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Type-2 neutrosophic number based multi-attributive border approximation area comparison (MABAC) approach for offshore wind farm site selection in USA

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ABSTRACT

The technical, logistical, and ecological challenges associated with offshore wind development necessitate an extensive site selection analysis. Technical parameters such as wind resource, logistical concerns such as distance to shore, and ecological considerations such as fisheries all must be evaluated and weighted, in many cases with incomplete or uncertain data. Making such a critical decision with severe potential economic and ecologic consequences requires a strong decision-making approach to ultimately guide the site selection process. This paper proposes a type-2 neutrosophic number (T2NN) fuzzy based multi-criteria decision-making (MCDM) model for offshore wind farm (OWF) site selection. This approach combines the advantages of neutrosophic numbers sets, which can utilize uncertain and incomplete information, with a multi-attributive border approximation area comparison that provides formulation flexibility and easy calculation. Further, this study develops and integrates a techno-economic model for OWFs in the decision-making. A case study is performed to evaluate and rank five proposed OWF sites off the coast of New Jersey. To validate the proposed model, a comparison against three alternative T2NN fuzzy based models is performed. It is demonstrated that the implemented model yields the same ranking order as the alternative approaches. Sensitivity analysis reveals that changing criteria weightings does not affect the ranking order.

1. Introduction

For the past two decades wind energy, primarily onshore, has been the world's fastest growing renewable energy source (Deveci et al., 2020a). Building off of learning and scale gained in onshore deployments, offshore wind costs have fallen significantly over the past 2–3 years. Offshore wind offers increased capacity factors relative to onshore, reducing some power system integration challenges, and provides a renewable energy option for many coastal and island regions where siting onshore wind or solar photovoltaics is challenging due to land constraints. These factors, taken together, have driven exponential growth in recently constructed and planned offshore wind installations. Specifically, the offshore wind industry has set yearly installed capacity records in each of the past two years with 5652 MW and 6145 MW installed in 2018 and 2019, respectively, bringing global installed capacity of offshore wind to 29,285 MW (Global wind energy council (GWEC), 2019).

The U.S. is estimated to have the second largest available coastal area of any country that is suitable for offshore wind installations, following only China (Neil et al., 2004). The rapidly-growing offshore wind market in the U.S. is driven primarily by state-level commitments and procurement goals, with total offshore wind procurement targets increasing three-fold from 2018 to 2019. This growth has prompted strong competition for offshore wind lease auctions in the U.S., which has resulted in increased lease prices and demonstrates industry belief in the commitments states are making for offshore wind capacity. Meanwhile, the power purchase agreement (PPA) price for the first commercial-scale offshore wind project in Massachusetts was lower than expected and competitive with European prices, signalling that European costs can serve as a proxy for expected offshore wind pricing

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the U.S. Due to these falling costs and strong policy support, forecasts for the U.S. offshore wind market project that capacity will grow to 16,000 MW by 2030 (Walter et al., 2004). Within the U.S., interest in offshore wind has been particularly high in the densely populated coastal regions of New England and the Middle Atlantic, with states such as New Jersey (NJ) showing particular interest due to strong renewable energy policy but poor solar and onshore wind resource.

In the U.S., currently 41 offshore lease areas with a total projected capacity of 25,824 MW are in various stages of development or deployment (Walter et al., 2004). Among these potential areas, NJ has access to the U.S.'s largest and most competitive offshore wind lease areas and is the location of the U.S.'s largest single solicitation for 1100 MW of offshore wind capacity, awarded in 2019. NJ has increased its commitment to offshore wind via an executive order requiring the purchase of 7500 MW of offshore wind by 2035. NJ's lease areas also have the characteristics necessary for low cost and accelerated development of Offshore wind farm (OWF). As such, the state's offshore wind energy feasibility study estimated that each MW of installed offshore capacity would result in the production of nearly 3000 MWh annually and the offshore wind resource could support power densities of approximately 20 MW per square mile (Neil et al., 2004).

The challenges and considerations for siting an offshore wind installation in the U.S. include *(i)* environmental impacts on the marine environment, *(ii)* necessary infrastructure for construction and maintenance of the offshore facility, *(iii)* total installation and operation costs, which are heavily dependent on site-specific factors (Neil et al., 2004). This multi-variate and diverse set of considerations requires an extensive site selection analysis (Argin et al., 2019). Therefore, offshore site selection is formulated as a multi-criteria decision-making (MCDM) problem (Ayodele et al., 2018) that considers technical, economic, environmental, and social aspects in an integrated manner. By addressing challenges associated with the site-specific nature of each project, the output of this analysis provides valuable inputs to regulatory bodies in developing site-specific support mechanisms and to offshore wind investors in making investment decisions more wisely while ensuring the sustainability of offshore wind development. The aim of this study is to develop a MCDM model to evaluate and rank OWF site proposals in NJ's offshore wind development pipeline for use by both policy makers and investors to validate or simplify their decisions. To do this, in addition to technical and site related parameters which include various environmental and social parameters, this study develops and integrates a techno-economic OWF model into the decision-making process that yields quantitative economic parameters. As such, this methodology enables individual expert evaluations to augment with quantitative outputs of the techno-economic model. To handle multiple uncertainties in the decision-making process, this study, then, proposes a new type-2 neutrosophic fuzzy numbers (T2NN) based multi-attribute border approximation area comparison (MABAC) model. As such, the advantages of neutrosophic numbers sets, which can represent uncertainties such as vagueness, imprecision, and inconsistency (Radwan, 2018), is combined with the MABAC approach that provides formulation flexibility and easy calculation. To test and validate the model, this study compares this new methodology to three established neutrosophic fuzzy number based approaches: a weighted aggregated sum product assessment (WASPAS), an additive ratio assessment (ARAS), and a combinative distance-based assessment (CODAS). Finally, the results obtained are compared with the neutrosophic sets via a Technique For Order Preference By Similarity To An Ideal Solution (TOPSIS) (Abdel-Basset et al., 2019).

This paper is organized as follows. Section 2 summarizes the application of the fuzzy based MCDM approaches for OWF site selection problem and relevant literature in the MCDM with neutrosophic fuzzy sets. Section 3 presents the proposed approach including the offshore site description and decision-making criteria considered along with detailing the techno-economic model. The T2NN based MCDM model is developed in Section 4. Experimental and comparison results, including a sensitivity analysis, are discussed in Section 5. Finally, Section 6 presents concluding remarks and future research needs.

2. Literature review

2.1. Fuzzy MCDM in OWF site selection

OWF site selection has been treated as a MCDM problem in the literature. In addition to the analytic hierarchy process (AHP), fuzzy based MCDM models have gained interest as they minimize ambiguities and inconsistencies, which are inherently present in the site selection analysis (Ayodele et al., 2018; Sánchez-Lozano et al., 2016).

A number of fuzzy sets based MCDM methods have been recently applied to OWF site selection. Fetanat and Khorasaninejad (2015) proposed a hybrid MCDM approach combining the fuzzy analytic network process (ANP), fuzzy decision-making trail and evaluation laboratory (DEMATEL), and fuzzy elimination and choice expressing the reality (ELECTRE) to find the best offshore site. In Wu et al. (2018), a fuzzy based MCDM approach established a three-layer decision-making framework. The decision matrix is derived by integrating influencing factors using fuzzy logic while the weights of the attributes are obtained using AHP. Deveci et al. (2020a) developed an interval type-2 fuzzy sets based MCDM model for offshore site selection analysis that integrates the score functions with positive and negative solutions to achieve better results. An intuitionistic fuzzy sets based MCDM approach was employed to handle imprecise information in decision-making applications in Deveci et al. (2020b). An extended MCDM framework was proposed to combine triangular intuitionistic fuzzy numbers, ANP, and the preference ranking organization method for enrichment evaluations (PROMETHEE) (Wu et al., 2020). In order to reduce information loss in an intuitionistic fuzzy environment, and thus improve evaluation quality, Wu et al. (2016) presented the ELECTRE-III based framework for OWF site selection. In Wu et al. (2017), another MCDM method based on interval numbers with probability distribution weighted operator and stochastic dominance degree was proposed for the same site selection problem. In Zhang et al. (2018), a consensus decision framework that uses picture fuzzy sets was developed to quantify the uncertain information inserted in another site selection problem.

In addition these, MCDM-based rough set studies have been applied to decision-making problems in various applications such as fuzzy α-neighbourhood-based fuzzy rough set model (Zhang et al., 2020b), decision-theoretic rough fuzzy set (Zhan et al., 2020b), rough set model based the VIKOR method, fuzzy rough sets based PROMETHEE-EDAS (Zhan et al., 2020a), and TOPSIS — the Weighted Arithmetic Average (WAA) method (Zhang et al., 2020a).

2.2. Fuzzy MCDM using neutrosophic sets

The MCDM methods with neutrosophic fuzzy sets have been used to better handle uncertainty for various applications, even though they have not been applied to the OWF site selection problem which inherently contains uncertainty. These studies are summarized in Table 1. The acronyms in the table are: QUALIFLEX is qualitative flexible multiple criteria, EDAS is evaluation based on distance from average solution, VIKOR is VIšeKriterijumska Optimizacija I Kompromisno Rešenje in Serbian, BWM is best worst method, and MCGDM is multi-criteria group decision-making.

2.3. Fuzzy MABAC and other MCDM methods

Apart from the MCDM approaches with fuzzy neutrosophic sets in Table 1, several studies have used various fuzzy sets such as MABAC, ARAS, WASPAS, and CODAS, as reported in Table 2. Recently, there has been a growing interest into the MABAC method which was originally introduced for MCDM problems by Pamučar and Ćirović (2015). In this method, the distance of the criteria function for each alternative from the border approximation area is described (Dragan et al., 2018b,a). Božanić et al. (2016) presented a fuzzy hybrid model that combines AHP and MABAC for a location selection problem. The implementation

Table 1
Overview of the studies on fuzzy MCDM with neutrosophic sets.

Reference	Method	Neutrosophic sets	Application
Abdel-Basset et al. (2019)	TOPSIS	Type-2 neutrosophic numbers	Supplier selection MCGDM
Peng et al. (2014)	ELECTRE	Simplified	Outranking approach for MCDM
Biswas et al. (2015)	Cosine similarity measure	Single-valued trapezoidal	Find best alternative in MCDM
Biswas et al. (2016)	Weighted arithmetic and geometric averaging operators	Single-valued triangular	Find best alternative in MCDM
Zhang et al. (2016)	ELECTRE IV	Interval-valued	Outranking approach for MCDM
Liang et al. (2017)	DEMATEL	Single-valued trapezoidal	E-commerce website evaluation
Peng et al. (2017b)	ELECTRE III	Multi-valued	Outranking approach for MCDM
Peng et al. (2017c)	Likelihood-based QUALIFLEX	Multi-valued	MCDM
Ji et al. (2018)	Projection-based TODIM	Multi-valued	Personnel selection
Pu et al. (2018)	MABAC–ELECTRE	Single-valued neutrosophic linguistic	Outsourcing provider selection
Karaşan and Kahraman (2018)	EDAS	Interval-valued	Prioritization of United Nations national sustainable development goals
Peng and Dai (2018)	MABAC, TOPSIS and similarity measure	Single-valued	MCDM
Vafadarnikjoo et al. (2018)	Weighted arithmetic averaging operator and fuzzy Delphi	Single-valued trapezoidal	Assessment of consumers' motivations
Wang et al. (2018)	Frank Choquet Bonferroni mean operators	Bipolar	MCDM
Joe and Janani (2019)	WASPAS	Interval-valued trapezoidal	Athlete classification in Paralympics
Liu and Cheng (2019)	ARAS	Probability multi-valued	MCGDM
Karaaslan and Hunu (2020)	TOPSIS	Type-2 single-valued	MCGDM
Nabeeh et al. (2020)	BWM, MABAC and PROMETHEE II	Bipolar	Hospital service assessment
Şahin and Altun (2020)	MABAC	Probabilistic single-valued neutrosophic hesitant fuzzy sets	MCDM

Table 2
Overview of the studies on fuzzy MABAC, WASPAS, ARAS, and CODAS.

Reference	Method	Fuzzy sets	Application
Pamučar and Ćirović (2015)	DEMATEL–MABAC	Triangular	Forklifts selection in logistics centre
Božanić et al. (2016)	AHP-MABAC	Triangular	Location selection for preparing laying-up positions
Peng and Yang (2016)	MABAC	Pythagorean	MCGDM
Xue et al. (2016)	MABAC	Interval-valued intuitionistic	Material selection
Gigović et al. (2017)	GIS-DEMATEL-ANP-MABAC	Triangular	Wind farm site selection
Peng et al. (2017a)	MABAC	Interval-valued fuzzy soft	MCDM
Yu et al. (2017)	MABAC	Interval type-2	Hotel selection on tourism website
Dragan et al. (2018a)	BWM-MABAC	Interval-valued fuzzy-rough	MCDM
Dragan et al. (2018b)	Interval rough-AHP-MABAC	Triangular	University web page evaluation MCGDM
Sun et al. (2018)	MABAC	Hesitant fuzzy linguistic term	Patients' prioritization
Jia et al. (2019)	MABAC	Intuitionistic fuzzy rough	MCGDM
Liang et al. (2019b)	MABAC	Intuitionistic	MCGDM
Liang et al. (2019a)	MABAC	Triangular	Risk assessment of rockburst
Mishra et al. (2020)	MABAC	Interval-valued intuitionistic	Programming language selection
Turskis and Zavadskas (2010)	ARAS	Triangular	Logistics centre location selection
Zamani et al. (2014)	ANP-ARAS	Triangular	Strategy selection in brand extension
Büyüközkan and Göçer (2018)	AHP-ARAS	Interval-valued intuitionistic	Digital supplier selection MCGDM
Zavadskas et al. (2014)	WASPAS	Interval-valued intuitionistic	MCDM
Keshavarz et al. (2016)	WASPAS	Interval type-2	Green supplier selection MCGDM
Deveci et al. (2018)	WASPAS-TOPSIS	Interval type-2	Car sharing station selection
Mishra and Rani (2018)	WASPAS	Interval-valued intuitionistic	Reservoir flood control management policy evaluation
Mishra et al. (2019)	WASPAS	Hesitant	Green supplier selection
Schitea et al. (2019)	WASPAS	Intuitionistic	Hydrogen mobility roll-up site selection
Rani et al. (2020)	WASPAS	Intuitionistic type-2	Physician selection for patients
Peng and Garg (2018)	CODAS	Interval-valued fuzzy soft	Emergency MCDM
Yeni and Özçelik (2019)	CODAS	Interval-valued Atanassov intuitionistic	MCGDM
Karagoz et al. (2020)	CODAS	Intuitionistic	Authorized dismantling centre location selection

of the proposed model has shown success in practice. Xue et al. in Xue et al. (2016) proposed a novel approach interval-valued intuitionistic fuzzy MABAC approach to solve material selection with incomplete weight information. The results showed that the approach is intelligible to selection process under uncertainty. Peng and Yang in Peng and Yang (2016) investigated the MABAC Method based on pythagorean fuzzy choquet integral operators that confirmed their effectiveness and practicality with two practical multiple attribute group decision-making problems. Peng et al. in Peng et al. (2017a) defined three algorithms to solve interval-valued fuzzy decision making problems by interval-valued fuzzy sets based MABAC, EDAS, and a new similarity measure. Sun et al. in Sun et al. (2017) studied a hesitant fuzzy linguistic projection based MABAC method for patients' prioritization. The feasibility of the proposed method was shown on a practical case study. Yu et al. in Yu et al. (2017) described an interval type-2 fuzzy likelihood-based MABAC approach for a hotel selection problem on a tourism website. Liang et al. in Liang et al. (2019a) presented a new framework for assessing the risk of rockburst by a MABAC under a fuzzy environment. The results showed that the proposed method is reliable and effective for use in assessing risk problems. Ji et al. in Pu et al. (2018) provided an integrated MABAC-ELECTRE method using single-valued neutrosophic linguistic sets for outsourcing provider selection. Liang et al. in Liang et al. (2019b) proposed an intuitionistic fuzzy information based MABAC method for human resource management problems. Bozanic et al. (2020) proposed Z-numbers based on FUCOM and MABAC model for a location selection problem.

2.4. Motivation

Compared with other MCDM methods, MABAC has the advantages of simple mathematical calculation and solution stability dependent upon changes in criteria measurement scale and formulation (Pamučar

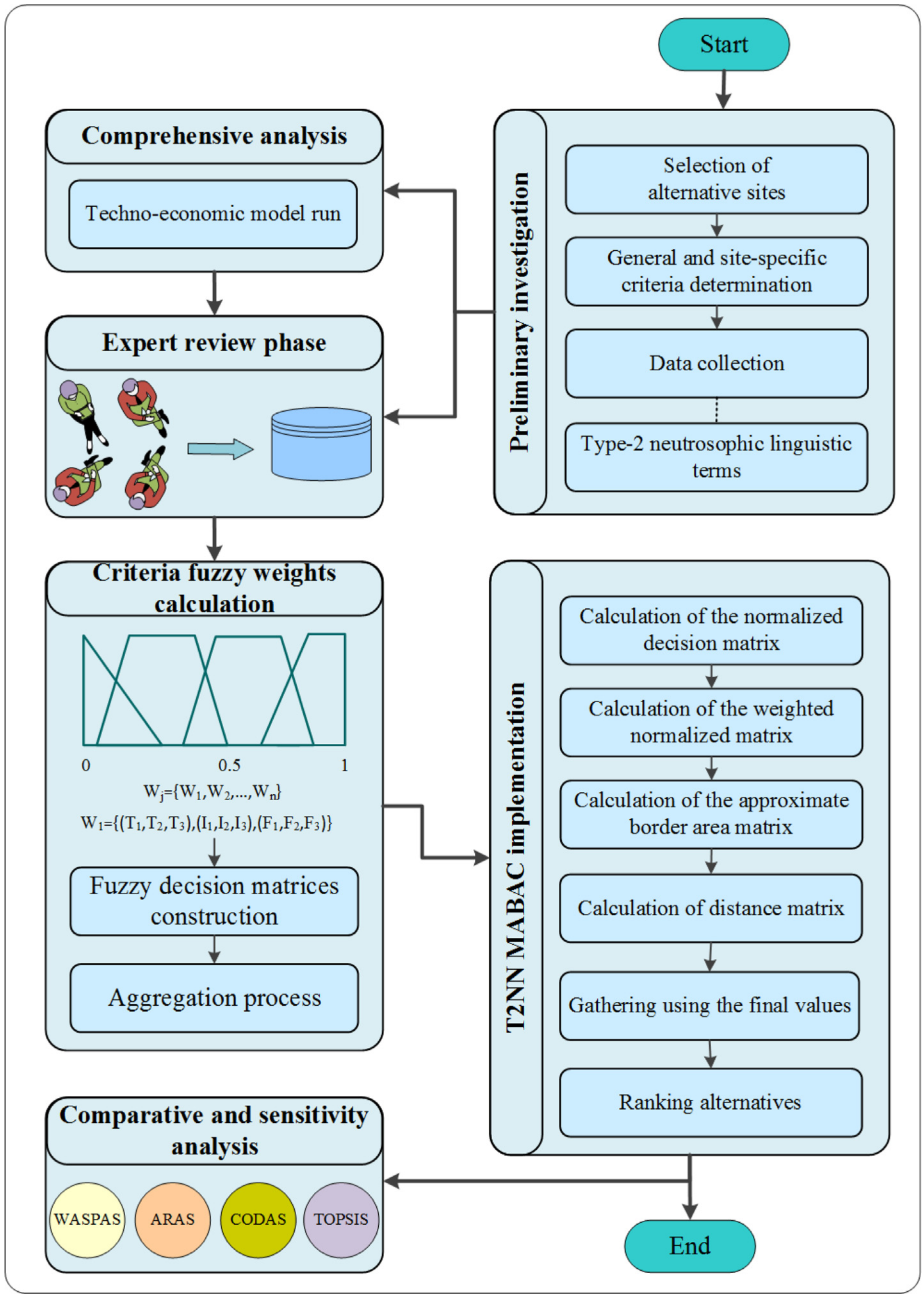

Fig. 1. Flowchart of proposed approach.

and Ćirović, 2015). T2NNs are, on the other hand, an effective tool to better address expert assessments with ambiguities and inconsistencies with a decision makers' appreciation over the alternative. To the best of the authors' knowledge, MABAC has not been combined with the type-2 neutrosophic number. This paper intends to synergize the advantages of neutrosophic number sets with the flexibility and ease of MABAC. Due to the uncertain and imprecise data used for the OWF site selection, this study employs the neutrosophic sets, which specialize in processing unclear, unpredictable, and indeterminate information, as they have proven to be an efficient tool for handling impreciseness or incompleteness in expert judgement (Abdel-Basset et al., 2019). Thus, this study will be the first attempt to implement the MABAC with type 2 neutrosophic fuzzy numbers to the OWF site selection problem.

3. Methodology

3.1. Approach

The proposed T2NN based MABAC approach follows four consecutive steps as shown in Fig. 1:

(1) Preliminary investigation: The objectives for site selection are defined, including the selection of alternatives and the determination of general and site-specific criteria. Type-2 neutrosophic linguistic terms are used to represent the judgement of experts. Data is collected for each alternative.

(2) Comprehensive analysis & expert review: A techno-economic model is run with data specific to each site. Individual expert evaluations are then augmented with the outputs of the techno-economic model.

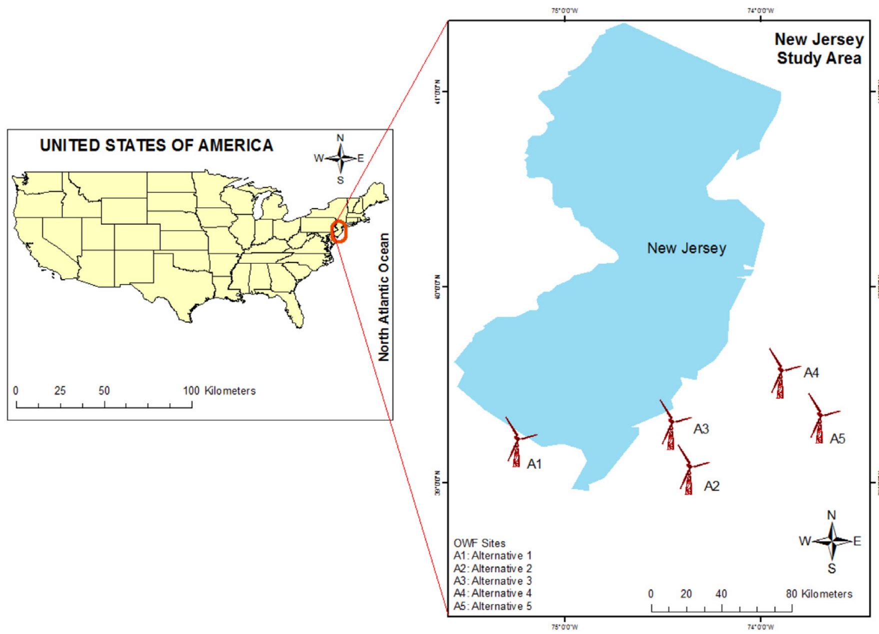

Fig. 2. The study area in NJ offshore waters.

(3) Criteria fuzzy weights calculation: Criteria weights are calculated using type-2 neutrosophic fuzzy scores and fuzzy decision matrices are created and aggregated.

(4) T2NN MABAC implementation: A T2NN based MABAC is conducted to rank alternatives.

3.2. Site description and alternatives

The study area stretches approximately from Egg Island in the Delaware Bay to Long Beach Island in the North Atlantic Ocean, extending up to 55 km from shore, located between latitudes 39–40°N and longitudes 33–75°W (Fig. 2). The water depth of the area ranges from 15 to 90 ft. This study considers five of the specific OWF proposed sites out of the eleven that are in NJ's offshore wind pipeline. The OWF capacities range from 25 MW to 1100 MW, offering the opportunity to investigate a wide-spectrum of wind farm sizes.

3.3. Determination of decision-making criteria

Based on the features of selected offshore sites, this study specifies 19 evaluation sub-criteria that are qualitatively or quantitatively assessed. These sub-criteria entail technical, economic, and environmental and social aspects which are described as either benefits or costs (Fig. 3). Criteria weighted are not pre-supposed, but the degree of importance for each criterion is evaluated individually by the experts. The expert reviews rely on existing data sources regarding New Jersey's coastal and offshore resources and the economic characteristics calculated via the techno-economic model.

3.3.1. Technical criteria

In addition to quantitative parameters commonly used in OWF site selection, such as wind speed, capacity factor, sea depth, and proximity to grid connection point, this study includes one additional quantitative and two additional qualitative parameters that are not commonly utilized in OWF site selection evaluations. *Offshore wind speed values* and *capacity factor* are gathered from wind speed profiles at 90 m above sea level and derived from the model output in the Wind Integration National Dataset Toolkit (Fig. 4.a) (Caroline et al., 2015). This study uses annual energy production (AEP) as the measure of power production, based on mid-term and long-term wind resource prediction models (Cali, 2011). AEP is calculated using the Virtual Wind Farm model (Cali et al., 2018). A Gamesa G128 5000 wind turbine with a 140 m hub height was selected for use in the AEP calculations. The power losses from electricity transmission are assumed to be 5% while the array efficiency is assumed to be 95% (Kucuksari et al., 2019). *Proximity to grid connection point* affects the cost of electricity transmission, which increases with distance. The 220 kV transmission line at the Atlantic City Electric Sherman Substation is assumed to be the connection point for A1, A2, and A3 while A4 and A5 are assumed to connect to a 500 kV transmission line at the JCPL Smithburg Switching station. *Sea depth* determines the foundation structure (e.g, monopile, jacket, etc.) needed at the site and affects the foundation cost, which is a considerable part of the total capital expenditures (CAPEX) for a OWF (Fig. 4.c). *Wind farm size* and *wind farm extension capability* are assumed to be benefit parameters since the unit cost of OWF installations generally decreases with increasing farm size. The specific values for these parameters used in the quantitative technical evaluation for each potential NJ OWF site are reported in Table 3.

3.3.2. Techno-economical model for economic criteria

An economic model was developed to calculate net present value (NPV), CAPEX, and levelized cost of electricity (LCOE) while accounting for NJ's specific offshore wind financial incentives.

The total cost of OWF is the sum of CAPEX and operational expenditures (OPEX). The CAPEX was derived from the model in Dicorato et al. (2011) as:

$$C_{OWF} = C_{OWT} + C_{OFT} + C_{UC} + C_{BES} + C_{OGI} + C_{OPD} [k\$], \quad (1)$$

where, C_{OWT} and C_{OFT} are the cost of the turbines and the cost of their foundation and tower, respectively. C_{UC} is the underwater electrical cable cost, C_{BES} is the cost of the electrical system installation which includes transformers, switchgear, backup generators, and the offshore substation, C_{OGI} is the cost of electrical transmission integration equipment including power regulation equipment and the SCADA system, and C_{OPD} is the project development cost. The cost for each component, including any required transportation cost, can be expressed by

$$C_{OWF} = 1.1 \times \left(2.95 \times 10^3 \times \ln\left(P_{OWT}\right) - 375.2\right) \times N_{OT} \times X_{eur/usd} [k\$], \quad (2)$$

Table 3
Characteristics of the alternatives for quantitative technical evaluation.

No	Criterion	Unit	Alternative sites				
			A1	A2	A3	A4	A5
C1	Mean offshore wind speed at 90 m	m/s	7.75–8.0	8.25–8.5	8.25–8.5	8.75–9.0	8.75–9.0
C2	Net Annual energy production per turbine	MWh	14,981.7	17,116.3	16,562.9	17,432.5	17,946.4
C3	Capacity factor	%	38	43	42	44	45
C4	Sea depth	feet	10–20	50–60	10–20	60–70	80-90
C5	Proximity to grid connection point	km	33	72	54	80	112
C6	Offshore wind farm size	MW	381.6	350	25	350	1,100

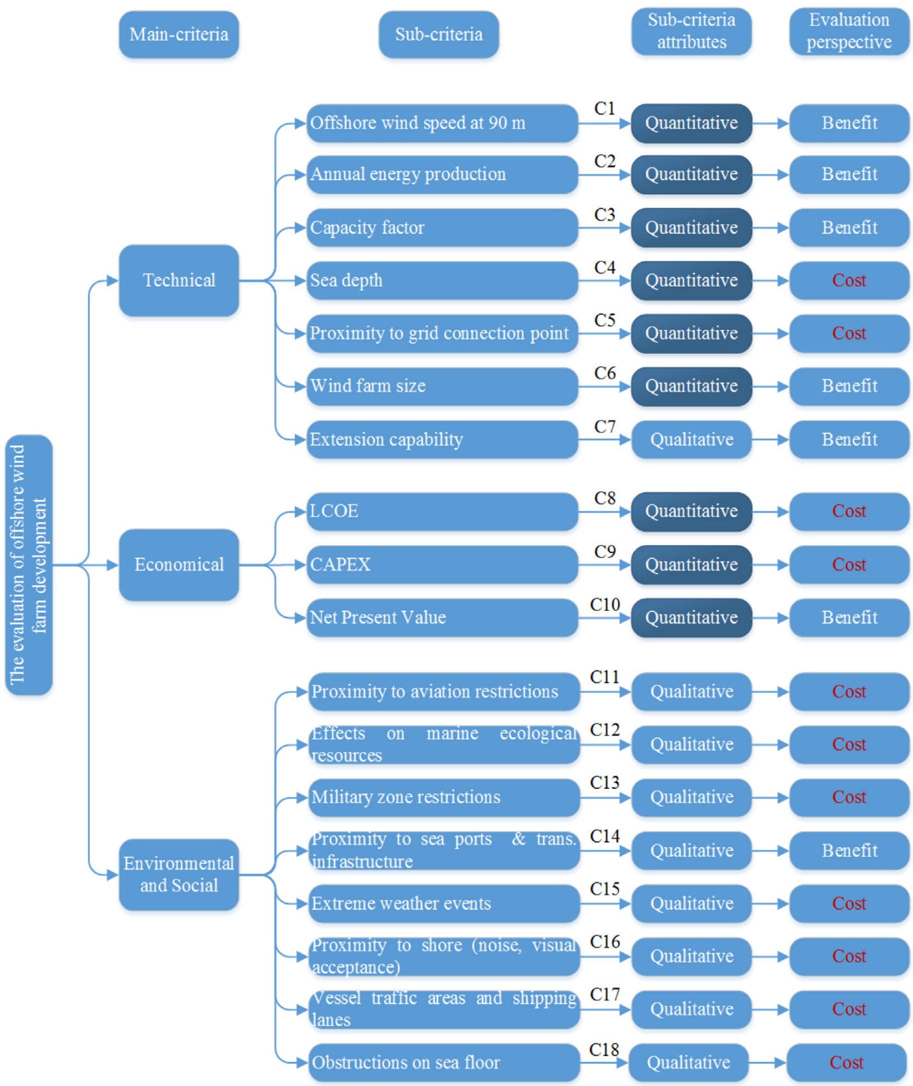

Fig. 3. Evaluation criteria, their attributes, and perspectives.

$$C_{OFT} = 1.5\times \left(320 \times P_{OWT} \times \left(1 + 0.02 * (D_s - 8)\right)\times \left(1 + 0.8 \times 10^{-6} \times \left(H_H \times \frac{D_R}{2}\right)^2 - 10^5\right) \right) \times N_{OT} \times X_{eur/usd} [k\$], \quad (3)$$

$$C_{UC} = \left((0.4818 \times D_{EC} + 99.153) \times L_{EC} + (365 \times L_{EC})\right) \times X_{eur/usd} [k\$], \quad (4)$$

$$C_{BES} = \left((42.69 \times P_T^{0.7513}) + \left((40.453 + 0.76 \times V_{SG}) \times N_{SG} + (21.242 + 2.069) \times N_{OT} \times N_{OWT} + (2534 + 88.7) \times N_{OT} \times N_{OWT} \right)\right) \times N_{OT} \times X_{eur/usd} [k\$], \quad (5)$$

$$C_{OGI} = 1.1 \times \left(\left(\frac{2}{3} \times (42.688 \times P_T^{0.7513})\right) + (75 \times N_{0T})\right) \times X_{eur/usd} [k\$], \quad (6)$$

$$C_{OPD} = 46.8 \times P_{0WT} \times N_{0T} \times X_{eur/usd} [k\$], \quad (7)$$

where, P_{0WT} is the individual turbine power capacity, N_{OT} is the number of turbines in the plant, $X_{eur/usd}$ is the exchange rate of the euro to U.S. dollar, $D_S(m)$ is sea depth, $H_H(m)$ is hub height, $D_R(m)$ is rotor diameter, $D_{EC}(mm)$ is the diameter of the electrical cable, $L_{EC}(km)$ is the underwater electrical cable length, $P_T(MVA)$ is the transformer's rated power output, $V_{SG}(kV)$ is the switchgear voltage, and N_{SG} is the number of switchgear. Note that a value of 1.31 is used for $X_{eur/usd}$ as in Dicorato et al. (2011) as it is assumed that CAPEX has fluctuated proportionally with exchange rates.

OPEX was assumed to be a fixed value, per kW, that is identical to those for New York found in Saraswati et al. (2017). The Surface Effect Ship methodology was selected to minimize OPEX and maintain greater than 95% equipment reliability.

The state of NJ is currently providing offshore wind renewable energy credits (ORECs). These ORECs are given via an auction process

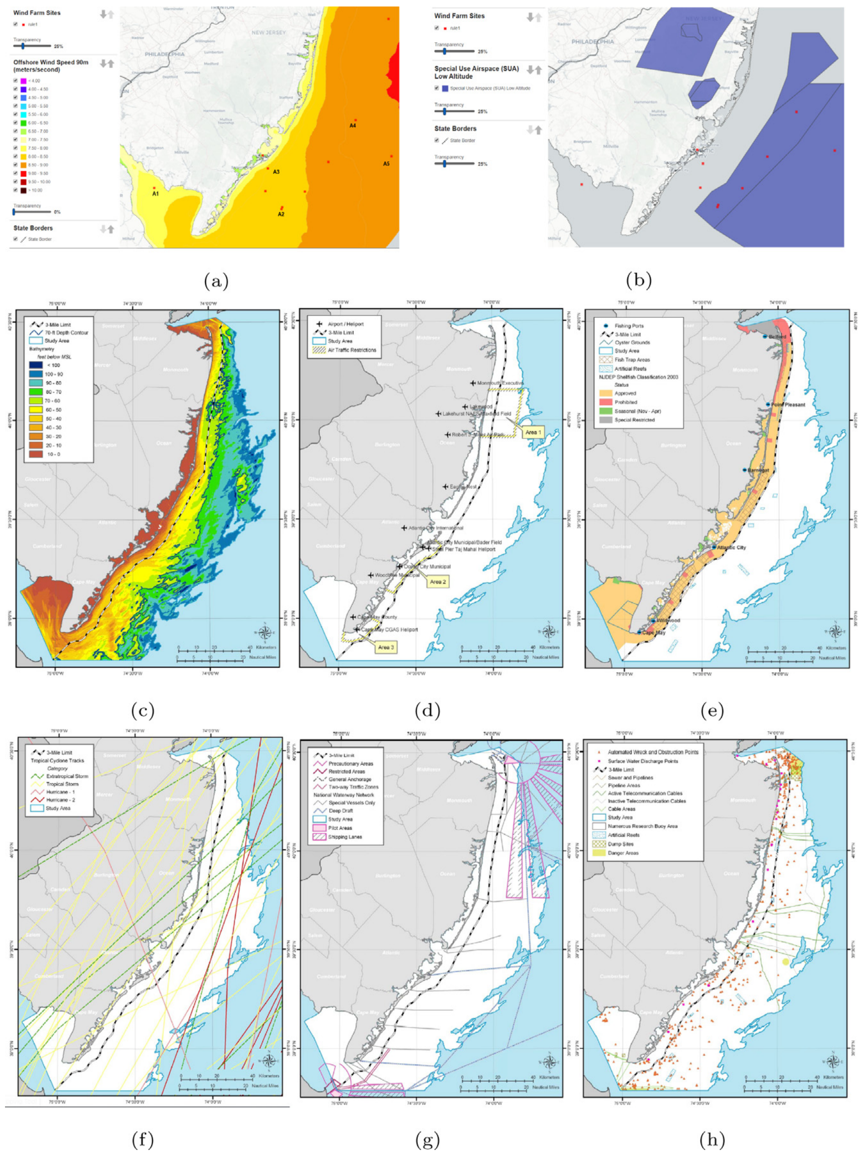

Fig. 4. Maps for evaluation criteria, (a) offshore wind speed*, (b) military zone restrictions*, (c) sea depth, (d) aviation restrictions, (e) fishing areas, (f) extreme weather events, (g) vessel and shipping lanes, (h) obstruction areas. * Maps are adopted from NREL's wind prospector (Caroline et al., 2015). The rest of maps are taken from Neil et al. (2004).

that requires bids be submitted using the required revenue model to calculate project LCOE. The lowest bid(s) wins ORECs equal in value to the LCOE given in the bid, but the project must reimburse NJ for any revenue received from power sales into the wholesale electricity market (State of New Jersey Board of Public Utilities, 2018). Therefore, the gross revenue, R_{gross}, to the project can be defined as

$$R_{gross} = E \times (P_{OREC} + P_{WM}), \tag{8}$$

where, E, P_{OREC}, and P_{WM} stand for the electricity generated, the OREC price, and the electricity price on the wholesale market, respectively. Net revenue, R_{net}, must account for reimbursement of wholesale market proceeds to NJ and is given by

$$R_{net} = R_{gross} - E \times P_{WM} = E \times P_{OREC}. \tag{9}$$

The financial assumptions for the base case are summarized in Table 4. It was also assumed that the project would not qualify for the U.S. production tax credit.

The $LCOE$ calculation methodology employed was the required revenue model, as specified by the NJ auction process (Short et al., 1995). $LCOE$ is expressed by Cali et al. (2018):

$$LCOE = \frac{\sum_{n=0}^{L} \frac{C_A}{(1+r_N)^n}}{\sum_{n=1}^{L} \frac{AEP}{(1+r_D)^n}}, \tag{10}$$

Table 4
Financial assumptions for the case of NJ state.

Item	Value
Project Life	25 years
Debt Fraction	0.55
Loan Period	7 years
Cost of Debt	0.06
Cost of Equity	0.09
Inflation	0.025
Property Tax Rate	3.85% [20]
Insurance Rate	0.01
Property Tax and Insurance Rate Escalation	1%/year
Federal Income Tax Rate	0.21
State Income Tax Rate	9% [19]
City/Local Tax Rate	0
Depreciation Schedule	5-year MACRS

Table 5
Estimated values of economical criteria.

No	Criteria	Unit	Alternative sites				
			A1	A2	A3	A4	A5
C8	LCOE	$/MWh	124.95	128.63	155.72	127.65	126.25
C9	CAPEX per MW	$	2,593,427.45	2,875,373.71	3,537,542.50	2,916,769.56	2,987,696.68
C10	Net present value	$	96,256,876.75	106,721,509.80	9,378,454.89	108,257,945.95	348,512,860.69

where C_A is total project costs, including $OPEX$ and financing; r_N is the nominal cost of debt, and L is the OWF lifetime. r_D is the nominal cost of debt if calculating the nominal $LCOE$ or the real cost of debt if calculating a real $LCOE$. NPV is calculated by Cali et al. (2018)

$$NPV = \sum_{n=0}^{N} \frac{C_n}{(1+r_N)^n}, \tag{11}$$

where C_n is the cash flow in year n and N is the economic lifetime of the plant, which is assumed to be the same as the OWF lifetime in this study. The economic results for each potential OWF site are given in Table 5.

3.3.3. Environmental and social criteria

This study included 8 qualitative criteria to address site-specific environmental and social considerations that are essential for an OWF development to meet associated regulations. While expert evaluation on these criteria is inherently subjective, to provide some objective context expert judgement was supported with data describing NJ's offshore areas (Neil et al., 2004). As the navigable airspace around an OWF is affected by the height and rotor diameter of the wind turbine and, due to the fact there are several public and military air facilities in proximity to the NJ coast, *proximity to aviation restrictions* and *military zone restrictions* are considered to be a cost parameter in the model (Fig. 4.b and d). The NJ coasts are on the migratory route of marine mammals and birds and are rich in fishery resources and sea turtles. Therefore, *effects of marine ecological resources* are included to account for ecological impact issues that must be considered by marine biologists (Fig. 4.e). *Proximity to seaports & infrastructure* is considered a benefit parameter that has a bearing on OWF installation costs and schedules. *Extreme weather events* are included to provide a scope for potential cost increases due to increased loading on turbines and foundations (Fig. 4.f). *Proximity to shore* accounts for visual and noise impact, both of which are concerns that residents and tourists may have with offshore wind turbines. NJ offshore waters are high sea traffic areas due to the proximity to New York City, which calls for the inclusion of *vessel and shipping lanes* (Fig. 4.g). Several *obstructions areas* on the sea floor, such as fishing areas, marine cable routes, and sand barrow areas, can also be found in NJ offshore waters (Fig. 4.h) and affect the siting of offshore wind turbines.

4. Development of multi-criteria decision-making models

4.1. Preliminaries

4.1.1. Type-1 neutrosophic set

Neutrosophic sets are a generalization of Inconsistent Intuitionistic Fuzzy Set which is equivalent to the Picture Fuzzy Set, Pythagorean Fuzzy Set, Spherical Fuzzy Set, and q-Rung Orthopair Fuzzy Set. Moreover, all these sets are more general than Intuitionistic Fuzzy Set (IFS) (Smarandache, 2019). IFS can handle incomplete information, but not indeterminate information and inconsistent information in fuzzy systems (Smarandache, 1998). A neutrosophic set can be characterized by three membership functions. Those are a truth membership function 'T', an indeterminacy membership function 'I', and a falsity membership function 'F' (Kahraman and Otay, 2019), where the new parameter "indeterminacy" was incorporated into the IFS definition (Smarandache, 1999).

Definition 1 (*Pawlak, 1982*)**.** Let $\breve{X}$ be an initial universe of discourse, with a generic element in $\breve{X}$ denoted by $\breve{x}$. The neutrosophic set is an object having the form

$$\breve{A} = \left\{ \langle \breve{x} : \alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x}), \gamma_{\breve{A}}(\breve{x}) \rangle | \breve{x} \in \breve{X} \right\}, \tag{12}$$

where, the functions $\alpha, \beta, \gamma : \breve{X} \to \;]^{-}0, 1^{+}[$ define, respectively, the degree of membership (or Truth), the degree of indeterminacy, and the degree of non-membership (or Falsehood) of the element $\breve{x} \in \breve{X}$ to the set $\breve{A}$ with the condition $0^{-} \le \alpha_{\breve{A}}(\breve{x}) + \beta_{\breve{A}}(\breve{x}) + \gamma_{\breve{A}}(\breve{x}) \le 3^{+}$. There is no restriction on the sum of $\alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x})$, and $\gamma_{\breve{A}}(\breve{x})$.

4.1.2. Type-2 neutrosophic set

T2NN set represents an expansion of single-valued neutrosophic sets using triangular fuzzy numbers. First, some basic concepts and operators of T2NN set are introduced.

Definition 2 (*Abdel-Basset et al., 2019*)**.** A T2NN set $\breve{A}$ in $\breve{X}$ is defined by:

$$\breve{A} = \left\{ \left\langle \breve{x}, \alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x}), \gamma_{\breve{A}}(\breve{x}) \right\rangle \middle| \breve{x} \in \breve{X} \right\}, \tag{13}$$

where $\alpha_{\breve{A}}(\breve{x}) : \breve{X} \to \alpha[0,1]$, $\beta_{\breve{A}}(\breve{x}) : \breve{X} \to \beta[0,1]$, and $\gamma_{\breve{A}}(\breve{x}) : \breve{X} \to \gamma[0,1]$. The elements of the T2NN set can be expressed as $\alpha_{\breve{A}}(\breve{x}) = \left(\alpha_{\alpha_{\breve{A}}}(\breve{x}), \alpha_{\beta_{\breve{A}}}(\breve{x}), \alpha_{\gamma_{\breve{A}}}(\breve{x})\right)$, $\beta_{\breve{A}}(\breve{x}) = \left(\beta_{\alpha_{\breve{A}}}(\breve{x}), \beta_{\beta_{\breve{A}}}(\breve{x}), \beta_{\gamma_{\breve{A}}}(\breve{x})\right)$, and $\gamma_{\breve{A}}(\breve{x}) = \left(\gamma_{\alpha_{\breve{A}}}(\breve{x}), \gamma_{\beta_{\breve{A}}}(\breve{x}), \gamma_{\gamma_{\breve{A}}}(\breve{x})\right)$.

$\alpha_{\breve{A}}(\breve{x}) = \left(\alpha^1_{\breve{A}}(\breve{x}), \alpha^2_{\breve{A}}(\breve{x}), \alpha^3_{\breve{A}}(\breve{x})\right)$, $\beta_{\breve{A}}(\breve{x}) = \left(\beta^1_{\breve{A}}(\breve{x}), \beta^2_{\breve{A}}(\breve{x}), \beta^3_{\breve{A}}(\breve{x})\right)$, and $\gamma_{\breve{A}}(\breve{x}) = \left(\gamma^1_{\breve{A}}(\breve{x}), \gamma^2_{\breve{A}}(\breve{x}), \gamma^3_{\breve{A}}(\breve{x})\right)$, where $\alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x})$ and $\gamma_{\breve{A}}(\breve{x})$ are $\breve{X} \to [0,1]$. For every $\breve{x} \in \breve{X} : 0 \le \alpha^1_{\breve{A}}(\breve{x}) + \beta^1_{\breve{A}}(\breve{x}) + \gamma^1_{\breve{A}}(\breve{x}) \le 3$ are stated.

Definition 3 (*Abdel-Basset et al., 2019*)**.** Let $\breve{A}_1 = \left\langle \left(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}), \alpha_{\beta_{\breve{A}_1}}(\breve{x}), \alpha_{\gamma_{\breve{A}_1}}(\breve{x})\right), \left(\beta_{\alpha_{\breve{A}_1}}(\breve{x}), \beta_{\beta_{\breve{A}_1}}(\breve{x}), \beta_{\gamma_{\breve{A}_1}}(\breve{x})\right), \left(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}), \gamma_{\beta_{\breve{A}_1}}(\breve{x}), \gamma_{\gamma_{\breve{A}_1}}(\breve{x})\right) \right\rangle$ and $\breve{A}_2 = \left\langle \left(\alpha_{\alpha_{\breve{A}_2}}(\breve{x}), \alpha_{\beta_{\breve{A}_2}}(\breve{x}), \alpha_{\gamma_{\breve{A}_2}}(\breve{x})\right), \left(\beta_{\alpha_{\breve{A}_2}}(\breve{x}), \beta_{\beta_{\breve{A}_2}}(\breve{x}), \beta_{\gamma_{\breve{A}_2}}(\breve{x})\right), \left(\gamma_{\alpha_{\breve{A}_2}}(\breve{x}), \gamma_{\beta_{\breve{A}_2}}(\breve{x}), \gamma_{\gamma_{\breve{A}_2}}(\breve{x})\right) \right\rangle$ be T2NNs in the set of real numbers. Some basic math operations for T2NNs can be defined as follow (Biswas et al., 2016; Abdel-Basset et al., 2019):

$$\begin{aligned} \breve{A}_1 \oplus \breve{A}_2 = \Big\langle \Big(& \alpha_{\alpha_{\breve{A}_1}}(\breve{x}) + \alpha_{\alpha_{\breve{A}_2}}(\breve{x}) - \alpha_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\alpha_{\breve{A}_2}}(\breve{x}), \alpha_{\beta_{\breve{A}_1}}(\breve{x}) + \alpha_{\beta_{\breve{A}_2}}(\breve{x}) - \\ & \alpha_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\beta_{\breve{A}_2}}(\breve{x}), \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) + \alpha_{\gamma_{\breve{A}_2}}(\breve{x}) - \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\gamma_{\breve{A}_2}}(\breve{x}) \Big), \\ & \left(\beta_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\alpha_{\breve{A}_2}}(\breve{x}), \beta_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\beta_{\breve{A}_2}}(\breve{x}), \beta_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\gamma_{\breve{A}_2}}(\breve{x}) \right), \\ & \left(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\alpha_{\breve{A}_2}}(\breve{x}), \gamma_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\beta_{\breve{A}_2}}(\breve{x}), \gamma_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\gamma_{\breve{A}_2}}(\breve{x}) \right) \Big\rangle . \end{aligned} \tag{14}$$

$$\begin{aligned} \breve{A}_1 \otimes \breve{A}_2 = \Big\langle \Big(& \left(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\alpha_{\breve{A}_2}}(\breve{x}), \alpha_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\beta_{\breve{A}_2}}(\breve{x}), \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\gamma_{\breve{A}_2}}(\breve{x})\right), \\ & \left(\beta_{\alpha_{\breve{A}_1}}(\breve{x}) + \beta_{\alpha_{\breve{A}_2}}(\breve{x}) - \beta_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\alpha_{\breve{A}_2}}(\breve{x})\right), \\ & \left(\beta_{\beta_{\breve{A}_1}}(\breve{x}) + \beta_{\beta_{\breve{A}_2}}(\breve{x}) - \beta_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\beta_{\breve{A}_2}}(\breve{x})\right), \\ & \left(\beta_{\gamma_{\breve{A}_1}}(\breve{x}) + \beta_{\gamma_{\breve{A}_2}}(\breve{x}) - \beta_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\gamma_{\breve{A}_2}}(\breve{x})\right) \Big), \\ & \Big(\left(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) + \gamma_{\alpha_{\breve{A}_2}}(\breve{x}) - \gamma_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\alpha_{\breve{A}_2}}(\breve{x})\right), \\ & \left(\gamma_{\beta_{\breve{A}_1}}(\breve{x}) + \gamma_{\beta_{\breve{A}_2}}(\breve{x}) - \gamma_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\beta_{\breve{A}_2}}(\breve{x})\right), \\ & \left(\gamma_{\gamma_{\breve{A}_1}}(\breve{x}) + \gamma_{\gamma_{\breve{A}_2}}(\breve{x}) - \gamma_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\gamma_{\breve{A}_2}}(\breve{x})\right) \Big) \Big\rangle . \end{aligned} \tag{15}$$

$$\theta\breve{A} = \Big\langle \Big(1-(1-\alpha_{\alpha_{\breve{A}}}(\breve{x}))^{\theta}, 1-(1-\alpha_{\beta_{\breve{A}}}(\breve{x}))^{\theta}, 1-(1-\alpha_{\gamma_{\breve{A}}}(\breve{x}))^{\theta}\Big), \Big((\beta_{\alpha_{\breve{A}}}(\breve{x}))^{\theta}, (\beta_{\beta_{\breve{A}}}(\breve{x}))^{\theta}, (\beta_{\gamma_{\breve{A}}}(\breve{x}))^{\theta}\Big), \Big((\gamma_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, (\gamma_{\beta_{\breve{A}}}(\breve{x}))^{\theta}, (\gamma_{\gamma_{\breve{A}}}(\breve{x}))^{\theta}\Big)\Big\rangle, \tag{16}$$

where $\theta > 0$.

$$\breve{A}^{\theta} = \Big\langle \Big((\alpha_{\alpha_{\breve{A}}}(\breve{x}))^{\theta}, (\alpha_{\beta_{\breve{A}}}(\breve{x}))^{\theta}, (\alpha_{\gamma_{\breve{A}}}(\breve{x}))^{\theta}\Big), \Big(1-(1-\beta_{\alpha_{\breve{A}}}(\breve{x}))^{\theta}, 1-(1-\beta_{\beta_{\breve{A}}}(\breve{x}))^{\theta}, 1-(1-\beta_{\gamma_{\breve{A}}}(\breve{x}))^{\theta}\Big), \Big(1-(1-\gamma_{\alpha_{\breve{A}}}(\breve{x}))^{\theta}, 1-(1-\gamma_{\beta_{\breve{A}}}(\breve{x}))^{\theta}, 1-(1-\gamma_{\gamma_{\breve{A}}}(\breve{x}))^{\theta}\Big)\Big\rangle, \tag{17}$$

where, $\theta > 0$.

Definition 4 (*Abdel-Basset et al., 2019*)**.** The score function of $\breve{A}_1$, $S(\breve{A}_1)$, is described by:

$$S(\breve{A}_1) = \frac{1}{12}\Big\langle 8 + \Big(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\alpha_{\beta_{\breve{A}_1}}(\breve{x})\Big) + \alpha_{\gamma_{\breve{A}_1}}(\breve{x})\Big) - \Big(\beta_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\beta_{\beta_{\breve{A}_1}}(\breve{x})\Big) + \beta_{\gamma_{\breve{A}_1}}(\breve{x})\Big) - \Big(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\gamma_{\beta_{\breve{A}_1}}(\breve{x})\Big) + \gamma_{\gamma_{\breve{A}_1}}(\breve{x})\Big)\Big\rangle. \tag{18}$$

Definition 5 (*Abdel-Basset et al., 2019*)**.** The accuracy function of $\breve{A}_1$, $A(\breve{A}_1)$, is expressed by:

$$A(\breve{A}_1) = \frac{1}{4}\Big\langle\Big(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\alpha_{\beta_{\breve{A}_1}}(\breve{x})\Big) + \alpha_{\gamma_{\breve{A}_1}}(\breve{x})\Big) - \Big(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\gamma_{\beta_{\breve{A}_1}}(\breve{x})\Big) + \gamma_{\gamma_{\breve{A}_1}}(\breve{x})\Big)\Big\rangle. \tag{19}$$

Definition 6 (*Abdel-Basset et al., 2019*)**.** Let $S(\breve{A}_i)$ and $A(\breve{A}_i)$ denote the score and accuracy functions for the T2NNs $\breve{A}_i (i = 1, 2)$, respectively. The following relations can be written:

1. If $S(\breve{A}_1) > S(\breve{A}_2)$, then $\breve{A}_1 > \breve{A}_2$,
2. If $S(\breve{A}_1) = S(\breve{A}_2)$ and $A(\breve{A}_1) > A(\breve{A}_2)$, then $\breve{A}_1 > \breve{A}_2$,
3. If $S(\breve{A}_1) = S(\breve{A}_2)$ and $A(\breve{A}_1) = A(\breve{A}_2)$, then $\breve{A}_1 = \breve{A}_2$.

Definition 7 (*Ruipu and Wende, 2017*)**.** Let $\breve{A}_1 = \Big((\alpha_1, \alpha_2, \alpha_3), (\beta_1, \beta_2, \beta_3), (\gamma_1, \gamma_2, \gamma_3)\Big)$ and $\breve{A}_2 = \Big((T_1, T_2, T_3), (I_1, I_2, I_3), (F_1, F_2, F_3)\Big)$ be T2NNs. The distance measure $d(\breve{A}_1, \breve{A}_2)$ between $\breve{A}_1$ and $\breve{A}_2$ can be defined as :

$$d(\breve{A}_1, \breve{A}_2) = 1 - \frac{\sum_{i=1}^{3}\alpha_i T_i + \sum_{i=1}^{3}\beta_i I_i + \sum_{i=1}^{3}\gamma_i F_i}{\Big(\sum_{i=1}^{3}(\alpha_i)^2 + \sum_{i=1}^{3}(\beta_i)^2 + \sum_{i=1}^{3}(\gamma_i)^2\Big) \times \Big(\sum_{i=1}^{3}(T_i)^2 + \sum_{i=1}^{3}(I_i)^2 + \sum_{i=1}^{3}(F_i)^2\Big)}. \tag{20}$$

4.2. MABAC method

The MABAC method is used to address uncertain and complex decision-making issues by calculating the distance between each alternative and the border approximation area (Dragan et al., 2018a). The steps of implementing the fuzzy MABAC method are as follows:

Step 1: Construct the fuzzy decision matrix $\breve{X} = (\breve{x}_{ij})_{m\times n}$. $\breve{x}_{ij}$ is the evaluation value of the alternatives a_i $(i = 1, 2, \dots, m)$ with respect to the criteria $s_j (j = 1, 2, \dots, n)$,

$$\tilde{X} = (\breve{x}_{ij})_{m\times n} = \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_n \end{array}\begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_m \end{array} \\ \begin{pmatrix} \breve{x}_{11} & \breve{x}_{12} & \cdots & \breve{x}_{1n} \\ \breve{x}_{21} & \breve{x}_{22} & \cdots & \breve{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \breve{x}_{1m} & \breve{x}_{2m} & \cdots & \breve{x}_{mn} \end{pmatrix} \end{array}, \tag{21}$$

where m and n indicate the number of alternatives and criteria, respectively.

Step 2: Normalization of the elements of the decision matrix $\breve{X} = (\breve{x}_{ij})_{m\times n}$ into $\breve{R} = (\breve{r}_{ij})_{m\times n}$. Normalization values for the *benefit* and the *cost* criteria are calculated by (22) and (23), respectively.

$$\breve{r}_{ij} = \frac{\breve{x}_{ij} - \breve{x}_i^-}{\breve{x}_i^+ - \breve{x}_i^-}, \tag{22}$$

$$\breve{r}_{ij} = \frac{\breve{x}_{ij} - \breve{x}_i^+}{\breve{x}_i^- - \breve{x}_i^+}, \tag{23}$$

where $\breve{x}_i^+ = \max(\breve{x}_{ij})$ and $\breve{x}_i^- = \min(\breve{x}_{ij})$ are benefit and cost criteria which represent maximum or minimum values of the observed criteria for alternatives, respectively. $\breve{r}_{ij}$ are the normalized values which are obtained from $\breve{x}_{ij}$.

Step 3: Calculate the weighted normalized matrix $V = (\breve{v}_{ij})_{m\times n}$ using $\breve{W} = \breve{w}_1, \breve{w}_2, \dots, \breve{w}_n$ of the criteria $s_j (j = 1, 2, \dots, n)$ as follows:

$$V = \breve{v}_{ij} = w_j \times \breve{r}_{ij} \Longrightarrow \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_n \end{array}\begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_m \end{array} \\ \begin{pmatrix} \breve{v}_{11} & \breve{v}_{12} & \cdots & \breve{v}_{1n} \\ \breve{v}_{21} & \breve{v}_{22} & \cdots & \breve{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \breve{v}_{1m} & \breve{v}_{2m} & \cdots & \breve{v}_{mn} \end{pmatrix} \end{array}, \tag{24}$$

where w_j represents the weight of each criterion.

Step 4: Calculate the approximate border area matrix B. The border approximate area (BAA) for each criterion is obtained by:

$$b_j = \left(\prod_{i=1}^{m} \breve{v}_{ij}\right)^{1/m}, \tag{25}$$

where b_j and m represent BAA for the criterion C_j and the total number of alternatives, respectively. The B can be also expressed in form $(1\times n)$ as follows:

$$B = \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_m \end{array} \\ \begin{pmatrix} b_1 & b_2 & \cdots & b_n \end{pmatrix} \end{array} \tag{26}$$

Step 5: Calculate the distance matrix $\Delta = (\partial_{ij})_{m\times n}$. The distances of each alternative from the BAA are calculated by:

$$\Delta = V - B \Longrightarrow \begin{bmatrix} \breve{v}_{11} - b_1 & \breve{v}_{12} - b_2 & \dots & \breve{v}_{1n} - b_n \\ \breve{v}_{21} - b_1 & \breve{v}_{22} - b_2 & \dots & \breve{v}_{2n} - b_1 \\ \vdots & \vdots & \ddots & \vdots \\ \breve{v}_{m1} - b_1 & \breve{v}_{m2} - b_2 & \cdots & \breve{v}_{mn} - b_n \end{bmatrix}. \tag{27}$$

The alternative A_i can belong to the upper approximate area (B^+), lower approximate area (B^-), or BAA (B), $\forall i \in \{B \vee B^+ \vee B^-\}$ as shown in Fig. 5. B^+ is an area in which the ideal alternative is found to be (A^+), while B^- is an area in which the anti-ideal alternative is found to be (A^-). Whether the alternative (A_i) belongs to the approximate area $(B^+, B$ or $B^-)$ is determined by:

$$A_i \in \begin{cases} B^+ & \text{if } \partial_{ij} > 0 \\ B & \text{if } \partial_{ij} = 0 \\ B^- & \text{if } \partial_{ij} < 0. \end{cases} \tag{28}$$

Step 6: Gather the final values of the criteria function and rank the alternatives. ω_i is the overall values of each alternative, which can be expressed by:

$$\omega_i = \sum_{i=1}^{m} \partial_{ij}, \quad \text{i=1, 2, \dots, m and j=1, 2, \dots, n} \tag{29}$$

After the summation the normalization process (Θ_i) is applied using the following equation:

$$\Theta_i = \frac{\omega_i}{\sum_{i=1}^{m}\omega_i} \tag{30}$$

Finally, the alternatives are ranked from highest to lowest according to their (Θ_i) values.

4.3. WASPAS method

The WASPAS method was introduced to solve multi-criteria decision-making problems in 2012 (Zavadskas et al., 2012). The steps of the WASPAS method are summarized below (Keshavarz et al., 2016):

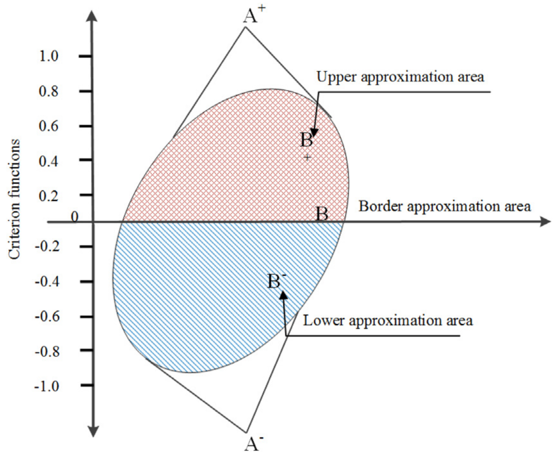

Fig. 5. The border approximation area.

Step 1: Linear normalization of performance values are obtained by:

$$\check{r}_{ij} = \begin{cases} \frac{\check{x}_{ij}}{max_i \check{x}_{ij}} & \forall i \quad \text{if } j \in Benefit \\ \frac{min_i \check{x}_{ij}}{\check{x}_{ij}} & \forall i \quad \text{if } j \in Cost, \end{cases} \tag{31}$$

Step 2: The measures of weighted sum (Π_i^1) and weighted product (Π_i^2) for each alternative are defined as follows:

$$\Pi_i^1 = \sum_{j=1}^{m} \check{w}_j \check{r}_{ij}, \tag{32}$$

and

$$\Pi_i^2 = \prod_{j=1}^{m} (\check{r}_{ij})^{\check{w}_j}. \tag{33}$$

Step 3: The aggregated measure is found by:

$$\Pi_i = \eta_{i.} \Pi_i^1 + (\eta_{i'.}) \Pi_i^2, \tag{34}$$

where the parameter of the WASPAS method is defined as η, which is the set of numbers between 0 and 1. If $\eta = 1$, the WASPAS method is transformed into WS, whereas $\eta = 0$ leads to WP.

Step 4: The alternatives are ranked in decreasing order according to the values of Π_i.

4.4. ARAS method

The ARAS method was proposed by Zavadskas and Turskis (2010) and is designed to solve complex problems, including MCDM. The steps of the ARAS method are summarized below:

Step 1: Normalize the decision matrix.

$$\check{r}_{ij} = \begin{cases} \frac{\check{x}_{ij}}{max_i \check{x}_{ij}} & \forall i \quad \text{if } j \in Benefit \\ \frac{min_i \check{x}_{ij}}{\check{x}_{ij}} & \forall i \quad \text{if } j \in Cost \end{cases} \tag{35}$$

Step 2: Obtain the weighted normalized matrix.

$$V = \check{v}_{ij} = \check{w}_j \times \check{r}_{ij} \tag{36}$$

where $\check{w}_j$ is the weight of the jth criterion and $\check{v}_{ij}$ is the weighted normalized decision matrix.

Step 3: Calculate the values of the optimality function.

$$O_i = \sum_{j=1}^{n} \check{v}_{ij} \tag{37}$$

where O_i represents the overall performance rating of the ith alternative.

Step 4: Calculate the utility degree (Y_i) of the alternative.

$$Y_i = \frac{O_i}{O_0} \tag{38}$$

Step 5: The alternatives are ranked in ascending order using Y_i values.

4.5. CODAS method

The CODAS method developed by Keshavarz Ghorabaee et al. (2016) uses Euclidean and Hamming distances from the negative-ideal point to calculate the overall performance of alternatives (Peng and Garg, 2018). The steps of CODAS method are summarized below:

Step 1: Obtain the normalized decision matrix.

$$\check{X} = [\check{x}_{ij}]_{nxm} \quad \text{and} \quad \check{r}_{ij} = \begin{cases} \frac{\check{x}_{ij}}{max_i \check{x}_{ij}} & \forall i \quad \text{if } j \in Benefit \\ 1 - \frac{\check{x}_{ij}}{max_i \check{x}_{ij}} & \forall i \quad \text{if } j \in Cost \end{cases} \tag{39}$$

Step 2: Determine the weighted normalized decision matrix.

$$V = [\check{v}_{ij}]_{nxm} \quad \text{and} \quad \check{v}_{ij} = \check{w}_j \times \check{r}_{ij} \tag{40}$$

Step 3: Calculate the negative-ideal solution.

$$NG = [ng_j]_{1xm} \quad \text{and} \quad ng_j = min\{\check{v}_{ij}\} \tag{41}$$

where ng_j represents the negative-ideal solution.

Step 4: Calculate Euclidean (ϕ_i^*) and Hamming distances (ϕ_i^-).

$$\phi_i^* = \sqrt{\frac{1}{2}\sum_{j=1}^{n}(ng_{ij} - ng_j^*)^2} \quad \text{and} \quad \phi_i^- = |\frac{1}{2}\sum_{j=1}^{n}(ng_{ij} - ng_j^-)^2| \tag{42}$$

Step 5. Calculate the relative assessment matrix (Ω).

$$\Omega = [\varsigma_{is}]_{m \times m} \quad \text{and} \quad \varsigma_{is} = (\phi_i^* - \phi_s^*) + (\xi(\phi_i^* - \phi_s^*) \times (\phi_i^- - \phi_s^-)) \tag{43}$$

where $s \in \{i = 1, 2, \ldots, m\}$ and ξ is a threshold function that can be defined as follows:

$$\xi(x) = \begin{cases} 1 & \text{if } |x| \geq \delta \\ 0 & \text{if } |x| < \delta \end{cases} \tag{44}$$

where δ denotes the threshold parameter of the ξ function, which can be set by the decision makers.

Step 6. Obtain the overall score (Λ_i) for each alternative.

$$\Lambda_i = \sum_{s=1}^{m} \varsigma_{is} \tag{45}$$

Step 7. The alternatives are ranked according to the decreasing order of the overall scores Λ_i.

5. Experimental results and discussions

Each criterion and alternative OWF site were evaluated by a set of independent decision makers (DMs). The importance degree of each criterion was evaluated independently using the linguistic terms given in Table A.1. Then, the alternative OWF sites were evaluated with respect to each criterion using the linguistic terms in Table A.2. The linguistic evaluations of the criteria and the evaluation ratings for each alternative are reported in Table A.3 and Table A.4, respectively.

5.1. Results of the T2NN based MABAC approach

Step 1. The fuzzy decision matrix was first constructed using the values in Table A.1. The aggregated fuzzy weights of the eighteen criteria were calculated using Eqs. (14), (20), and (21). The normalized weights of each criterion calculated are provided in Table 6. For example, the evaluations of the C_2 criterion for four potential decision makers are defined as H, VH, VH, and M. The corresponding type-2 neutrosophic numbers are given in Table A1. These neutrosophic

Table 6
The normalized criteria weights.

Criteria	$\alpha_{\tilde{A}}(\tilde{x})$			$\beta_{\tilde{A}}(\tilde{x})$			$\gamma_{\tilde{A}}(\tilde{x})$			Score value	Normalized value
	$\alpha_{\tilde{A}}(\tilde{x})$	$\beta_{\tilde{A}}(\tilde{x})$	$\gamma_{\tilde{A}}(\tilde{x})$	$\alpha_{\tilde{A}}(\tilde{x})$	$\beta_{\tilde{A}}(\tilde{x})$	$\gamma_{\tilde{A}}(\tilde{x})$	$\alpha_{\tilde{A}}(\tilde{x})$	$\beta_{\tilde{A}}(\tilde{x})$	$\gamma_{\tilde{A}}(\tilde{x})$		
C1	0.736	0.719	0.746	0.000	0.000	0.000	0.000	0.000	0.000	0.910	0.059
C2	0.694	0.675	0.701	0.000	0.000	0.000	0.000	0.000	0.000	0.895	0.058
C3	0.729	0.710	0.737	0.000	0.000	0.000	0.000	0.000	0.000	0.907	0.058
C4	0.694	0.675	0.701	0.000	0.000	0.000	0.000	0.000	0.000	0.895	0.058
C5	0.630	0.627	0.637	0.001	0.001	0.002	0.000	0.000	0.001	0.876	0.056
C6	0.419	0.475	0.454	0.010	0.016	0.033	0.005	0.012	0.008	0.809	0.052
C7	0.323	0.359	0.299	0.016	0.030	0.035	0.008	0.034	0.027	0.760	0.049
C8	0.736	0.719	0.746	0.000	0.000	0.000	0.000	0.000	0.000	0.910	0.059
C9	0.593	0.564	0.533	0.002	0.001	0.005	0.001	0.001	0.002	0.853	0.055
C10	0.678	0.659	0.661	0.000	0.000	0.001	0.000	0.000	0.000	0.888	0.057
C11	0.421	0.432	0.398	0.004	0.010	0.006	0.001	0.004	0.008	0.803	0.052
C12	0.720	0.698	0.714	0.000	0.000	0.000	0.000	0.000	0.000	0.903	0.058
C13	0.561	0.536	0.517	0.001	0.002	0.002	0.000	0.001	0.002	0.845	0.054
C14	0.484	0.527	0.527	0.006	0.010	0.023	0.004	0.006	0.004	0.833	0.054
C15	0.685	0.647	0.673	0.000	0.000	0.000	0.000	0.000	0.000	0.888	0.057
C16	0.532	0.489	0.492	0.002	0.005	0.002	0.001	0.002	0.003	0.832	0.054
C17	0.532	0.489	0.492	0.002	0.005	0.002	0.001	0.002	0.003	0.832	0.054
C18	0.729	0.710	0.737	0.000	0.000	0.000	0.000	0.000	0.000	0.907	0.058

Table 7
The ranking of the alternatives utilizing the proposed model.

Alternatives	Score values	Normalized values	Ranking
A1	0.4174	0.1522	4
A2	0.6617	0.2412	1
A3	0.4154	0.1514	5
A4	0.5975	0.2178	3
A5	0.6512	0.2374	2

numbers were aggregated by Eqs. (14) and (21). The average value of C_2 were found to be: (0.694, 0.675, 0.701), (0,0,0), (0,0,0). The score values were then calculated using Eq. (20) as follows: $(1/12) * (8 + (0.694 + 2 * 0.675 + 0.701) - (0 + 2 * 0 + 0) - (0 + 2 * 0 + 0)) = 0.895$.

The aggregated decision matrix for each alternative is given in Table A.7 using the values in Table A.4 and Eqs. (14), (20), and (21).

Step 2. The fuzzy normalized decision matrix was calculated by Eqs. (22) and (23) and is reported in Table A.5.

Step 3. The weighted normalized decision matrix was calculated by Eq. (24) using Table A.5 and is reported in Table A.6.

Step 4. The approximate border area matrix was found by Eq. (25) using Table A.6.

Step 5. The distance matrix for the alternatives was obtained by Eqs. (27) and (28) using the border approximation values given in Table A.8.

Step 6. The overall values were calculated by Eq. (29) using Table A.8 . These values were normalized by Eq. (30) and are reported in Table 7.

The alternatives were ranked with respect to their normalized values. The final ranking for each alternative is given in Table 7. $A2$ was found to be the most feasible alternative while $A3$ was the least feasible option. Regarding the expert ranking of criteria, the results in Table A.3 reveal that wind speed, LCOE, and obstructions on the sea floor were found to have the highest importance degree while OWF size and extension capability had the lowest importance degree.

If more traditional and simplistic methodologies were utilized to rank the alternatives the results would have differed from what was found. If ranking were based upon mean wind speed and AEP values, as reported in Table 3, the alternative ranking would be $A5 \succ A4 \succ A2 \succ A3 \succ A1$. If LCOE, which is reported in Table 5, were used the ranking would be $A1 \succ A5 \succ A4 \succ A2 \succ A3$. However, the mean wind speed and LCOE values for $A2$, $A4$, and $A5$ are very similar, which makes a decision process based solely upon these metrics both risky and difficult. Therefore, even though the use of these straightforward approaches does provide value into the site selection decision-making process, the inclusion of other technical, economic, environmental, and social aspects into the investigation, as done with the proposed approach, reveals salient features (advantages and disadvantages) that results in a more robust and, ultimately, differing rank order of the OWF site alternatives.

5.2. Comparative analysis

To test and validate the proposed approach, it has been compared with other T2NN based fuzzy MCDM models, including the T2NN based fuzzy TOPSIS (Abdel-Basset et al., 2019). The neutrosophic numbers based fuzzy WASPAS, ARAS, CODAS and TOPSIS approaches were also implemented. The implemented models used the same normalized criteria weights given in Table 6 that are calculated using the same expressions given by Eqs. (14), (20), and (21). The ranking results for each of these methodologies are reported in Table 8.

Each approach found $A2$ to be the best alternative while $A3$ is the less feasible alternative for all approaches. The primary reason for $A3$ being the worst alternative is that it has the highest LCOE and lowest NPV owing to its relatively small proposed OWF capacity. The community/public acceptance criterion also brings down the score of this site, as it is located in the vicinity of marine wildlife and is nearest to land. Moreover, $A3$ also has the lowest size extension capability due to its location. While $A2$, $A5$, and $A4$ have similar techno-economic metrics in terms of wind speed, capacity factor, CAPEX, and LCOE, $A2$ became the most prominent option due to some less prominent technical, environmental, and social aspects. Among the three options, $A2$ has the shallowest sea depth and is closest to a grid connection point, seaports, and transportation infrastructure. $A2$ is also less affected by obstructions on sea floor and proximity to shipping lanes. $A5$ has a significantly larger NPV relative to the alternatives due to it having the largest OWF capacity. However, it is also located furthest from the shore, making it far from a grid connection point and causing the sea depth to be the deepest in this location. Each of these factors increase CAPEX and LCOE values for $A5$. Additionally, the proposed OWF size for $A5$ requires 500 kV transmission lines, which do not currently exist along the NJ coastline. Access to transmission lines with this higher capacity nearer to the coastline would likely make $A5$ become the best alternative.

In general, each of the T2NN based fuzzy models yielded very similar ranking results for each of the alternatives. The only difference found between the methodologies was how the TOPSIS approach ranked $A4$ and $A5$. The main reason for this difference lies in the positive and negative ideal solution characteristics of TOPSIS. However, based on the surveyed decision makers' industrial experience in

Table 8
Comparison of T2NN based fuzzy MCDM approaches.

Models	Alternatives				
	Newport Nearshore (A1)	Garden State (A2)	FERN Blue (A3)	Brigantine (A4)	Pavillion (A5)
M1: T2NN based MABAC	4	1	5	3	2
M2: T2NN based WASPAS	4	1	5	3	2
M3: T2NN based ARAS	4	1	5	3	2
M4: T2NN based CODAS	4	1	5	3	2
M5: T2NN based TOPSIS (Abdel-Basset et al., 2019)	4	1	5	2	3

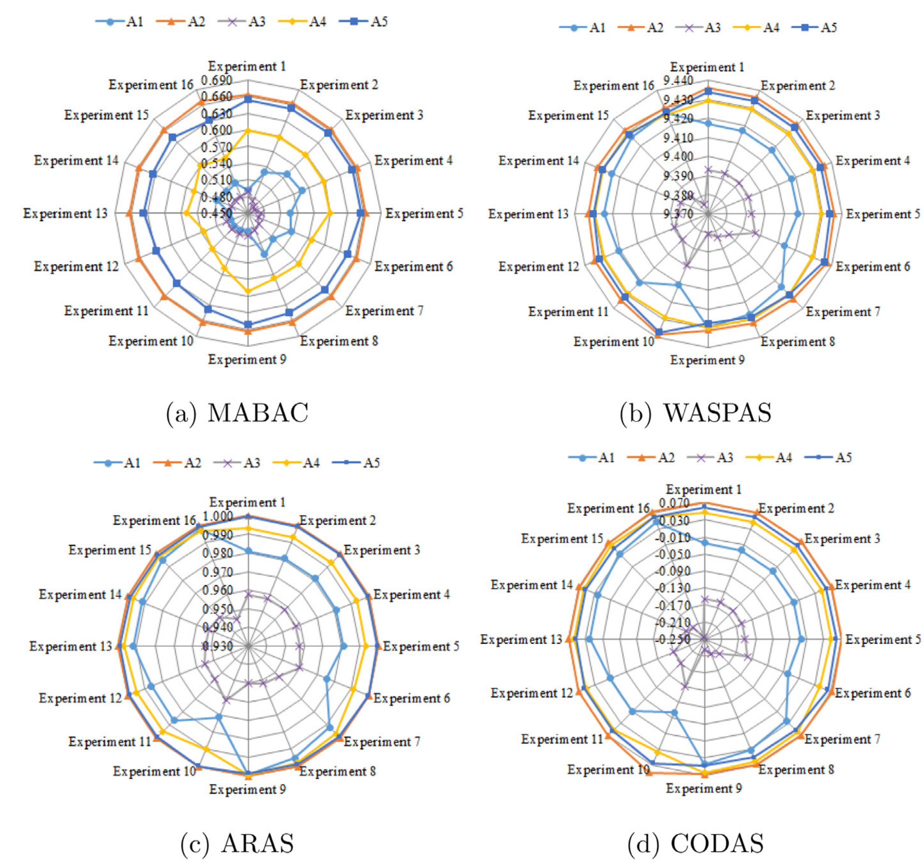

Fig. 6. Sensitivity analysis of four proposed approaches using differing criteria weights.

offshore wind energy, $A5$ should in fact be a better alternative relative to $A4$ thanks to its relatively higher wind resource, resulting in a higher NPV and lower LCOE. Therefore, consistency with the majority of the T2NN based fuzzy models and this additional expert validation serves to verify the reliability of the proposed model.

5.3. Sensitivity analysis

Given there was a range of criteria weightings, a sensitivity analysis was performed for each proposed approach to study the impact of weightings on the ranking. The weightings considered are reported in Table A.9 in the supplementary document. The obtained rankings of alternatives for each experiment are shown in Fig. 6. The sensitivity analysis revealed that varying the weighting of the criteria did not change the ranking order of the alternatives.

5.4. Limitations

Although the proposed MCDM method has provided considerable insights into the decision-making process, there are still some limitations that warrant further study and model enhancement. As some OWF proposals considered are relatively near to each other, more site-specific criteria such as seabed conditions and more specific and detailed marine impacts could be included into the site evaluation to improve decision making. Further, this study considered only one type of turbine. Dependent upon the wind class at each site, several different wind turbine types could be utilized and this should be evaluated.

Additionally, the proposed MCDM approaches could be hybridized with the BWM approach developed in Rezaei (2015) where the best and worst criteria are identified first by decision makers, which could improve the decision making. Finally, the approach could be improved through building the linguistic evaluations of criteria with a pairwise comparison matrix.

6. Conclusion

This study proposed a T2NN based fuzzy MABAC model for an OWF site selection problem. Unlike general qualitative evaluation criteria commonly used in the literature, this study developed a techno-economic model and integrated quantitative outputs into the decision-making process.

Considering multiple technical, economic, environmental, and social criteria, the proposed model was used to evaluate 5 potential OWF sites in NJ. The model chose site $A2$ as the best alternative while $A3$ was found to be the least attractive option. The ranking order for the other alternatives was found to be $A5 > A4 > A1$. The results demonstrate that the inclusion of some technical, economic, environmental, and social parameters into the decision-making process can reveal distinguishing features in alternatives which otherwise have similar techno-economic parameters, as is the case with sites $A2$, $A4$ and $A5$ in this study, which makes the decision process difficult when using more traditional and simplistic decision-making processes. As a result, this approach has identified a different ranking order than the traditional OWF site selection practices. Moreover, the comparison analysis revealed a consistency among the results of the implemented MCDM models. As such, all T2NN based fuzzy models, apart from TOPSIS, yielded the same ranking order with the lone difference stemming from the positive and negative ideal solution characteristics of the TOPSIS approach. However, the decision makers' practical offshore wind experience validated the results of the proposed model given this singular discrepancy with the other MCDM models. Finally, a sensitivity analysis confirmed that changing criteria weightings did not affect the ranking order of the alternatives.

Additionally, this study calculated techno-economic characteristics of potential offshore wind energy investments in NJ as a case study. The LCOE findings were found to be slightly less competitive relative to European counterparts. Future studies of U.S. offshore wind may consider other locations, improvements in the U.S. offshore wind supply chain, and improvements in technology such as novel foundations types and larger turbine sizes that may result in improved CAPEX and OPEX values. Additionally, other states may offer differing support mechanisms from NJ for offshore wind installations, which would affect project LCOE, NPV, and payback period, that warrant further study. Finally, deep sea (>100 m) installations would require changes in technology, to floating foundations, and may present differing logistic, environmental, and social challenges that require further analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.engappai.2021.104311.

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Supplementary Material for Type-2 neutrosophic number based multi-attributive border approximation area comparison approach for offshore wind farm site selection in USA

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1. PRELIMINARIES

A. Type-1 neutrosophic set

The neutrosophic sets are extensions and generalizations of intuitionistic fuzzy sets (IFS). IFS can handle incomplete information, but not indeterminate information and inconsistent information in fuzzy systems [1]. A neutrosophic set can be characterized by three membership functions. Those are a truth membership function 'T', an indeterminacy membership function 'I', and a falsity membership function 'F' [2], where the new parameter "indeterminacy" was incorporated into the IFS definition [3].

Definition 1 [4]. Let $\breve{X}$ be an initial universe of discourse, with a generic element in $\breve{X}$ denoted by $\breve{x}$. The neutrosophic set is an object having the form

$$\breve{A} = \{\langle \breve{x} : \alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x}), \gamma_{\breve{A}}(\breve{x})\rangle | \breve{x} \in \breve{X}\}, \tag{S1}$$

where, the functions $\alpha, \beta, \gamma : \breve{X} \to\ ]^-0, 1^+[$ define, respectively, the degree of membership (or Truth), the degree of indeterminacy, and the degree of non-membership (or Falsehood) of the element $\breve{x} \in \breve{X}$ to the set $\breve{A}$ with the condition $0^- \leq \alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x}), \gamma_{\breve{A}}(\breve{x}) \leq 3^+$.

B. Type-2 Neutrosophic Set

T2NN set represents expansions of single-valued neutrosophic sets using triangular fuzzy numbers. First, some basic concepts and operators of T2NN set are introduced.

Definition 2 [5]. A T2NN set $\breve{A}$ in $\breve{X}$ is defined by:

$$\breve{A} = \left\{\left\langle \breve{x}, \alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x}), \gamma_{\breve{A}}(\breve{x}) \right\rangle \middle| \breve{x} \in \breve{X}\right\}, \tag{S2}$$

where, $\alpha_{\breve{A}}(\breve{x}) : \breve{X} \to \alpha[0,1]$, $\beta_{\breve{A}}(\breve{x}) : \breve{X} \to \beta[0,1]$, and $\gamma_{\breve{A}}(\breve{x}) : \breve{X} \to \gamma[0,1]$. The elements of T2NN set can be expressed as $\alpha_{\breve{A}}(\breve{x}) = \left(\alpha_{\alpha_{\breve{A}}}(\breve{x}), \alpha_{\beta_{\breve{A}}}(\breve{x}), \alpha_{\gamma_{\breve{A}}}(\breve{x})\right)$, $\beta_{\breve{A}}(\breve{x}) = \left(\beta_{\alpha_{\breve{A}}}(\breve{x}), \beta_{\beta_{\breve{A}}}(\breve{x}), \beta_{\gamma_{\breve{A}}}(\breve{x})\right)$, and $\gamma_{\breve{A}}(\breve{x}) = \left(\gamma_{\alpha_{\breve{A}}}(\breve{x}), \gamma_{\beta_{\breve{A}}}(\breve{x}), \gamma_{\gamma_{\breve{A}}}(\breve{x})\right)$.

$\alpha_{\breve{A}}(\breve{x}) = \left(\alpha^1_{\breve{A}}(\breve{x}), \alpha^2_{\breve{A}}(\breve{x}), \alpha^3_{\breve{A}}(\breve{x})\right)$, $\beta_{\breve{A}}(\breve{x}) = \left(\beta^1_{\breve{A}}(\breve{x}), \beta^2_{\breve{A}}(\breve{x}), \beta^3_{\breve{A}}(\breve{x})\right)$, and $\gamma_{\breve{A}}(\breve{x}) = \left(\gamma^1_{\breve{A}}(\breve{x}), \gamma^2_{\breve{A}}(\breve{x}), \gamma^3_{\breve{A}}(\breve{x})\right)$, where $\alpha_{\breve{A}}(\breve{x}), \beta_{\breve{A}}(\breve{x})$ and $\gamma_{\breve{A}}(\breve{x})$ are $\breve{X} \to [0,1]$. For every $\breve{x} \in \breve{X} : 0 \leq \alpha^1_{\breve{A}}(\breve{x}) + \beta^1_{\breve{A}}(\breve{x}) + \gamma^1_{\breve{A}}(\breve{x}) \leq 3$ are stated.

Definition 3 [5]. Let $\breve{A}_1 = \left\langle \left(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}), \alpha_{\beta_{\breve{A}_1}}(\breve{x}), \alpha_{\gamma_{\breve{A}_1}}(\breve{x})\right), \left(\beta_{\alpha_{\breve{A}_1}}(\breve{x}), \beta_{\beta_{\breve{A}_1}}(\breve{x}), \beta_{\gamma_{\breve{A}_1}}(\breve{x})\right), \left(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}), \gamma_{\beta_{\breve{A}_1}}(\breve{x}), \gamma_{\gamma_{\breve{A}_1}}(\breve{x})\right) \right\rangle$ and $\breve{A}_2 = \left\langle \left(\alpha_{\alpha_{\breve{A}_2}}(\breve{x}), \alpha_{\beta_{\breve{A}_2}}(\breve{x}), \alpha_{\gamma_{\breve{A}_2}}(\breve{x})\right), \left(\beta_{\alpha_{\breve{A}_2}}(\breve{x}), \beta_{\beta_{\breve{A}_2}}(\breve{x}), \beta_{\gamma_{\breve{A}_2}}(\breve{x})\right), \left(\gamma_{\alpha_{\breve{A}_2}}(\breve{x}), \gamma_{\beta_{\breve{A}_2}}(\breve{x}), \gamma_{\gamma_{\breve{A}_2}}(\breve{x})\right) \right\rangle$ be

T2NNs in the set of real numbers. Some basic math operations for T2NNs can be defined as follow [5, 6]:

$$\begin{aligned}\breve{A}_1 \oplus \breve{A}_2 = \Big\langle \Big(& \alpha_{\alpha_{\breve{A}_1}}(\breve{x}) + \alpha_{\alpha_{\breve{x}_2}}(\breve{x}) - \alpha_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\alpha_{\breve{A}_2}}(\breve{x}), \alpha_{\beta_{\breve{A}_1}}(\breve{x}) + \alpha_{\beta_{\breve{A}_2}}(\breve{x}) - \\ & \alpha_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\beta_{\breve{A}_2}}(\breve{x}), \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) + \alpha_{\gamma_{\breve{A}_2}}(\breve{x}) - \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\gamma_{\breve{A}_2}}(\breve{x}) \Big), \\ & \Big(\beta_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\alpha_{\breve{A}_2}}(\breve{x}), \beta_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\beta_{\breve{A}_2}}(\breve{x}), \beta_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\gamma_{\breve{A}_2}}(\breve{x}) \Big), \\ & \Big(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\alpha_{\breve{A}_2}}(\breve{x}), \gamma_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\beta_{\breve{A}_2}}(\breve{x}), \gamma_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\gamma_{\breve{A}_2}}(\breve{x}) \Big) \Big\rangle.\end{aligned} \tag{S3}$$

$$\begin{aligned}\breve{A}_1 \otimes \breve{A}_2 = \Big\langle \Big(& (\alpha_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\alpha_{\breve{A}_2}}(\breve{x}), \alpha_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\beta_{\breve{A}_2}}(\breve{x}), \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \alpha_{\gamma_{\breve{A}_2}}(\breve{x})), \\ & (\beta_{\alpha_{\breve{A}_1}}(\breve{x}) + \beta_{\alpha_{\breve{A}_2}}(\breve{x}) - \beta_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\alpha_{\breve{A}_2}}(\breve{x})), (\beta_{\beta_{\breve{A}_1}}(\breve{x}) + \beta_{\beta_{\breve{A}_2}}(\breve{x}) - \beta_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\beta_{\breve{A}_2}}(\breve{x})), \\ & (\beta_{\gamma_{\breve{A}_1}}(\breve{x}) + \beta_{\gamma_{\breve{A}_2}}(\breve{x}) - \beta_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \beta_{\gamma_{\breve{A}_2}}(\breve{x})) \Big), \Big((\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) + \gamma_{\alpha_{\breve{A}_2}}(\breve{x}) - \gamma_{\alpha_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\alpha_{\breve{A}_2}}(\breve{x})), \\ & (\gamma_{\beta_{\breve{A}_1}}(\breve{x}) + \gamma_{\beta_{\breve{A}_2}}(\breve{x}) - \gamma_{\beta_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\beta_{\breve{A}_2}}(\breve{x})), (\gamma_{\gamma_{\breve{A}_1}}(\breve{x}) + \gamma_{\gamma_{\breve{A}_2}}(\breve{x}) - \gamma_{\gamma_{\breve{A}_1}}(\breve{x}) \cdot \gamma_{\gamma_{\breve{A}_2}}(\breve{x})) \Big) \Big\rangle.\end{aligned} \tag{S4}$$

$$\begin{aligned}\theta\breve{A} = \Big\langle & \Big(1 - (1 - \alpha_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, 1 - (1 - \alpha_{\beta_{\breve{A}_1}}(\breve{x}))^{\theta}, 1 - (1 - \alpha_{\gamma_{\breve{A}_1}}(\breve{x}))^{\theta} \Big), \\ & \Big((\beta_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, (\beta_{\beta_{\breve{A}_1}}(\breve{x}))^{\theta}, (\beta_{\gamma_{\breve{A}_1}}(\breve{x}))^{\theta} \Big), \\ & \Big((\gamma_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, (\gamma_{\beta_{\breve{A}_1}}(\breve{x}))^{\theta}, (\gamma_{\gamma_{\breve{A}_1}}(\breve{x}))^{\theta} \Big) \Big\rangle,\end{aligned} \tag{S5}$$

where $\theta > 0$.

$$\begin{aligned}\breve{A}^{\theta} = \Big\langle & \Big((\alpha_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, (\alpha_{\beta_{\breve{A}_1}}(\breve{x}))^{\theta}, (\alpha_{\gamma_{\breve{A}_1}}(\breve{x}))^{\theta} \Big), \\ & \Big(1 - (1 - \beta_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, 1 - (1 - \beta_{\beta_{\breve{A}_1}}(\breve{x}))^{\theta}, 1 - (1 - \beta_{\gamma_{\breve{A}_1}}(\breve{x}))^{\theta} \Big), \\ & \Big(1 - (1 - \gamma_{\alpha_{\breve{A}_1}}(\breve{x}))^{\theta}, 1 - (1 - \gamma_{\beta_{\breve{A}_1}}(\breve{x}))^{\theta}, 1 - (1 - \gamma_{\gamma_{\breve{A}_1}}(\breve{x}))^{\theta} \Big) \Big\rangle,\end{aligned} \tag{S6}$$

where, $\theta > 0$.

Definition 4 [5]. The score function of $\breve{A}_1$, $S(\breve{A}_1)$ is described by:

$$S(\breve{A}_1) = \frac{1}{12}\Big\langle 8 + \Big(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\alpha_{\beta_{\breve{A}_1}}(\breve{x}) \Big) + \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) \Big) - \Big(\beta_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\beta_{\beta_{\breve{A}_1}}(\breve{x}) \Big) + \beta_{\gamma_{\breve{A}_1}}(\breve{x}) \Big) - \Big(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\gamma_{\beta_{\breve{A}_1}}(\breve{x}) \Big) + \gamma_{\gamma_{\breve{A}_1}}(\breve{x}) \Big) \Big\rangle. \tag{S7}$$

*Definition 5 [5].*The accuracy function of $\breve{A}_1$, $A(\breve{A}_1)$ is expressed by:

$$A(\breve{A}_1) = \frac{1}{4}\Big\langle \Big(\alpha_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\alpha_{\beta_{\breve{A}_1}}(\breve{x}) \Big) + \alpha_{\gamma_{\breve{A}_1}}(\breve{x}) \Big) - \Big(\gamma_{\alpha_{\breve{A}_1}}(\breve{x}) + 2\Big(\gamma_{\beta_{\breve{A}_1}}(\breve{x}) \Big) + \gamma_{\gamma_{\breve{A}_1}}(\breve{x}) \Big) \Big\rangle. \tag{S8}$$

Definition 6 [5]. Let $S(\breve{A}_i)$ and $A(\breve{A}_i)$ denote the score and accuracy functions, for the T2NNs $\breve{A}_i (i = 1, 2)$, respectively. The following relations can be written:

1. If $S(\breve{A}_1) > S(\breve{A}_2)$, then $\breve{A}_1 > \breve{A}_2$,
2. If $S(\breve{A}_1) = S(\breve{A}_2)$, $A(\breve{A}_1) > A(\breve{A}_2)$ then $\breve{A}_1 > \breve{A}_2$,
3. If $S(\breve{A}_1) = S(\breve{A}_2)$, $A(\breve{A}_1) = A(\breve{A}_2)$ then $\breve{A}_1 = \breve{A}_2$.

Definition 7 [7]. Let $\breve{A}_1 = \Big((\alpha_1, \alpha_2, \alpha_3), (\beta_1, \beta_2, \beta_3), (\gamma_1, \gamma_2, \gamma_3) \Big)$ and $\breve{A}_2 = \Big((T_1, T_2, T_3), (I_1, I_2, I_3), (F_1, F_2, F_3) \Big)$ be T2NNs. The distance measure $d(\breve{A}_1, \breve{A}_2)$ between $\breve{A}_1$ and $\breve{A}_2$ can be defined as :

$$d(\breve{A}_1, \breve{A}_2) = 1 - \frac{\sum_{i=1}^{3} \alpha_i T_i + \sum_{i=1}^{3} \beta_i I_i + \sum_{i=1}^{3} \gamma_i F_i}{\Big(\sum_{i=1}^{3} (\alpha_i)^2 + \sum_{i=1}^{3} (\beta_i)^2 + \sum_{i=1}^{3} (\gamma_i)^2 \Big) \times \Big(\sum_{i=1}^{3} (T_i)^2 + \sum_{i=1}^{3} (I_i)^2 + \sum_{i=1}^{3} (F_i)^2 \Big)}. \tag{S9}$$

The evaluation and calculation tables

Table A.1. The type-2 neutrosophic number linguistic variables for evaluating the criteria [5].

Linguistic variables/terms	$A = [(\alpha_\alpha, \alpha_\beta, \alpha_\gamma), (\beta_\alpha, \beta_\beta, \beta_\gamma), (\gamma_\alpha, \gamma_\beta, \gamma_\gamma)]$
Low (L)	((0.20,0.30,0.20), (0.60,0.70,0.80), (0.45,0.75,0.75))
Medium Low (ML)	((0.40,0.30,0.25), (0.45,0.55,0.40), (0.45,0.60,0.55))
Medium (M)	((0.50,0.55,0.55), (0.40,0.45,0.55), (0.35,0.40,0.35))
High (H)	((0.80,0.75,0.70), (0.20,0.15,0.30), (0.15,0.10,0.20))
Very High (VH)	((0.90,0.85,0.95), (0.10,0.15,0.10), (0.05,0.05,0.10))

Table A.2. The type-2 neutrosophic number linguistic variables for evaluating the alternatives [5].

Linguistic variables/terms	$A = [(\alpha_\alpha, \alpha_\beta, \alpha_\gamma), (\beta_\alpha, \beta_\beta, \beta_\gamma), (\gamma_\alpha, \gamma_\beta, \gamma_\gamma)]$
Very Bad (VB)	((0.20,0.20,0.10), (0.65,0.80,0.85), (0.45,0.80,0.70))
Bad (B)	((0.35,0.35,0.10), (0.50,0.75,0.80), (0.50,0.75,0.65))
Medium Bad (MB)	((0.50,0.30,0.50), (0.50,0.35,0.45), (0.45,0.30,0.60))
Medium (M)	((0.40,0.45,0.50), (0.40,0.45,0.50), (0.35,0.40,0.45))
Medium Good (MG)	((0.60,0.45,0.50), (0.20,0.15,0.25), (0.10,0.25,0.15))
Good (G)	((0.70,0.75,0.80), (0.15,0.20,0.25), (0.10,0.15,0.20))
Very Good (VG)	((0.95,0.90,0.95), (0.10,0.10,0.05), (0.05,0.05,0.05))

Table A.3. The importance ratings of the criteria by decision makers.

Decision	Criteria																	
Makers	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
DM1	VH	H	H	VH	M	M	M	VH	M	H	ML	VH	ML	M	VH	ML	ML	H
DM2	VH	VH	VH	M	M	L	ML	VH	ML	VH	L	H	L	M	VH	M	ML	VH
DM3	VH	VH	VH	H	H	M	L	VH	H	H	L	H	H	M	H	ML	M	VH
DM4	VH	M	VH	VH	VH	M	L	VH	H	M	VH	VH	VH	M	ML	VH	VH	VH

Table A.4. Evaluation ratings of offshore wind farm alternatives.

Alternatives	Decision makers	Criteria																	
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
A1: Newport Nearshore Windpark	DM1	MG	B	B	B	VB	M	VB	B	VB	VB	M	M	G	G	G	G	VG	MG
	DM2	MG	M	M	VB	VB	G	VB	MB	B	M	MB	VB	G	MG	MG	G	G	M
	DM3	MG	MG	MG	B	VB	MG	B	M	B	M	MB	B	VG	M	G	G	G	MG
	DM4	M	M	VB	VB	G	M	MB	B	M	MB	MB	G	G	B	G	B	MB	MB
A2: Garden State OWF	DM1	G	MG	M	MB	M	MB	MG	M	B	MB	MB	MG	B	M	MG	B	MB	MB
	DM2	MG	G	G	B	MB	G	VB	MG	MB	MG	B	G	B	MG	MG	MB	B	B
	DM3	G	VG	VG	M	M	MG	B	MG	MB	G	B	MG	MB	M	G	MB	MB	B
	DM4	MG	VG	VG	B	M	G	M	MB	M	MG	B	M	MB	B	MG	M	MB	B
A3: FERN Blue Ribbon Wind Farm I	DM1	G	M	MB	B	MB	VB	VB	VG	G	B	M	M	MB	VG	M	VG	MG	M
	DM2	MG	MG	MG	VB	VB	VB	VB	VG	VG	VB	MG	B	MB	VG	MB	VG	B	B
	DM3	G	G	G	B	VB	VB	B	VG	VG	B	M	B	M	G	M	VG	B	M
	DM4	MG	G	G	VB	MB	VB	VB	MG	VG	VB	M	B	MG	MG	MG	G	G	MG
A4: Brigantine OffshoreMW Phase 1	DM1	VG	G	MG	MG	MG	MB	MG	MB	MB	M	MB	MG	B	MB	MG	MB	MB	MB
	DM2	G	G	G	MG	MB	G	G	M	M	G	B	G	B	MG	MG	B	MB	M
	DM3	VG	VG	VG	G	M	MG	MG	MG	M	G	B	MG	MB	M	M	M	MB	MB
	DM4	G	G	VG	MG	M	G	M	MB	M	MG	G	MG	MB	MB	MG	M	G	MG
A5: Pavillion Energy Surf City W	DM1	VG	VG	G	VG	VG	VG	VG	MB	M	VG	B	MG	MB	B	B	VB	B	B
	DM2	G	VG	VG	G	VG	VG	G	M	M	VG	VB	VG	B	VB	B	VB	MG	MG
	DM3	VG	VG	VG	VG	VG	VG	MG	M	M	VG	VB	G	MB	B	MB	B	MG	B
	DM4	G	VG	VG	VG	VG	VG	VB	MB	MG	VG	G	MG	MB	MB	MG	B	G	MG

Table A.5. The normalized decision matrix.

Alternatives	Criteria								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.000	0.000	0.000	1.000	1.000	0.779	0.258	1.000	1.000
A2	0.480	0.862	0.870	0.654	0.451	0.766	0.533	0.744	0.623
A3	0.480	0.522	0.507	1.000	0.686	0.000	0.000	0.000	0.000
A4	1.000	0.865	0.885	0.303	0.423	0.766	0.915	0.818	0.529
A5	1.000	1.000	1.000	0.000	0.000	1.000	1.000	0.875	0.476

Alternatives	C10	C11	C12	C13	C14	C15	C16	C17	C18
A1	0.397	0.291	0.916	0.000	0.760	0.000	0.098	0.000	0.000
A2	0.655	1.000	0.260	1.000	0.392	0.062	0.588	1.000	1.000
A3	0.000	0.000	1.000	0.696	1.000	0.576	0.000	0.673	0.223
A4	0.752	0.184	0.233	1.000	0.429	0.386	0.570	0.583	0.133
A5	1.000	0.686	0.000	0.899	0.000	1.000	1.000	0.491	0.346

Table A.6. The weighted normalized decision matrix.

Alternatives	Criteria								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.000	0.000	0.000	0.058	0.056	0.041	0.013	0.059	0.055
A2	0.028	0.050	0.051	0.038	0.025	0.040	0.026	0.044	0.034
A3	0.028	0.030	0.030	0.058	0.039	0.000	0.000	0.000	0.000
A4	0.059	0.050	0.052	0.017	0.024	0.040	0.045	0.048	0.029
A5	0.059	0.058	0.058	0.000	0.000	0.052	0.049	0.051	0.026
Alternatives	C10	C11	C12	C13	C14	C15	C16	C17	C18
A1	0.023	0.015	0.053	0.000	0.041	0.000	0.005	0.000	0.000
A2	0.037	0.052	0.015	0.054	0.021	0.004	0.031	0.054	0.058
A3	0.000	0.000	0.058	0.038	0.054	0.033	0.000	0.036	0.013
A4	0.043	0.009	0.014	0.054	0.023	0.022	0.030	0.031	0.008
A5	0.057	0.035	0.000	0.049	0.000	0.057	0.054	0.026	0.020

Table A.7. The aggregated decision matrix of the alternatives.

Alternatives	Criteria								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.824	0.801	0.801	0.696	0.670	0.860	0.728	0.785	0.709
A2	0.863	0.898	0.897	0.770	0.804	0.857	0.776	0.816	0.785
A3	0.863	0.860	0.857	0.696	0.747	0.670	0.684	0.906	0.911
A4	0.906	0.898	0.898	0.846	0.811	0.857	0.842	0.807	0.804
A5	0.906	0.914	0.911	0.911	0.914	0.914	0.857	0.800	0.814
Alternatives	C10	C11	C12	C13	C14	C15	C16	C17	C18
A1	0.782	0.795	0.761	0.898	0.860	0.850	0.890	0.880	0.816
A2	0.839	0.749	0.842	0.767	0.801	0.846	0.785	0.780	0.749
A3	0.696	0.814	0.750	0.807	0.898	0.811	0.911	0.813	0.801
A4	0.860	0.802	0.846	0.767	0.807	0.824	0.789	0.822	0.807
A5	0.914	0.769	0.875	0.780	0.738	0.782	0.696	0.831	0.793

Table A.8. The distance matrix of the alternatives.

Alternatives	Criteria								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.000	0.000	0.000	0.058	0.056	0.041	0.013	0.059	0.055
A2	0.028	0.050	0.051	0.038	0.025	0.040	0.026	0.044	0.034
A3	0.028	0.030	0.030	0.058	0.039	0.000	0.000	0.000	0.000
A4	0.059	0.050	0.052	0.017	0.024	0.040	0.045	0.048	0.029
A5	0.059	0.058	0.058	0.000	0.000	0.052	0.049	0.051	0.026
Alternatives	C10	C11	C12	C13	C14	C15	C16	C17	C18
A1	0.023	0.015	0.053	0.000	0.041	0.000	0.005	0.000	0.000
A2	0.037	0.052	0.015	0.054	0.021	0.004	0.031	0.054	0.058
A3	0.000	0.000	0.058	0.038	0.054	0.033	0.000	0.036	0.013
A4	0.043	0.009	0.014	0.054	0.023	0.022	0.030	0.031	0.008
A5	0.057	0.035	0.000	0.049	0.000	0.057	0.054	0.026	0.020

Table A.9. The sensitivity analysis of T2NN based MABAC approach.

Experiment	Alternatives					Description
number	A1	A2	A3	A4	A5	
1	0.417	0.663	0.409	0.598	0.654	Set 1 (All criteria=L)
2	0.417	0.663	0.409	0.598	0.654	Set 2 (All criteria= ML)
3	0.417	0.663	0.409	0.598	0.654	Set 3 (All criteria= M)
4	0.417	0.663	0.409	0.598	0.654	Set 4 (All criteria= H)
5	0.417	0.663	0.409	0.598	0.654	Set 5 (All criteria= VH)
6	0.390	0.663	0.419	0.575	0.644	Set 6 (Half criteria= L; Half criteria=ML)
7	0.396	0.663	0.417	0.581	0.647	Set 7 (Half criteria= ML; Half criteria=M)
8	0.392	0.663	0.418	0.577	0.645	Set 8 (Half criteria= M; Half criteria=H)
9	0.409	0.663	0.412	0.591	0.651	Set 9 (Half criteria= H; Half criteria=VH)
10	0.371	0.663	0.426	0.559	0.637	Set 10 (Half criteria= L; Half criteria=M)
11	0.350	0.663	0.434	0.540	0.630	Set 11 (Half criteria= L; Half criteria=H)
12	0.344	0.663	0.437	0.535	0.628	Set 12 (Half criteria= L; Half criteria=VH)
13	0.372	0.663	0.426	0.560	0.638	Set 13 (Half criteria= ML; Half criteria=H)
14	0.365	0.663	0.428	0.554	0.636	Set 14 (Half criteria= ML; Half criteria=VH)
15	0.384	0.663	0.421	0.570	0.642	Set 15 (Half criteria= M; Half criteria=VH)
16	0.369	0.668	0.416	0.557	0.631	Set 16 (C1-C4= L;C5-C8= ML; C9-C12= M; C13-C16= H; C17-C18= VH;)

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