	0.28	0.29	0.27	0.122	0.24	0.20	0.16

4.6. Ranking alternatives using the IRN MARCOS methodology

After the IRN weight coefficients of criteria were calculated, an experts evaluation of the alternatives was carried out $A_i (i = 1, 2, \ldots, 4)$ using the predefined 23 sub-criteria $C_j (i = 1, 2, \ldots, 23)$.

Steps 1 and 2: The expert correspondence matrices, in which the alternatives were evaluated, are provided in Table 9.

Table 9: Expert correspondent matrices.

Crit.	A1	A2	A3	A4
C1	(6;8); (7;8); (5;5); (5;7)	(8;9); (9;9); (5;7); (6;8)	(4;6); (6;7); (5;6); (3;4)	(3;4); (5;6); (4;4); (7;9)
C2	(3;5); (7;7); (4;6); (5;8)	(2;3); (7;7); (4;6); (5;7)	(5;7); (7;7); (2;4); (3;5)	(7;9); (7;7); (2;4); (2;4)
C3	(4;6); (6;6); (5;7); (6;9)	(5;5); (6;6); (4;6); (3;6)	(5;6); (6;6); (1;2); (2;5)	(8;9); (6;6); (4;6); (4;7)
C4	(7;9); (8;8); (6;7); (4;6)	(3;5); (8;8); (6;8); (2;4)	(4;4); (8;8); (6;7); (2;3)	(9;9); (8;8); (4;5); (2;5)
C5	(7;9); (7;7); (6;7); (4;7)	(9;9); (7;7); (6;8); (8;9)	(4;7); (7;7); (6;7); (7;9)	(8;9); (7;7); (4;5); (5;8)
C6	(2;5); (9;9); (6;7); (5;7)	(7;8); (9;9); (6;8); (3;3)	(7;9); (9;9); (6;7); (2;3)	(1;2); (9;9); (4;5); (3;4)
C7	(8;8); (6;6); (6;7); (4;7)	(4;5); (6;6); (6;8); (2;3)	(3;6); (6;6); (8;9); (1;2)	(9;9); (6;6); (4;5); (6;9)
C8	(3;4); (8;8); (4;6); (3;5)	(9;9); (8;8); (4;6); (3;5)	(4;5); (8;8); (2;4); (1;3)	(3;7); (8;8); (2;4); (2;3)
C9	(5;6); (7;8); (5;7); (5;7)	(6;8); (7;8); (5;7); (5;7)	(3;3); (7;8); (5;7); (5;7)	(6;6); (7;8); (6;8); (7;9)
C10	(2;4); (5;5); (7;9); (6;8)	(3;3); (5;5); (7;9); (6;8)	(5;5); (5;5); (7;9); (6;8)	(4;6); (5;5); (5;7); (4;6)
C11	(3;6); (7;7); (3;6); (2;5)	(2;5); (8;8); (5;8); (6;9)	(6;8); (7;7); (7;8); (7;9)	(7;9); (7;7); (8;9); (6;8)
C12	(5;8); (6;7); (4;6); (3;5)	(9;9); (8;8); (5;8); (4;7)	(8;9); (7;7); (7;8); (6;9)	(4;7); (6;7); (8;9); (7;9)
C13	(3;4); (5;5); (1;3); (2;4)	(1;2); (5;5); (1;3); (2;4)	(3;5); (5;5); (2;4); (3;5)	(2;3); (5;5); (1;3); (2;4)
C14	(4;7); (7;7); (5;8); (1;3)	(5;7); (8;8); (6;8); (2;4)	(8;9); (6;6); (7;9); (7;9)	(3;6); (7;8); (4;7); (5;7)
C15	(7;9); (6;6); (4;5); (5;6)	(5;7); (6;6); (4;5); (5;6)	(9;9); (6;6); (4;5); (5;6)	(5;6); (6;6); (3;4); (4;5)
C16	(3;6); (6;6); (6;9); (1;4)	(7;9); (7;7); (6;9); (7;9)	(1;3); (5;6); (6;9); (1;3)	(6;8); (5;5); (3;5); (6;9)
C17	(4;6); (7;7); (5;5); (2;4)	(3;4); (7;7); (5;5); (2;4)	(9;9); (7;7); (8;9); (6;8)	(4;5); (7;7); (7;8); (1;3)
C18	(2;4); (6;6); (5;5); (4;5)	(2;5); (6;6); (5;5); (3;5)	(8;9); (6;6); (8;9); (8;9)	(3;6); (6;6); (7;8); (6;8)
C19	(2;3); (7;7); (1;3); (4;6)	(2;3); (7;7); (1;3); (4;6)	(7;9); (7;7); (8;9); (7;9)	(3;4); (7;7); (2;4); (5;7)
C20	(3;4); (8;8); (5;5); (4;6)	(3;4); (8;8); (5;5); (4;6)	(6;8); (8;8); (5;8); (5;9)	(5;7); (8;8); (5;6); (5;7)
C21	(7;9); (9;9); (5;9); (6;8)	(7;9); (8;8); (5;9); (7;9)	(1;3); (8;8); (1;2); (1;3)	(2;4); (8;8); (1;3); (2;3)
C22	(7;7); (8;8); (5;5); (4;6)	(7;7); (8;8); (5;5); (4;6)	(7;7); (8;8); (5;5); (4;6)	(7;7); (8;8); (5;5); (4;6)
C23	(6;6); (8;8); (5;5); (5;7)	(6;6); (8;8); (5;5); (5;7)	(6;6); (8;8); (5;5); (5;7)	(6;6); (8;8); (5;5); (5;7)

In order to apply the IRN MARCOS methodology, the expert preferences from Table 9, were transformed into IRNs (using Eqs. (1) - (9)) and aggregated into the IRN initial decision matrix using the IRNDWGA operator (see Table 10). For example, at position $C_1 - A_1$ we obtain the following values in expert correspondence matrices: $IRN(x_{11}^{E1}) = [(5.33, 6.50), (7.00, 8.00)]$, $IRN(x_{11}^{E2}) = [(5.75, 7.00), (7.00, 8.00)]$, $IRN(x_{11}^{E3}) = [(5.00, 5.75), (5.00, 7.00)]$ and $IRN(x_{11}^{E4}) = [(5.00, 5.75), (6.00, 7.67)]$. As mentioned in the previous part of the paper, four experts participated in the study and were assigned the following weight values $w_E = (0.182, 0.273, 0.227, 0.316)^T$. Based on the values shown, Eq. (8) and assuming that $\rho = 1$, at position $C_1 - A_1$, value aggregation was performed:

$IRNDWGA(x_{11}) =$

$$\begin{cases} x_{11}^{L'} = \dfrac{21.08}{1+\left(0.182\times\left(\frac{1-0.25}{0.25}\right)+0.273\times\right.}\left(\frac{1-0.27}{0.27}\right)+\cdots+0.318\times\left(\frac{1-0.24}{0.24}\right)=5.256 \\ x_{11}^{U'} = \dfrac{25}{1+\left(0.182\times\left(\frac{1-0.26}{0.26}\right)+0.273\times\right.}\left(\frac{1-0.28}{0.28}\right)+\cdots+0.318\times\left(\frac{1-0.23}{0.23}\right)=6.181 \\ x_{11}^{L} = \dfrac{25}{1+\left(0.182\times\left(\frac{1-0.28}{0.28}\right)+0.273\times\right.}\left(\frac{1-0.28}{0.28}\right)+\cdots+0.318\times\left(\frac{1-0.24}{0.24}\right)=6.119 \\ x_{11}^{U} = \dfrac{30.67}{1+\left(0.182\times\left(\frac{1-0.26}{0.26}\right)+0.273\times\right.}\left(\frac{1-0.26}{0.26}\right)+\cdots+0.318\times\left(\frac{1-0.25}{0.25}\right)=7.647 \end{cases}$$

$= [(5.25, 6.18), (6.12, 7.65)]$

In the next step (*Step 2*), the initial decision matrix is extended by applying Eq. (25) and (26).

Table 10: IRN initial decision matrix.

Crit.	AAI	A1	A2	A3	A	AI
C1	[(3.63, 3.63), (3.63, 3.63)]	[(5.25, 6.18), (6.12, 7.65)]	[(5.85, 7.96), (7.69, 8.71)]	[(3.63, 5.16), (6.38, 7.82)]	[(3.84, 5.82), (4.13, 4.83)]	[(8.71, 8.71), (8.71, 8.71)]
C2	[(7.32, 7.32), (7.32, 7.32)]	[(3.81, 5.78), (5.81, 7.32)]	[(3.19, 5.71), (4.68, 6.66)]	[(2.78, 5.37), (4.84, 6.46)]	[(2.68, 5.37), (4.52, 6.89)]	[(2.68, 2.68), (2.68, 2.68)]
C3	[(7.77, 7.77), (7.77, 7.77)]	[(4.8, 5.77), (6.36, 7.77)]	[(3.61, 5.14), (5.6, 5.95)]	[(1.71, 4.61), (3.33, 5.56)]	[(4.39, 6.22), (6.27, 7.61)]	[(1.71, 1.71), (1.71, 1.71)]
C4	[(8.12, 8.12), (8.12, 8.12)]	[(4.98, 7.06), (6.61, 8.12)]	[(2.85, 6.04), (5, 7.17)]	[(3.02, 6.23), (3.9, 6.62)]	[(3.08, 7.14), (5.51, 7.51)]	[(2.85, 2.85), (2.85, 2.85)]
C5	[(4.78, 4.78), (4.78, 4.78)]	[(4.98, 6.58), (7.09, 7.73)]	[(6.69, 8.19), (7.7, 8.71)]	[(5.28, 6.72), (7.15, 7.92)]	[(4.78, 6.91), (6.11, 8.13)]	[(8.71, 8.71), (8.71, 8.71)]
C6	[(8.11, 8.11), (8.11, 8.11)]	[(3.52, 7.07), (6.19, 7.85)]	[(4.27, 7.41), (4.77, 8.01)]	[(3.36, 7.3), (4.62, 8.11)]	[(2.04, 5.96), (3.19, 6.57)]	[(2.04, 2.04), (2.04, 2.04)]
C7	[(8.26, 8.26), (8.26, 8.26)]	[(4.91, 6.63), (6.53, 7.35)]	[(3.02, 5.31), (3.98, 6.5)]	[(1.85, 5.88), (3.38, 6.87)]	[(5.08, 7.09), (6.1, 8.26)]	[(1.85, 1.85), (1.85, 1.85)]
C8	[(1.61, 1.61), (1.61, 1.61)]	[(3.38, 5.46), (4.78, 6.74)]	[(3.91, 7.26), (5.75, 7.85)]	[(1.61, 5.05), (3.69, 6.03)]	[(2.36, 4.7), (3.85, 6.58)]	[(7.85, 7.85), (7.85, 7.85)]
C9	[(4.15, 4.15), (4.15, 4.15)]	[(5.13, 5.84), (6.62, 7.44)]	[(5.25, 6.18), (7.22, 7.72)]	[(4.15, 5.83), (4.99, 7.27)]	[(5.22, 6.69), (7.16, 8.41)]	[(8.41, 8.41), (8.41, 8.41)]
C10	[(7.82, 7.82), (7.82, 7.82)]	[(3.48, 6.13), (5.07, 7.82)]	[(4.16, 6.19), (4.45, 7.75)]	[(5.26, 6.23), (5.63, 7.69)]	[(4.24, 4.74), (5.54, 6.37)]	[(3.48, 3.48), (3.48, 3.48)]
C11	[(2.6, 2.6), (2.6, 2.6)]	[(2.6, 4.58), (5.52, 6.38)]	[(3.56, 6.66), (6.66, 8.36)]	[(6.6, 6.95), (7.57, 8.43)]	[(6.51, 7.36), (7.64, 8.68)]	[(8.68, 8.68), (8.68, 8.68)]
C12	[(3.61, 3.61), (3.61, 3.61)]	[(3.61, 5.14), (5.61, 7.12)]	[(4.85, 7.56), (7.5, 8.33)]	[(6.49, 7.33), (7.7, 8.71)]	[(5.2, 7.2), (7.51, 8.52)]	[(8.71, 8.71), (8.71, 8.71)]
C13	[(4.94, 4.94), (4.94, 4.94)]	[(1.59, 3.59), (3.57, 4.41)]	[(1.3, 3.06), (2.73, 4.27)]	[(2.6, 3.84), (4.56, 4.94)]	[(1.57, 3.2), (3.28, 4.27)]	[(1.3, 1.3), (1.3, 1.3)]
C14	[(8.78, 8.78), (8.78, 8.78)]	[(1.91, 5.38), (4.49, 7.08)]	[(3.17, 6.41), (5.36, 7.5)]	[(6.53, 7.35), (7.48, 8.78)]	[(3.81, 5.78), (6.62, 7.44)]	[(1.91, 1.91), (1.91, 1.91)]
C15	[(7.16, 7.16), (7.16, 7.16)]	[(4.65, 6.16), (5.63, 7.16)]	[(4.58, 5.41), (5.56, 6.36)]	[(4.71, 7.03), (5.63, 7.16)]	[(3.67, 5.19), (4.67, 5.71)]	[(3.67, 3.67), (3.67, 3.67)]
C16	[(1.46, 1.46), (1.46, 1.46)]	[(1.87, 5.02), (4.97, 7.09)]	[(6.56, 6.94), (8.03, 8.86)]	[(1.46, 4.14), (3.6, 6.38)]	[(4.1, 5.65), (5.64, 7.64)]	[(8.86, 8.86), (8.86, 8.86)]
C17	[(8.68, 8.68), (8.68, 8.68)]	[(2.92, 5.5), (4.63, 6.15)]	[(2.75, 5.32), (4.31, 5.65)]	[(6.59, 8.1), (7.64, 8.68)]	[(2.02, 5.93), (4.07, 6.79)]	[(2.02, 2.02), (2.02, 2.02)]
C18	[(8.78, 8.78), (8.78, 8.78)]	[(3.1, 5.18), (4.61, 5.43)]	[(2.82, 4.99), (5.07, 5.44)]	[(7.02, 7.86), (7.48, 8.78)]	[(4.54, 6.29), (6.51, 7.51)]	[(2.82, 2.82), (2.82, 2.82)]
C19	[(8.86, 8.86), (8.86, 8.86)]	[(1.78, 4.91), (3.66, 5.75)]	[(1.78, 4.91), (3.66, 5.75)]	[(7.06, 7.41), (8.03, 8.86)]	[(2.89, 5.5), (4.77, 6.3)]	[(1.78, 1.78), (1.78, 1.78)]
C20	[(3.8, 3.8), (3.8, 3.8)]	[(3.8, 6.19), (4.83, 6.8)]	[(3.8, 6.19), (4.83, 6.8)]	[(5.3, 6.62), (8.08, 8.47)]	[(5.18, 6.23), (6.59, 7.42)]	[(8.47, 8.47), (8.47, 8.47)]
C21	[(1.21, 1.21), (1.21, 1.21)]	[(5.75, 7.69), (8.5, 8.92)]	[(6.07, 7.35), (8.53, 8.93)]	[(1.21, 3.35), (2.71, 5.05)]	[(1.64, 4.37), (3.37, 5.39)]	[(8.93, 8.93), (8.93, 8.93)]
C22	[(4.77, 4.77), (4.77, 4.77]	[(4.77, 6.88), (5.7, 7.21)]	[(4.77, 6.88), (5.7, 7.21)]	[(4.77, 6.88), (5.7, 7.21)]	[(4.77, 6.88), (5.7, 7.21)]	[(7.21, 7.21), (7.21, 7.21)]
C23	[(5.3, 5.3), (5.3, 5.3)]	[(5.3, 6.62), (5.76, 7.28)]	[(5.3, 6.62), (5.76, 7.28)]	[(5.3, 6.62), (5.76, 7.28)]	[(5.3, 6.62), (5.76, 7.28)]	[(7.28, 7.28), (7.28, 7.28)]

Step 3: Using Eqs. (27) and (28), the elements of the IRN initial decision matrix were normalized, e.g.:

$$IRN(\hat{y}_{11}) = \left(\left[\frac{x_{ij}^{L'}}{maxx_{ij}^{U}}, \frac{x_{ij}^{U'}}{maxx_{ij}^{U}}\right], \left[\frac{x_{ij}^{L}}{maxx_{ij}^{U}}, \frac{x_{ij}^{U}}{maxx_{ij}^{U}}\right]\right)$$

$$= \left(\left[\frac{5.25}{8.71}, \frac{6.18}{8.71}\right], \left[\frac{6.12}{8.71}, \frac{6.12}{8.71}\right]\right) = ([0.602, 0.709], [0.702, 0.878])$$

The normalized IRN initial decision matrix is given in Table 11.

Table 11: Normalized IRN initial decision matrix.

Crit.	AAI	A1	A2	A3	A	AI
C1	[(0.42, 0.42), (0.42, 0.42)]	[(0.6, 0.71), (0.7, 0.88)]	[(0.67, 0.91), (0.88, 1)]	[(0.42, 0.59), (0.73, 0.9)]	[(0.44, 0.67), (0.47, 0.55)]	[(1.00, 1.00), (1.00, 1.00)]
C2	[(0.37, 0.37), (0.37, 0.37)]	[(0.37, 0.46), (0.46, 0.7)]	[(0.4, 0.57), (0.47, 0.84)]	[(0.41, 0.55), (0.5, 0.96)]	[(0.39, 0.59), (0.5, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C3	[(0.22, 0.22), (0.22, 0.22)]	[(0.22, 0.27), (0.3, 0.36)]	[(0.29, 0.31), (0.33, 0.47)]	[(0.31, 0.51), (0.37, 1)]	[(0.22, 0.27), (0.27, 0.39)]	[(1.00, 1.00), (1.00, 1.00)]
C4	[(0.35, 0.35), (0.35, 0.35)]	[(0.35, 0.43), (0.4, 0.57)]	[(0.4, 0.57), (0.47, 1)]	[(0.43, 0.73), (0.46, 0.94)]	[(0.38, 0.52), (0.4, 0.93)]	[(1.00, 1.00), (1.00, 1.00)]
C5	[(0.55, 0.55), (0.55, 0.55)]	[(0.57, 0.76), (0.81, 0.89)]	[(0.77, 0.94), (0.88, 1)]	[(0.61, 0.77)), (0.82, 0.91)]	[(0.55, 0.79), (0.7, 0.93)]	[(1.00, 1.00), (1.00, 1.00)]
C6	[(0.25, 0.25), (0.25, 0.25)]	[(0.26, 0.33), (0.29, 0.58)]	[(0.25, 0.43), (0.28, 0.48)]	[(0.25, 0.44), (0.28, 0.61)]	[(0.31, 0.64), (0.34, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C7	[(0.22, 0.22), (0.22, 0.22)]	[(0.25, 0.28), (0.28, 0.38)]	[(0.28, 0.46), (0.35, 0.61)]	[(0.27, 0.55), (0.31, 1)]	[(0.22, 0.3), (0.26, 0.36)]	[(1.00, 1.00), (1.00, 1.00)]
C8	[(0.21, 0.21), (0.21, 0.21)]	[(0.43, 0.7), (0.61, 0.86)]	[(0.5, 0.92), (0.73, 1)]	[(0.21, 0.64), (0.47, 0.77)]	[(0.3, 0.6), (0.49, 0.84)]	[(1.00, 1.00), (1.00, 1.00)]
C9	[(0.49, 0.49), (0.49, 0.49)]	[(0.61, 0.69), (0.79, 0.88)]	[(0.62, 0.73), (0.86, 0.92)]	[(0.49, 0.69), (0.59, 0.86)]	[(0.62, 0.79), (0.85, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C10	[(0.44, 0.44), (0.44, 0.44)]	[(0.44, 0.69), (0.57, 1)]	[(0.45, 0.78), (0.56, 0.83)]	[(0.45, 0.62), (0.56, 0.66)]	[(0.55, 0.63), (0.73, 0.82)]	[(1.00, 1.00), (1.00, 1.00)]
C11	[(0.3, 0.3), (0.3, 0.3)]	[(0.3, 0.53), (0.64, 0.74)]	[(0.41, 0.77), (0.77, 0.96)]	[(0.76, 0.8), (0.87, 0.97)]	[(0.75, 0.85), (0.88, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C12	[(0.41, 0.41), (0.41, 0.41)]	[(0.41, 0.59), (0.64, 0.82)]	[(0.56, 0.87), (0.86, 0.96)]	[(0.75, 0.84), (0.88, 1)]	[(0.6, 0.83), (0.86, 0.98)]	[(1.00, 1.00), (1.00, 1.00)]
C13	[(0.26, 0.26), (0.26, 0.26)]	[(0.29, 0.36), (0.36, 0.82)]	[(0.3, 0.48), (0.43, 1)]	[(0.26, 0.29), (0.34, 0.5)]	[(0.3, 0.4), (0.41, 0.83)]	[(1.00, 1.00), (1.00, 1.00)]
C14	[(0.22, 0.22), (0.22, 0.22)]	[(0.27, 0.43), (0.36, 1)]	[(0.25, 0.36), (0.3, 0.6)]	[(0.22, 0.26), (0.26, 0.29)]	[(0.26, 0.29), (0.33, 0.5)	[(1.00, 1.00), (1.00, 1.00)]
C15	[(0.51, 0.51), (0.51, 0.51)]	[(0.51, 0.65), (0.6, 0.79)]	[(0.58, 0.66), (0.68, 0.8)]	[(0.51, 0.65), (0.52, 0.78)]	[(0.64, 0.79), (0.71, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C16	[(0.16, 0.16), (0.16, 0.16)]	[(0.21, 0.57), (0.56, 0.8)]	[(0.74, 0.78), (0.91, 1)]	[(0.16, 0.47), (0.41, 0.72)]	[(0.46, 0.64), (0.64, 0.86)]	[(1.00, 1.00), (1.00, 1.00)]
C17	[(0.23, 0.23), (0.23, 0.23)]	[(0.33, 0.44), (0.37, 0.69)]	[(0.36, 0.47), (0.38, 0.73)]	[(0.23, 0.26), (0.25, 0.31)]	[(0.3, 0.49), (0.34, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C18	[(0.32, 0.32), (0.32, 0.32]	[(0.52, 0.61), (0.54, 0.91)]	[(0.52, 0.56), (0.57, 1)]	[(0.32, 0.38), (0.36, 0.4)]	[(0.38, 0.43), (0.45, 0.62]	[(1.00, 1.00), (1.00, 1.00)]
C19	[(0.2, 0.2), (0.2, 0.2)]	[(0.31, 0.49), (0.36, 1)]	[(0.31, 0.49), (0.36, 1)]	[(0.2, 0.22), (0.24, 0.25)]	[(0.28, 0.37), (0.32, 0.61)]	[(1.00, 1.00), (1.00, 1.00)]
C20	[(0.45, 0.45), (0.45, 0.45)]	[(0.45, 0.73), (0.57, 0.8)]	[(0.45, 0.73), (0.57, 0.8)]	[(0.63, 0.78), (0.95, 1)]	[(0.61, 0.73), (0.78, 0.88)]	[(1.00, 1.00), (1.00, 1.00)]
C21	[(0.14, 0.14), (0.14, 0.14)]	[(0.64, 0.86), (0.95, 1)]	[(0.68, 0.82), (0.96, 1)]	[(0.14, 0.38), (0.3, 0.57)]	[(0.18, 0.49), (0.38, 0.6)]	[(1.00, 1.00), (1.00, 1.00)]
C22	[(0.66, 0.66), (0.66, 0.66)]	[(0.66, 0.95), (0.79, 1)]	[(0.66, 0.95), (0.79, 1)]	[(0.66, 0.95), (0.79, 1)]	[(0.66, 0.95), (0.79, 1)]	[(1.00, 1.00), (1.00, 1.00)]
C23	[(0.73, 0.73), (0.73, 0.73)]	[(0.73, 0.91), (0.79, 1)]	[(0.73, 0.91), (0.79, 1)]	[(0.73, 0.91), (0.79, 1)]	[(0.73, 0.91), (0.79, 1)]	[(1.00, 1.00), (1.00, 1.00)]

Steps 4-7: Multiplying the IRN weighting coefficients of the criteria (see Table 7) with the elements of the normalized IRN decision matrix, elements of the IRN weighted matrix were obtained (V). Based on the IRN weighted matrix, using Eqs. (29) and (30), utility degrees in relation to the ideal and anti-ideal solution are calculated, e.g.:

$$IRN(K_1^-) = \frac{IRN(S_1}{IRN(S_{aai}} = \frac{[(0.208{,}0.476),(0.300{,}0.890)]}{[(0.167{,}0.297),(0.194{,}0.398)]}$$
$$= \left[\left(\frac{0.208}{1.142}, \frac{0.476}{0.555}\right), \left(\frac{0.300}{0.297}, \frac{0.890}{0.167}\right)\right] = [(0.523, 2.459), (1.010, 5.319)]$$
$$IRN(K_1^+) = \frac{IRN(S_1}{IRN(S_{ai}} = \frac{[(0.208{,}0.476),(0.300{,}0.890)]}{[(0.481{,}0.847),(0.555{,}1.142)]}$$
$$= \left[\left(\frac{0.208}{1.142}, \frac{0.476}{0.555}\right), \left(\frac{0.300}{0.847}, \frac{0.890}{0.481}\right)\right] = [(0.18, 0.86), (0.35, 1.85)]$$

The utility degrees have been used to calculate the IRN utility function of alternatives $IRN\Big(f(K_i)\Big)$. Then the final ranking of alternatives are obtained based on the IRN utility function as shown in Table 12. Using Eqs. (32)-(34), IRN utility functions are defined as follows.

a) Utility functions in relation to the anti-ideal solution is determined by applying Eq. (33)

$$IRN\Big(f(K_i^-)\Big) = \left[\left(\frac{K_1^{+L'}}{K_1^{+U}+K_1^{-U}}, \frac{K_1^{+U'}}{K_1^{+U}+K_1^{-U}}\right), \left(\frac{K_1^{+L}}{K_1^{+U}+K_1^{-U}}, \frac{K_1^{+U}}{K_1^{+U}+K_1^{-U}}\right)\right]$$
$$\left[\left(\frac{0.52}{5.32+1.85}, \frac{2.46}{5.32+1.85}\right), \left(\frac{1.01}{5.32+1.85}, \frac{5.32}{5.32+1.85}\right)\right] = [(0.07, 0.34), (0.14, 0.74)]$$

b) Utility function in relation to the ideal solution is determined by applying Eq. (34)

$$IRN\Big(f(K_i^+)\Big) = \left[\left(\frac{K_1^{-L'}}{K_1^{+U}+K_1^{-U}}, \frac{K_1^{-U'}}{K_1^{+U}+K_1^{-U}}\right), \left(\frac{K_1^{-L}}{K_1^{+U}+K_1^{-U}}, \frac{K_1^{-U}}{K_1^{+U}+K_1^{-U}}\right)\right]$$

$$\left[\left(\frac{0.18}{5.32+1.85}, \frac{0.86}{5.32+1.85}\right), \left(\frac{0.35}{5.32+1.85}, \frac{1.85}{5.32+1.85}\right)\right] = [(0.03, 0.12), (0.05, 0.26)]$$

Finally, using Eq. (32), the final utility functions for the alternatives are obtained, Table 12.

Table 12: IRN utility functions of alternatives and final ranking.

Alt.	A1	A2	A3	A4
$IRN(S_i)$	[(0.21, 0.48), (0.30, 0.89)]	[(0.23, 0.57), (0.34, 0.99)]	[(0.18, 0.47), (0.29, 0.88)]	[(0.19, 0.50), (0.27, 0.82)]
$IRN(K_i^+)$	[(0.18, 0.86), (0.35, 1.85)]	[(0.20, 1.02), (0.40, 2.05)]	[(0.16, 0.86), (0.35, 1.82)]	[(0.17, 0.89), (0.32, 1.71)]
$IRN(K_i^-)$	[(0.52, 2.46), (1.01, 5.32)]	[(0.58, 2.94), (1.14, 5.89)]	[(0.46, 2.45), (0.99, 5.23)]	[(0.49, 2.57), (0.92, 4.92)]
$f(K_i^+)$	[(0.03, 0.12), (0.05, 0.26)]	[(0.03, 0.13), (0.05, 0.26)]	[(0.02, 0.12), (0.05, 0.26)]	[(0.03, 0.14), (0.05, 0.26)]
$f(K_i^-)$	[(0.07, 0.34), (0.14, 0.74)]	[(0.07, 0.37), (0.14, 0.74)]	[(0.07, 0.35), (0.14, 0.74)]	[(0.07, 0.39), (0.14, 0.74)]
$IRN(f(K_i))$	[(0.01, 0.32), (0.05, 1.70)]	[(0.02, 0.42), (0.06, 1.88)]	[(0.01, 0.33), (0.05, 1.67)]	[(0.01, 0.38), (0.05, 1.57)]
K_i	0.2800	0.3536	0.2815	0.3184
Rank	*4*	*1*	*3*	*2*

Since the final values of the utility functions are represented as interval rough numbers, applying Eqs. (35) and (36), the interval rough values are transformed into crisp values. Based on the obtained crisp values of the utility functions, the alternatives were ranked according to the following $A_2 > A_4 > A_3 > A_1$. A_2 *(Bozcaada)* is the best site among the four alternative sites because it has the largest weight (0.3534), while A_1 *(Gokçeada)* is the worst alternative. Table 13 provides the suitability of four alternative sites with respect to some selected criteria.

Table 13: The suitable alternatives for OWF development based on site selection criteria (✓: suitable, X: unsuitable, ≈: partially suitable) ([13]).

Alternatives	Territorial waters	Military zone	Shipping routes	Pipelines	Environmeantal concerns	Social concerns
A1: Gokceada	✓	≈	✓	✓	✓	✓
A2: Bozcaada	✓	≈	✓	✓	✓	✓
A3: Ayvalik	✓	≈	✓	✓	✓	✓
A4: Saros Gulf	✓	≈	x	≈	✓	✓

The existing wind resource distribution in terms of probability density function for one of the sites, that is A_2 as a sample are shown in Fig. 6.

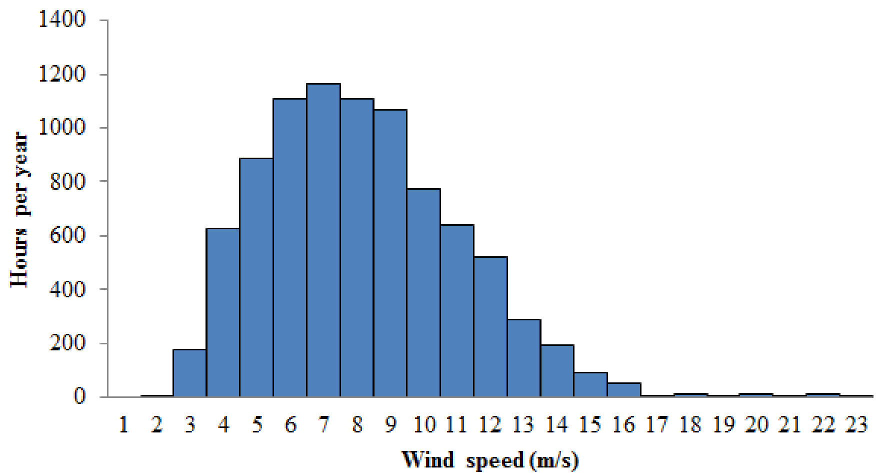


Figure 6: Probability density function for wind speed distribution.

4.7. Sensitivity Analysis and Validation of the Results

Since the data in multi-criteria decision-making (MCDM) problems are often imprecise and highly variable, a significant step in applying MCMD techniques to solve real-world problems is conducting sensitivity analysis of input data to validate the results [88, 89]. There are numerous examples of sensitivity analysis in the literature for some models in operational research and management [90, 91, 92, 93]. Saltelli et al. [94] defined a sensitivity analysis in decision-making models that considers the influence of uncertain input parameters on model results. Also, Stewart et al. [95] advised that it is necessary to measure the performance of the obtained solution in MCDM models depending on the change in the weight of the criteria.

Following these recommendations, to check the robustness of the results, this study conducts a sensitivity analysis and validation of the IRN BWM-MARCOS model results through three phases: (i) validation of the results through comparison to the other MCDM techniques, (ii) analysis of the effect of the parameter ρ and (iii) the most important criteria weight on the ranking results.

4.7.1. Comparison of the results from the proposed approach to the other MCDM techniques

The reliability of the results from a new MCDM technique is often questioned. One way of addressing this issue involves in comparing the obtained results to those from the other well-known MCDM techniques. In this section, the results of the IRN BWM-MARCOS model are compared to the results from the IRN BWM-MABAC [96], IRN BWM-WASPAS [96], and IRN BWM-MAIRCA models [44]. There are various options for the aggregation function that can be used within well-known MCDM techniques, hence we have preferred using IRN for a fair comparison of our approach to IRN BWM-MABAC, IRN BWM-MAIRCA, and BWM-IRN WASPAS. The rankings based on using IRN BWM-MABAC, IRN BWM-MAIRCA, and BWM-IRN WASPAS methods are presented in Fig. 7. In addition to the above similarities, these four models differ in the methodology used to normalize the values of the initial decision matrix: IRN BWM-MABAC, IRN BWM-MAIRCA, and IRN BWM-MAROCS methods use linear normalization while IRN BWM-WASPAS method uses additive. In MCDM models with linear normalization, the normalized value does not depend on the evaluation unit of a criterion [97]. Pamucar and Cirovic [98] showed that in models with additive normalization, the normalized value could be different for different evaluation unit of a particular criterion. A comparative view of the rankings according to the above multi-criteria techniques is shown in Fig. 7.

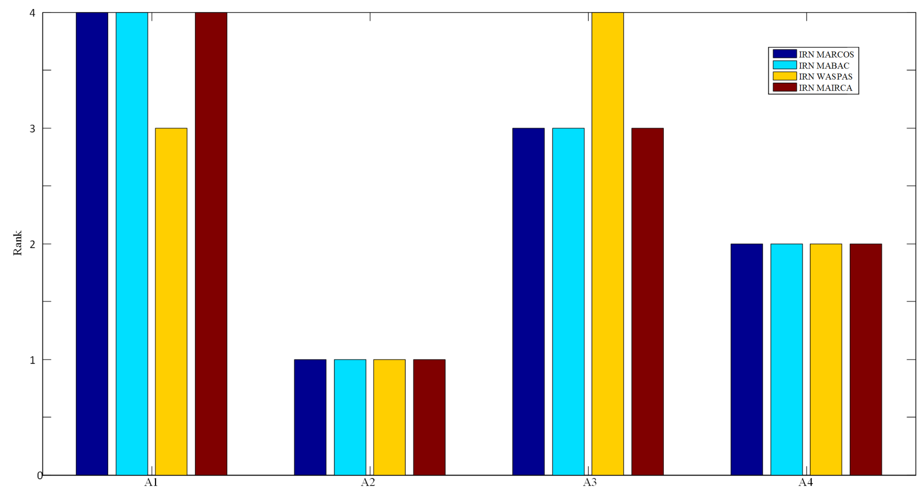


Figure 7: The ranks of the alternatives.

From Fig. 7, we can distinguish two groups of alternatives, dominant and non-dominant. Fig. 7 illustrates that the alternatives A_2 and A_4 are dominant, where A_2 stands out as a more dominant alternative than A_4. The third-ranked and fourth-ranked alternatives A_1 and A_3, respectively, are both non-dominant alternatives. A_3 is a more dominant alternative than A_1 based on the three models of IRN BWM-MARCOS, IRN BWM-MABAC, and IRN BWM-MAIRCA. There is substantial alignment between the results from the proposed approach and the other tested MCDM techniques. Hence, we can safely conclude that the proposed ranking is validated and so the proposed approach is credible.

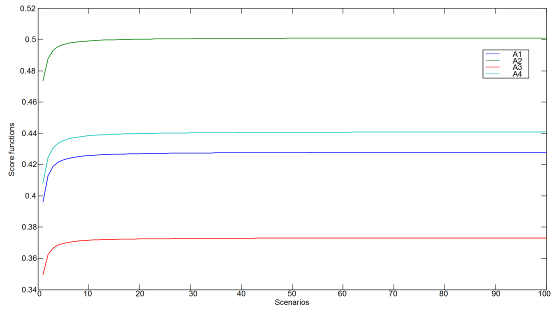
A comparison of the results given in Fig. 7 shows that the alternative ranking achieved by IRN BWM-MABAC, IRN BWM-MAIRCA, and IRN BWM-MARCOS are the same, that is $A_2 > A_4 > A_3 > A_1$. The ranking obtained by the IRN BWM-WASPAS is slightly different producing the ranking of $A_2 > A_4 > A_1 > A_3$. Yet, all methods ranked A_2 and A_4 as the first and second top alternatives, respectively. The results indicate $\{A_2, A_4\}$ as a good subset of alternatives, while alternative A_2 is chosen as dominant from the set. IRN BWM-MAIRCA has produced a ranking that is the same as the one from IRN BWM-MABAC and similar to IRN BWM-WASPAS. The initially best-ranked alternative by IRN BWM-MAIRCA is A_2 with the smallest total gap value $Q_j = 0.0204$. Since the dominance index of the alternative A_2 in relation to alternative A_4 (initially the second-ranked alternative) is higher than $ID = 0.114$, we conclude that A_2 has enough advantage in relation to A_4, and thus alternative A_2 is indicated as the dominant alternative. The other values of the dominance index are also higher than 0.114 so the initial rank is retained for the other alternatives. So, the alternatives $\{A_2, A_4\}$ can be considered as good solutions, but A_2 is the dominant one, while A_4 is ranked as the second alternative.

During the validation of the results, the results from the IRN BWM-MARCOS and IRN BWM-TOPSIS models are compared. Certain discrepancies between those results are observed. Some results achieved by IRN BWM-TOPSIS are different from the results by IRN BWM-MABAC, IRN BWM-MAIRCA and IRN BWM-WASPAS, and we noticed that the result by IRN BWM-TOPSIS is not always the closest to the ideal solution. The alternative ranked as the top by IRN BWM-TOPSIS is A_4, whereas the closest to the ideal is A_2. According to IRN BWM-TOPSIS method Q_j the best solution is A_4 since $Q4 = 0.7599$. The alternative A4 is the best according to $D* = 0.115$ (the separation of each alternative from the ideal solution). However, A_4 is not the closest to the ideal since $D_4^- = 0.364$ and $D_2^- = 0.315$ (the separation of each alternative from the negative ideal solution). From these values, we can see that A_4 is ranked as the top alternative by IRN BWM-TOPSIS, although it is not the closest to the ideal, because $D_4^- = 0.364$ and $D_2^- < D_4^-$. According to the formulation of ranking index (Q_j) in IRN BWM-TOPSIS model, alternative a_j is better then a_k if $Q_j > Q_k$ or $D_j^-/(D_j^* + D_j^-) > D_k^-/(D_k^* + D_k^-)$ which is satisfied if: (1) $D_j^* < D_k^*$ and $D_j^- > D_k^-$; or (2) $D_j^* > D_k^*$ and $D_j^- > D_k^-$, but $D_j^* < D_k^*$ and D_j^-/D_k^-. Based on this analysis, A_2 is the closest alternative to the ideal one and that the initial rank obtained by applying the IRN BWM-MARCOS model was confirmed.

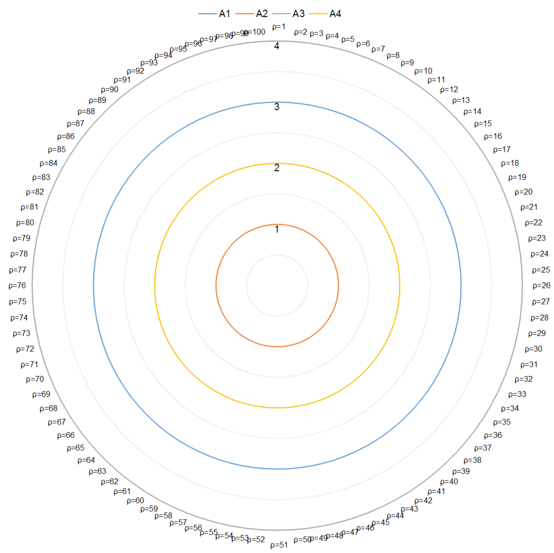
The IRN BWM-MARCOS, IRN BWM-MABAC, IRN BWM-MAIRCA, and IRN BWM-WASPAS results stand only for the given set of alternatives. The inclusion (or exclusion) of an alternative could affect the IRN BWM-MARCOS, IRN BWM-MABAC, IRN BWM-MAIRCA, and IRN BWM-WASPAS ranking of the new set of alternatives. By fixing the best and the worst values, this effect could be avoided, but that would mean that the decision-maker could define a fixed ideal and anti-ideal solution. This study does not consider the trade-offs involved by normalization in obtaining the aggregation function in MARCOS method and this topic remains for further research.

4.7.2. Influence of parameter ρ on the ranking results

When applying the Dombi class of mathematical aggregators in MCDM problems, it is an indispensable step to consider the influence of the parameter ρ on the ranking results. Therefore, to validate the results of the IRN BWM-MARCOS model, the effect of the parameter ρ on the aggregation of values of the initial decision matrix was analyzed. Furthermore, the effect of changing the aggregated values on the final ranking of alternatives was considered. The value of the parameter ρ is varied over the interval $[1, 100]$ leading to a total of 100 different scenarios. The direct and indirect impact of changing ρ values are analyzed looking into how the (i) criteria scoring functions for alternatives also change as illustrated in Fig. 8(a), and (ii) ranks of the alternatives as shown in Fig. 8(b).



(a)



(b)

Figure 8: The impact of varying values of the parameter ρ on (a) score functions, (b) rankings of the alternatives for IRN BWM-MARCOS.

As the value of the parameter ρ increases, the IRNDWGA operator takes a non-linear form and the calculations become more complex. When solving real problems, it is generally recommended to define the parameter value as $\rho = 1$, which is only intuitionistic and simple. Fig. 8a shows the effect of changing the parameter ρ on changing the value of score functions in the IRN BWM-MARCOS methodology. From Fig. 8(a), it can be observed that a change in the value of the parameter ρ significantly influences the changes in the values of the criteria of the model functions. However, these changes in the values of the score functions are not large enough to cause changes in the rankings of alternatives (see Fig. 8(b)), since the ranking of the alternatives remained unchanged despite the significant changes made in the value of the parameter ρ.

Finally, we can conclude that the variation of the parameter ρ influences the variation of the score functions in the IRN BWM-MARCOS methodology. Also, based on our analysis, we can conclude that the two alternatives $\{A2, A4\}$ are indicated as good solutions. However, this applies only to our case study. Depending on the problem dealt with, the initial decision matrix would change, and varying the ρ values could lead to significantly different rankings. Therefore, as a part of the whole decision-making process, this analysis should be performed as an indispensable step to validate the results before the final decision is made.

4.7.3. Changing the weights of the criteria

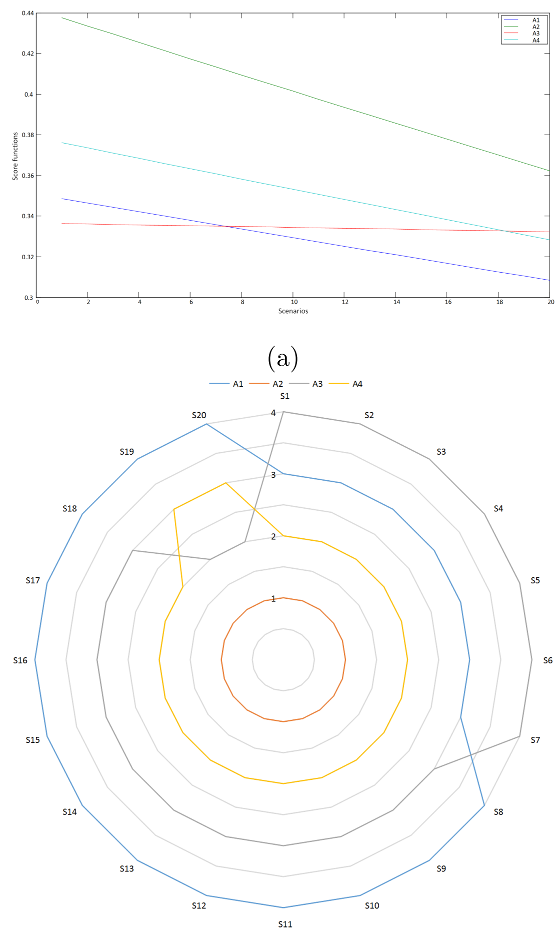
This subsection analyzes the impact of varying the weighting coefficient of the most significant criterion ($C1$) on the ranking results of the IRN BWM-MARCOS methodology. Since in this study, the IRN values are used to rank the alternatives, to comprehensively validate the results, we have conducted this analysis in two phases. In the first phase, the IRN values of the criterion weights are transformed into crisp values, while in the second phase, they are retained and the impact of both cases on the rankings of alternatives is analyzed.

a) The first phase of the analysis varying the criteria weights. A total of 20 scenarios are created using Eq. (37) based on the obtained crisp values of the criteria weights and as suggested in [44],.

$$W_{n\beta} = (1 - W_{n\alpha}) \frac{W_{\beta}}{(1 - W_n)} \tag{37}$$

where $W_{n\beta}$ is the adjusted value of the criterion computed using $W_{n\alpha}$ representing the reduced value of the criterion $C1$, and W_{β} indicating the original value of the considered criterion, and W_n denoting the original value of the criterion $C1$.

Similar to the first scenario, the value of the $C1$ criterion is reduced by 2%, while the values of the remaining criteria are proportionally adjusted using Eq. (37). Similarly, in each successive scenario, the value of criterion $C1$ is decreased by 5% while the values of the remaining criteria are updated maintaining the sum of all weights as 1. After the generation of the 20 new vectors of the criteria weights, new values of the score functions and ranks for the IRN BWM-MARCOS model were obtained as shown in Fig. 9.



(a)

(b)

Figure 9: The changes in the (a) ranking of sites and (b) score functions for IRN BWM-MARCOS for each of the 20 scenarios.

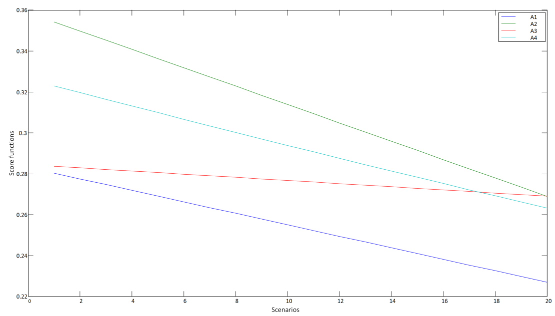
Fig. 9 shows that changes in the value of criterion C_1 lead to a change of the ranks of alternatives A_1, A_3 and $A4$ (see Fig. 9(a)), while the best alternative A_2 did not change its position through all 20 scenarios denoted as $\{S1, \dots, S20\}$. This is confirmed by the changes in the score functions shown in Fig. 9(b). Through the 18 scenarios, the second top alternative A_4 has retained its rank, while for $S19$ and $S20$, it is ranked as the third alternative. Such changes are not surprising, since in $S19$ and $S20$ the value of the most influential criterion C_1 is reduced by 92% and 97%, respectively. Similar changes have occurred with the last two ranked alternatives. After reducing the value of C_1 by 47% (Scenario 8), alternatives A_1 and A_3 switched their places. This leads us to the conclusion that, despite the drastic changes in the C_1 criterion, A_2 and A_4 stand out as the dominant alternatives. On the other hand, A_1 and A_4 are non-dominant alternatives. Based on our analysis, we notice that the alternative A_2 remains dominant for the varying values of the criterion C_1 in $[0.0074, 0.2409]$. Also, the A_4 alternative remains the second for the weight coefficient values in $[0.0442, 0.2409]$.

b) The second phase of the analysis varying the criteria weights. In this phase, the IRN values of the criteria weights were transformed into crisp values using Eq. (38).

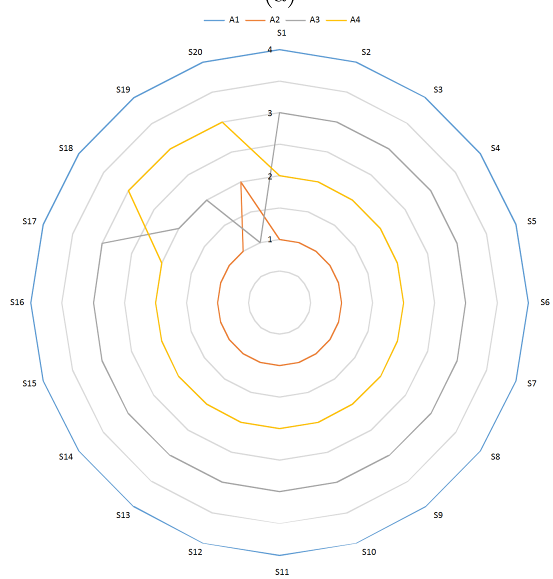
$$IRN(W_{n\beta}) = (1 - IRN(W_{n\alpha})) \frac{IRN(W_\beta}{(1 - IRN(W_n))} \tag{38}$$

where $IRN(W_{n\beta})$ is the adjusted value of the criterion, computed based on $IRN(W_{n\alpha})$ and $IRN(W_n)$ that represent the reduced and original values of criterion C_1, respectively, and $IRN(W_{n\beta})$ indicating the original value of the considered criterion. As in the previous part of the analysis, in the first scenario, the IRN value of the C_1 criterion is reduced by 2%, while the values of the remaining criteria are proportionally updated using Eq. (38). In each successive scenario, the IRN value of the C_1 criterion was decreased by 5% while the values of the remaining criteria were modified, accordingly.

A similar impact of changing the IRN weight criteria was confirmed at this stage of the sensitivity analysis as shown in Fig. 10.



(a)



(b)

Figure 10: The impact of varying the IRN value of criterion $C1$ on the (a) score functions, and (b) rankings of the alternatives for IRN BWM-MARCOS.

The changes in the IRN values of criterion C_1 lead to changes in the score functions shown in Fig. 10(a), which in turn leads to changes in the rankings of the top three alternatives of A_2, A_3 and A_4 (see Fig. 10(b), while the rank of the worst alternative (A_1) remains unchanged for all 20 scenarios.

Throughout the 19 scenarios, the top alternative A_2 has retained its position, while in scenario $S20$ its rank was reduced by one position. A similar deterioration in its rank is observed for the second top alternative A_4 for the last three scenarios ($S18 - S20$). For all values of the IRN criteria weights of the best criterion $IRN(w_i) = [(w_1^{L-}, w_1^{U-}), (w_1^{L+}, w_1^{U+})]$ from the interval $w_1^{L-} = (0.0033, 0.1100)$; $w_1^{U-} = (0.0067, 0.2196)$; $w_1^{L+} = (0.0038, 0.1228)$ and $w_1^{U+} = (0.0084, 0.2759)$ alternative A_2 remains dominant (ranked first), while alternative A_4 remains ranked second for the values of the criteria weights from the interval $w_1^{L-} = (0.0202, 0.1100)$; $w_1^{U-} = (0.0403, 0.2196)$; $w_1^{L+} = (0.0225, 0.1228)$ and $w_1^{U+} = (0.0506, 0.2759)$. In the $S18 - S20$, the $C1$ criterion was reduced by 87% - 97%, so changes in the position of the second-ranked and third-ranked alternatives were not surprising. After reducing the most influential criterion by 87% (Scenario 18), the alternatives A_3 and A_4 (ranking second and third, respectively) switched places. This leads us to the conclusion that, despite the variation in the IRN values of the C_1 criterion, A_2 and A_4 stand out as the dominant alternatives. A_2 stands out as the best solution, as it has maintained its rank during both phases of sensitivity analyses covered in this section despite the drastic changes imposed on the value of the most influential criterion. The location of the best alternative are shown in Fig. 11.

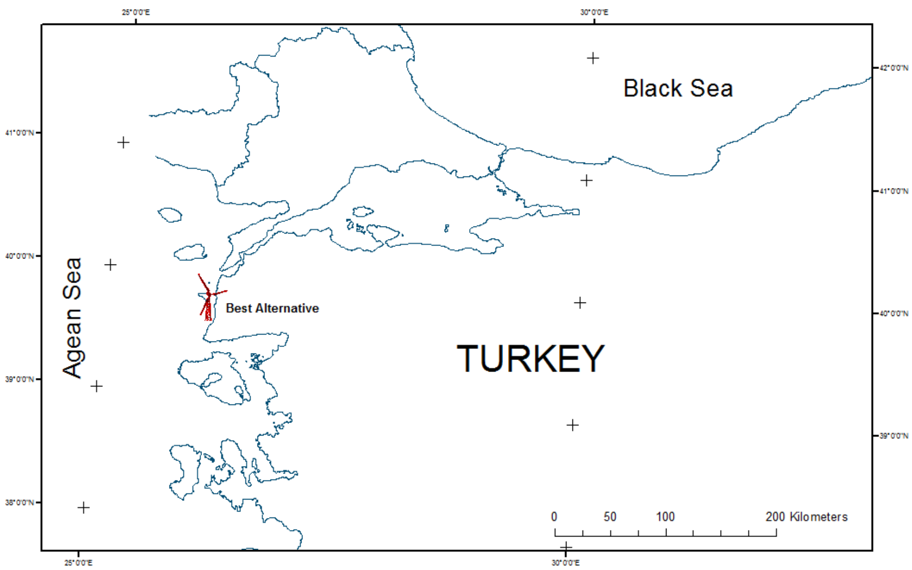


Figure 11: The location of the best alternative.

4.8. Limitations of the Proposed Approach

Many decision makers and relevant users embrace the decision-making tools based on models having a simple mathematical formulation, which are easy to understand to them. A limitation of the IRN BWM-MARCOS model is in the complex mathematical apparatus for capturing the imprecision in the expert preferences and converting them into interval rough numbers. Then an additional complexity is introduced due to the algorithm used to calculate the criteria weights within the proposed approach. Hence, although the usefulness of the proposed decision-making tool is evident with a sound theoretical background, its acceptance by the management and other relevant users could be a concern.

Many decision-making models considering complex environmental conditions for site selection are mathematically complex. Although this issue is not particular to our approach, the process of calculating the IRN Dombi functions is also complicated. The sensitivity of the approach to the changes in its parameter setting ρ imposes a further challenge for the application of this model. Integrating the IRN BWM-MARCOS model into the decision-making system would be more acceptable to the users, particularly who have to deal with a high degree of uncertainty and inaccuracy in the decision-making process realising its benefits beyond its complexities. Hence, the IRN BWM-MARCOS model would be a useful tool for the decision makers who have incomplete information about the choice of sites for the offshore wind farms.

Another limitation of our study is the relatively large number of criteria used to evaluate the potential sites, while surveying a small number of participants (although still reasonable), and the potential impact of the format as well as the content of the questionnaire on the survey results. As a future work, an additional survey informed by the current survey in this paper can be carried out reaching out to a larger number of participants at different levels of expertise relevant to the study. Moreover, the criteria can be reduced and grouped into clusters.

5. Conclusion

This study evaluates four alternatives for choosing the best offshore wind farm site in Turkey's Aegean sea areas using a fuzzy multi-criteria decision-making system based on 6 main and 23 sub-criteria.

We proposed an integrated interval rough numbers and BMW-MARCOS approaches to solving the decision-making problem. The hybrid approach used in this study provides a more precise and accurate analysis by integrating interdependent relationships within and among a set of criteria. In addition, the proposed method helps to select the ideal site location for OWFs, efficiently. The ranking results and reliability of the proposed approach are also verified by the experts. The sensitivity analysis of the IRN BWM-MARCOS model enables the measurement and comparison of the performance of the proposed solutions with different settings. The decision makers can perform the sensitivity analysis flexibly at different levels of the decision-making process and thus obtain robust and relevant solutions.

The most suitable location for the offshore wind farm regardless of the proposed method is *Bozcaada* that is an island located in the northern Aegean Sea. Since the water depth in this region is around 20-30 m, they are suitable for shorter substructures that consequently lead to lower capital costs. The proposed wind turbine model is SWT-3.6-130 for this site and the hub height is 80 m. *Bozcaada* is not close to the military training areas along the Aegean Sea coast and neither to the sea traffic routes of Dardanelles.

Different fuzzy decision-making techniques such as interval-valued intuitionistic fuzzy sets can be adapted for improving the proposed methodology and also, the results can be compared with the results that are found in this study. In addition to these extensions, for future research, the interval rough numbers based MCDM model can be extended by including other characteristic aggregation and arithmetic operators. Also, the proposed approach in this paper can be utilized for solving onshore wind farm problems to additionally show its generality, robustness, and efficiency.

Acknowledgement

This work was supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under the BIDEB-2219 Postdoctoral Research Programme grant number 1059B191701014. The authors also would like to thank Abdulkadir Akpınar from TÜV SÜD Turkey for the useful discussions and feedback about alternatives and ranking.

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Appendix A

Definition 1. Assuming that $IRN(\phi_1) = [(\phi_1^{L-}, \phi_1^{U-}), (\phi_1^{L+}, \phi_1^{U+})]$ and $IRN(\phi_2) = [(\phi_2^{L-}, \phi_2^{U-}), (\phi_2^{L+}, \phi_2^{U+})]$ are two interval rough numbers, $\rho, \gamma > 0$ and let it be $f(IRN(\phi_i)) = [(\phi_i^{L-}, \phi_i^{U-}), (\phi_i^{L+}, \phi_i^{U+})] = \left[\left(\frac{\phi_i^{L-}}{\sum_{i=1}^{n}\phi_i^{L-}}, \frac{\phi_i^{U-}}{\sum_{i=1}^{n}\phi_i^{U-}}\right), \left(\frac{\phi_i^{L+}}{\sum_{i=1}^{n}\phi_i^{L+}}, \frac{\phi_i^{U+}}{\sum_{i=1}^{n}\phi_i^{U+}}\right)\right]$ interval rough function, then some operational lows of rough numbers based on the Dombi T-norm and T-conorm [99] can be defined as follows:

(1) Addition "+"

$$
\begin{aligned}
IRN(\phi_1) + IRN(\phi_2) = \Bigg[\Bigg\{ & \sum_{i=1}^{2}\phi_i^{L-} - \frac{\sum_{i=1}^{2}\phi_i^{L-}}{1 + \left\{\left\{\frac{\phi_1^{L-}}{1-\phi_1^{L-}}\right\}^{\rho} + \left\{\frac{\phi_2^{L-}}{1-\phi_2^{L-}}\right\}^{\rho}\right\}^{1/\rho}} \\
& \sum_{i=1}^{2}\phi_i^{U-} - \frac{\sum_{i=1}^{2}\phi_i^{U-}}{1 + \left\{\left\{\frac{\phi_1^{U-}}{1-\phi_1^{U-}}\right\}^{\rho} + \left\{\frac{\phi_2^{U-}}{1-\phi_2^{U-}}\right\}^{\rho}\right\}^{1/\rho}}, \\
& \Bigg\{\sum_{i=1}^{2}\phi_i^{L+} - \frac{\sum_{i=1}^{2}\phi_i^{L+}}{1 + \left\{\left\{\frac{\phi_1^{L+}}{1-\phi_1^{L+}}\right\}^{\rho} + \left\{\frac{\phi_2^{L+}}{1-\phi_2^{L+}}\right\}^{\rho}\right\}^{1/\rho}}, \\
& \sum_{i=1}^{2}\phi_i^{U+} - \frac{\sum_{i=1}^{2}\phi_i^{U+}}{1 + \left\{\left\{\frac{\phi_1^{U+}}{1-\phi_1^{U+}}\right\}^{\rho} + \left\{\frac{\phi_2^{U+}}{1-\phi_2^{U+}}\right\}^{\rho}\right\}^{1/\rho}}\Bigg\}\Bigg]
\end{aligned}
\tag{A-1}
$$

(2) Multiplication "$\times$"

$$IRN(\phi_1) \times IRN(\phi_2) = \left[\left\{ \sum_{i=1}^{2} \phi_i^{L-} - \frac{\sum_{i=1}^{2} \phi_i^{L-}}{1 + \left\{ \left\{ \frac{1-\phi_1^{L-}}{\phi_1^{L-}} \right\}^{\rho} + \left\{ \frac{1-\phi_2^{L-}}{\phi_2^{L-}} \right\}^{\rho} \right\}^{1/\rho}} \right.\right.$$
$$\sum_{i=1}^{2} \phi_i^{U-} - \frac{\sum_{i=1}^{2} \phi_i^{U-}}{1 + \left\{ \left\{ \frac{1-\phi_1^{U-}}{\phi_1^{U-}} \right\}^{\rho} + \left\{ \frac{1-\phi_2^{U-}}{\phi_2^{U-}} \right\}^{\rho} \right\}^{1/\rho}},$$
$$\left\{ \sum_{i=1}^{2} \phi_i^{L+} - \frac{\sum_{i=1}^{2} \phi_i^{L+}}{1 + \left\{ \left\{ \frac{1-\phi_1^{L+}}{\phi_1^{L+}} \right\}^{\rho} + \left\{ \frac{1-\phi_2^{L+}}{\phi_2^{L+}} \right\}^{\rho} \right\}^{1/\rho}}, \right.$$
$$\left.\left. \sum_{i=1}^{2} \phi_i^{U+} - \frac{\sum_{i=1}^{2} \phi_i^{U+}}{1 + \left\{ \left\{ \frac{1-\phi_1^{U+}}{\phi_1^{U+}} \right\}^{\rho} + \left\{ \frac{1-\phi_2^{U+}}{\phi_2^{U+}} \right\}^{\rho} \right\}^{1/\rho}} \right\}\right] \tag{A-2}$$

(3) Scalar multiplication, where $\gamma > 0$

$$\gamma IRN(\phi_1) = \left[\left\{ \phi_i^{L-} - \frac{\phi_i^{L-}}{1 + \left\{ \gamma \left\{ \frac{\phi_1^{L-}}{1-\phi_1^{L-}} \right\}^{\rho} \right\}^{1/\rho}}, \right.\right.$$
$$\left. \phi_i^{U-} - \frac{\phi_i^{U-}}{1 + \left\{ \gamma \left\{ \frac{\phi_1^{U-}}{1-\phi_1^{U-}} \right\}^{\rho} \right\}^{1/\rho}} \right\},$$
$$\left\{ \phi_i^{L+} - \frac{\phi_i^{L+}}{1 + \left\{ \gamma \left\{ \frac{\phi_1^{L+}}{1-\phi_1^{L+}} \right\}^{\rho} \right\}^{1/\rho}}, \right. \tag{A-3}$$
$$\left.\left. \phi_i^{U+} - \frac{\phi_i^{U+}}{1 + \left\{ \gamma \left\{ \frac{\phi_1^{U+}}{1-\phi_1^{U+}} \right\}^{\rho} \right\}^{1/\rho}} \right\}\right]$$

(4) pOWER, where $\gamma > 0$

$$\{IRN(\phi_1)\}^{\gamma} = \left[\left\{ \frac{\phi_i^{L-}}{1 + \left\{ \gamma \left\{ \frac{1-\phi_1^{L-}}{\phi_1^{L-}} \right\}^{\rho} \right\}^{1/\rho}}, \frac{\phi_i^{U-}}{1 + \left\{ \gamma \left\{ \frac{1-\phi_1^{U-}}{\phi_1^{U-}} \right\}^{\rho} \right\}^{1/\rho}} \right\}, \right. \tag{A-4}$$
$$\left. \left\{ \frac{\phi_i^{L+}}{1 + \left\{ \gamma \left\{ \frac{1-\phi_1^{L+}}{\phi_1^{L+}} \right\}^{\rho} \right\}^{1/\rho}}, \frac{\phi_i^{U+}}{1 + \left\{ \gamma \left\{ \frac{1-\phi_1^{U+}}{\phi_1^{U+}} \right\}^{\rho} \right\}^{1/\rho}} \right\}\right]$$

On the basis of rough operators presented above, the rough Dombi weighted geometric averaging (RNDWGA) operator was derived.

Definition 2. If $IRN(\phi_j) = [(\phi_j^{L-}, \phi_j^{U-}), (\phi_j^{L+}, \phi_j^{U+})]; (j = 1, 2, \cdots, n)$, the set of IRNs in R, and $w_j \in [0, 1]$ represents the weight coefficient of $IRN(\phi_j), (j = 1, 2, \cdots, n)$, which fulfills the requirement that $\sum_{j=1}^{n} w_j = 1$. We can then define the IRNDWGA operator as follows:

$$IRNDWGA\{IRN(\phi_1), IRN(\phi_2), \cdots, IRN(\phi_n)\} = \prod_{j=1}^{n} \big(IRN(\phi_j)\big)^{w_j} \quad \text{(A-5)}$$

Theorem 1. If $IRN(\phi_j) = [(\phi_j^{L-}, \phi_j^{U-}), (\phi_j^{L+}, \phi_j^{U+})]; (j = 1, 2, \cdots, n)$, the set of IRNs in R, then we can define the aggregated values of rough numbers from the set R with the expression (A5). The aggregated values of IRN are obtained with the expression (A6)

$$\begin{aligned} IRNDWGA\{IRN(\phi_1), \cdots, IRN(\phi_n)\} = & \left[\left\{ \frac{\sum_{j=1}^{n} \phi_j^{L-}}{1 + \left\{ \sum_{j=1}^{n} w_j \left\{ \frac{1-f(\phi_j^{L-})}{f(\phi_j^{L-})} \right\}^{\rho} \right\}^{1/\rho}}, \right.\right. \\ & \left. \frac{\sum_{j=1}^{n} \phi_j^{U-}}{1 + \left\{ \sum_{j=1}^{n} w_j \left\{ \frac{1-f(\phi_j^{U-})}{f(\phi_j^{U-})} \right\}^{\rho} \right\}^{1/\rho}} \right\} \\ & \left\{ \frac{\sum_{j=1}^{n} \phi_j^{L+}}{1 + \left\{ \sum_{j=1}^{n} w_j \left\{ \frac{1-f(\phi_j^{L+})}{f(\phi_j^{L+})} \right\}^{\rho} \right\}^{1/\rho}}, \right. \\ & \left.\left. \frac{\sum_{j=1}^{n} \phi_j^{U+}}{1 + \left\{ \sum_{j=1}^{n} w_j \left\{ \frac{1-f(\phi_j^{U+})}{f(\phi_j^{U+})} \right\}^{\rho} \right\}^{1/\rho}} \right\}\right] \end{aligned} \quad \text{(A-6)}$$