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Comparison of multicriteria analysis techniques for decision making on floating offshore wind farms site selection

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Abstract

This work compares two methodologies to assess different selection approaches, the Analytic Hierarchy Process (AHP) and Multiple Attribute Decision Analysis (MADA) using a combined Evidential Reasoning (ER) and AHP approach. This evaluation is done depending on: the number of alternative criteria, agility through the process of decision-making, computational complexity, adequacy in supporting a group decision, and consistency of results. Case studies are presented to analyze the robustness of the methodology evaluation. The criteria used to evaluate and identify the best locations are adapted for each methodology to proceed with the comparison. The results show that each approach is suitable for the problems of wind farm location selection, particularly toward the support of group decision-making and uncertainty modelling. The sites are ranked based on their respective weights for AHP and MADA. In terms of computational complexity, the complete AHP method performs better than the combined MADA and AHP approaches. Nevertheless, the MADA method is less time-consuming and convenient for selecting floating farm locations due to the smaller involvement of experts and corresponding higher agility during decision-making. Both methodologies demonstrate several alternative processes and criteria, adequacy in supporting a group decision, and adaptation in terms of criteria insertion or removal.

Keywords: Analytic Hierarchy Process (AHP); Evidential Reasoning (ER); Floating offshore wind farms; Multi-Criteria Decision Methods (MCDM); Multiple Attribute Decision Analysis (MADA); Site selection.

Abbreviations

AHP	Analytical Hierarchy Process
CI	Consistency Index
CR	Consistency Ratio
EEZ	Economic Exclusive Zone
ER	Evidential Reasoning
FOW	Floating Offshore Wind
GIS	Geographical Information System
MADA	Multiple Attribute Decision Analysis
MCDA	Multi-criteria Decision Analysis
MCDM	Multi-criteria Decision-Making Methods
MCE	Multicriteria Evaluation techniques

1 Introduction

European legislation calls for a well-planned sustainable maritime space development. As such, it must include a social, economic as well as environmental dimension. According to the 2030 Agenda for Sustainable Development (United Nations, 2015), countries should undertake efforts to build up a comprehensive national inventory of their marine resources to establish a maritime spatial planning system. The overall objective is to provide information for the improvement or the restructuring of maritime-use decision processes, including the consideration of socio-economic and environmental issues (Ehler and Douvere, 2009).

In the last decades, conflicts caused by competing marine uses have increased, particularly in coastal waters. Consequently, a lot of research has been done to develop methods and tools that assist complex spatial decision problems (Alexander, 2019; Queffelec et al., 2021). The development of Spatial Decision Support Systems (SDSS) has turned out to be very beneficial in helping to solve complex space-use problems (Keenan and Jankowski, 2019; Pınarbaşı et al., 2017). In addition, any planning process must focus on a mix of objective and subjective information. The former is derived from reported facts, quantitative estimates, and systematic opinion surveys. The subjective information denotes the opinions (preferences, priorities, judgments) of the interest groups and decision-makers (Li et al., 2021). The idea of combining the objective and subjective elements of the planning process in a computer-based system lies at the core of the concept of SDSS (Buchanan et al., 1998).

These methods can be defined as an interactive, computer-based system designed to support a user or a group of users in achieving a greater degree of effectiveness in decision making when solving a semi-structured spatial decision problem (Malczewski, 2004). SDSS also refers to the combination of GIS and sophisticated decision support methodologies, e.g., multicriteria analysis techniques (Díaz and Guedes Soares, 2020a; Greco et al., 2017), and are therefore suitable to manage sustainable development of maritime areas. Although multicriteria analysis began mainly in the '70s (the first scientific meeting devoted entirely to decision-making was held in 1972 in South Carolina), and its origins can be dated back to the eighteenth century (Eastman, 1999), reflections on French policies in the action of judges and their translation into the policy (social choice) led people like Condorcet to deepen in the decision taken supported in several criteria (Eastman, 1999).

In the 1980s and 1990s, there was an increasing trend of integrating Multicriteria Evaluation techniques (MCE) and Geographic Information Systems (GIS), trying to solve some of the analytical shortcomings of GIS (Eastman, 1999; Stewart Fotheringham and Rogerson, 1993). Since maritime-use decision making, in general, is considered as an intrinsic multicriteria decision problem, these are valid methodologies to support the maritime-use decision process employing a maritime-use suitability analysis. Maritime-use suitability analysis aims to identify the most appropriate spatial pattern for future marine uses according to specified requirements or preferences (Dapueto et al., 2015; Díaz and Guedes Soares, 2021, 2022a; Queffelec et al., 2021). GIS-based maritime-use suitability analyses have been applied in a wide variety of situations, including ecological and geological approaches, suitability for maritime activities, environmental impact assessment, site selection for facilities, and coastal planning (Díaz and Guedes Soares, 2020a; Lester et al., 2018; Sainz et al., 2019).

Different attempts to classify Multicriteria Decision Making (MCDM) methods by diverse authors exist in the literature (Mardani et al., 2015; Velasquez and Hester, 2013). Many of them agree that additive decision rules are the best known and most widely used Multiattribute Decision Making (MADM) methods in GIS-based decision-making. Some of the techniques more commonly described in the literature are the Analytical Hierarchy Process (AHP), Simple Additive Weighting (SAW), ideal point methods (e.g. TOPSIS), concordance methods or outranking techniques (e.g. PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation), ELECTRE (Elimination and Choice Expressing Reality)). Nevertheless, the integration of these techniques continues to pose problems or difficulties when developing specific applications. The most notable drawbacks are (Belton and Stewart, 2002; Kou et al., 2011; Oteroay, 1987):

- The impracticality of applying pairwise comparison techniques as PROMETHEE with long data because of limitations posed by existing informatics systems.
- The difficulty of implementing some MCE methods, thereby leading to a complex analysis of the results and ignorance of the internal procedure of the methods by non-specialist users.

The need to generate data processing software attached to the GIS, based on algorithms that describe MCE methods, naturally implies that many users cannot access these methods.

This study compares the results obtained by applying two distinctive maritime space use suitability analyses to the location of floating offshore wind farm sites, applying two different multicriteria analysis techniques. The multicriteria analysis employed has been performed in a geographic environment and has been used in two objectives. During the site search analysis, each technique considered several location alternatives. The analyses used an AHP method (Díaz and Guedes Soares, 2022a, 2022b) and the MADA (ER and AHP combined) methodology (Loughney et al., 2021, 2020; Loughney and Wang, 2020), within the Arcwind project and a set of predefined options that can easily be performed in GIS. All the techniques were coded and adapted through visualisation techniques (Díaz and Guedes Soares, 2020a).

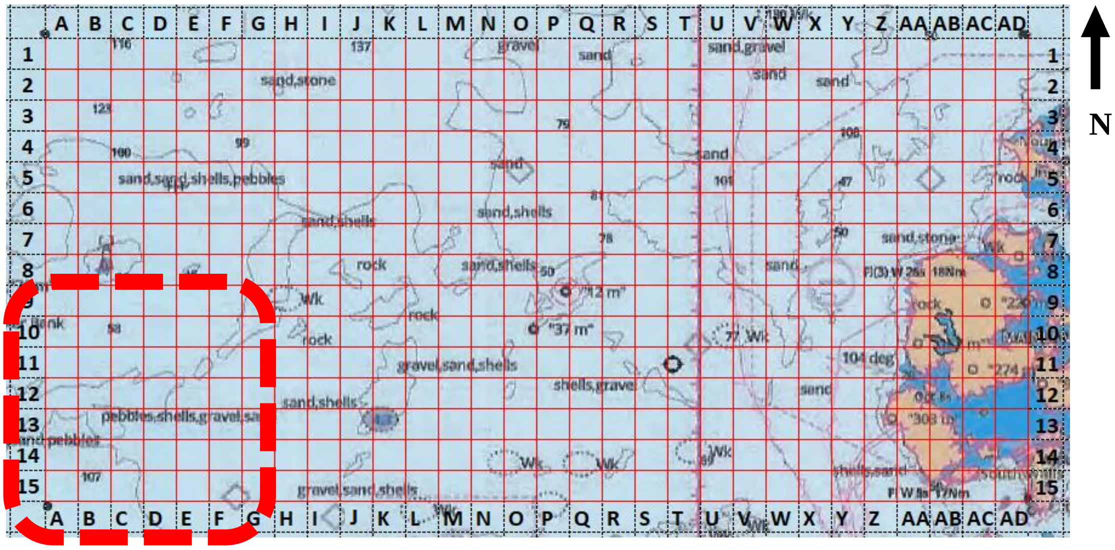

Fig. 1. Large area, north of Scotland for FOW site selection analysis utilised in [24] with a smaller region outlined for comparison utilising the AHP methodology.

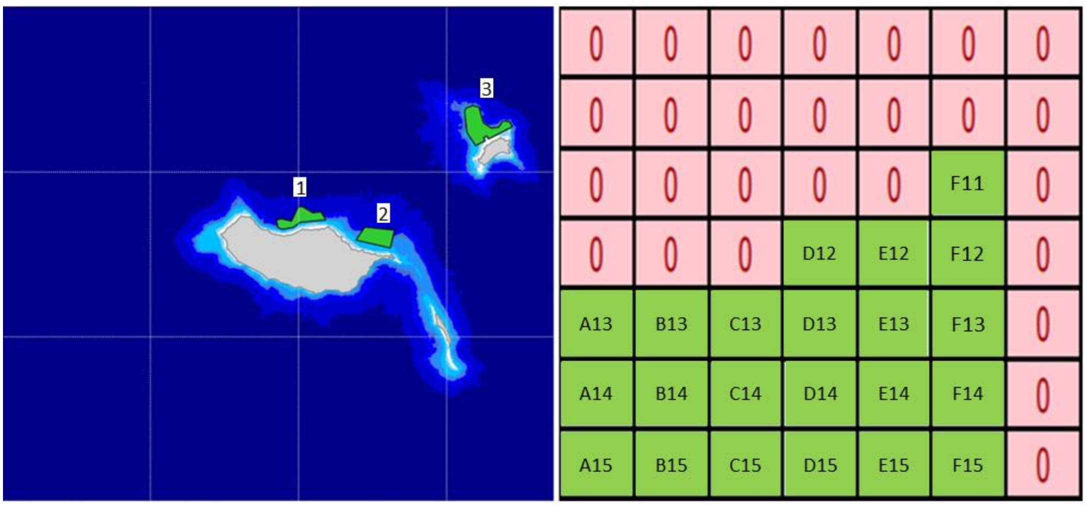

Fig. 2. Proposed locations identified by each original methodology in Madeira region (left) and Scotland (right – see the red section in Fig. 1). Locations 1 to 3 are identified with the areas of Sao Vicente, Porto da Cruz and Porto Santo.

A problem in applying multicriteria analysis is the definition of weights for a given set of criteria. A variety of approaches exist, see for example (Chaouachi et al., 2017), and probably the best-known weight evaluation method is the AHP (Vagiona and Kamilakis, 2018; Vagiona and Karanikolas, 2012), which has been used in the present cases. Another problem is the specification of the criteria performance scores, which are often subjective in their determination. Data that has been measured directly will undoubtedly be regarded as more reliable than data that has been estimated, interpolated, taken from a map or interpreted. Thus, the method of criteria data collection plays a central role. A stochastic approach that considers the experts' knowledge of input values could be a way out of this dilemma. Figs. 1 and 2 demonstrate the locations utilised in the comparison of methodologies. Both sets of locations were utilised to demonstrate the original methodologies in (Díaz and Guedes Soares, 2021, 2022a; Loughney et al., 2021; Loughney and Wang, 2020).

2 Study area and project background

The European Atlantic region and its surroundings are located in Western Europe, a highly dynamic economic area (see Fig. 3). The climate in this area is oceanic, with mean annual precipitation of about 1.000 mm and a mean annual temperature of about 10 °C. This area is crossed by several navigation lines and the main migratory paths in Europe. Geologically, the Atlantic Arc coast is formed mainly by rocky shores and deep waters. In addition, it hosts important mineral reservoirs used for industrial purposes.

Fig. 3. The Atlantic Area region includes the coastlines of northern and western UK, Ireland, Northwest, and west France, the northern and some of the southern coastlines of Spain, and all of Portugal, as well as the Azores, Madeira, and the Canary Islands.

The availability of offshore wind resources has been one reason for the fast development of floating wind technology in the last decade (Díaz and Guedes Soares, 2020b). However, this rapid development can also add negative interactions with the environment and other maritime activities (Rudolph, 2014). The floating offshore wind farms deployment could cause costly damage and destruction of environmental protected areas such as bird sanctuaries and marine habitats (Fox and Petersen, 2019). Many infrastructures that have been built occupy areas where the wind resource is high, making these areas inaccessible for wind farm installation. Also, many important areas have been occupied with military activities, underwater facilities (cables and pipelines) or navigational (shipping) routes (Smith et al., 2015).

Based on the above, the EEZ area surrounding Portugal, Spain, France, the UK, and Ireland, represents a rapidly growing floating wind area and merits closer investigation in terms of geoscientific factors. Thus, the research project Arcwind was initiated to develop a methodological workflow that will facilitate sustainable development in the surroundings of floating wind farms. The present main objective is to perform a maritime use suitability analysis to identify the most appropriate future wind farm locations. Therefore, a variety of tasks needed to be performed, such as:

- Characterisation of the study area and collection, analysis, and processing of the available information for its introduction into a GIS environment.
- Geo-resources and geo-hazards detection, description, and modelling with the help of GIS and other techniques.
- Land-use suitability analysis using MCDM.

Here, the marine-use suitability analysis to find the most suitable locations for floating wind facilities is presented. As mentioned above, results are compared by applying two distinctive multicriteria analysis techniques for decision making on floating wind farms location. For more details on the general project workflow and geo-resources and geo-hazards modelling, see (Chaouachi et al., 2017; Fetanat and Khorasaninejad, 2015; Mahdy and Bahaj, 2018; Vagiona and Kamilakis, 2018; Wu et al., 2018; Ziemba et al., 2017). The case study to compare both methodologies in the scope of the Arcwind project considered the proposed locations of Madeira and Scotland (see Table 1).

Table 1. Proposed locations in Madeira and Scotland. Geographic coordinates (WGS84). Scotland coordinates indicate the centre of a 5.5km × 5.5km area.

Madeira region		
Location	Latitude	Longitude
Sao Vicente	38.6	-26.8
Porto da Cruz	37.9	-25.7
Porto Santo	37	-25.2
Scotland region		
Location	Latitude	Longitude
A15	58.75	-6
B15	58.75	-5.9
C15	58.75	-5.8
D15	58.75	-5.7
E15	58.75	-5.6
F15	58.75	-5.5
A14	58.8	-6
B14	58.8	-5.9
C14	58.8	-5.8
D14	58.8	-5.7
E14	58.8	-5.6
F14	58.8	-5.5
A13	58.85	-6
B13	58.85	-5.9
C13	58.85	-5.8
D13	58.85	-5.7
E13	58.85	-5.6
F13	58.85	-5.5
D12	58.9	-5.7
E12	58.9	-5.6
F12	58.9	-5.5
F11	58.95	-5.5

3 Outline of the Developed Methodologies

It is essential to differentiate between the site selection problem and the site search problem. Site selection analysis aims to identify the best location for a particular activity from a given set of potential (feasible) sites. Where there is no predetermined set of candidate sites, the problem is referred to as site search analysis (Díaz and Guedes Soares, 2020a; Loughney et al., 2021). In terms of the MCDM applied, the main advantage of the AHP approach can be considered its low degree of complexity which made it attractive to be used for the site search analysis in this project. It is precisely this simplicity and the possibility to integrate experts' knowledge that makes weighted summation quite widely applied in real-world settings (Benítez et al., 2011).

The site selection analysis has also been performed by implementing MADA, which belongs to the 'family' of ranking techniques. Since the mentioned techniques require pairwise or global comparisons among alternatives, these methods become impractical for applications where the number of alternatives ranges in the tens or hundreds of thousands. For a more detailed description of both methodologies, see (Benítez et al., 2011; Guo et al., 2009; Russo and Camanho, 2015; Yang and Xu, 2002).

To perform both site search and site selection, several steps needed to be covered:

- Definition of alternatives (decision options): feasible location areas.
- Definition of constraints: areas with land-use restrictions.
- Definition of important factors in the decision process: identification of criteria (see Table 2).
- Determination of criteria weights.

The criteria weights are determined with the AHP in both techniques (Saaty, 1977). This multicriteria decision method involves a pairwise comparison of criteria where preferences between criteria are expressed on a numerical (Likert) scale, usually ranging from 1/9 (strongly unimportant) to 1 (equal importance) to 9 (strongly more important) (Franek and Kresta, 2014). This preference information is used to compute the weights through an eigenvalue computation where the normalized eigenvector of the maximum eigenvalue characterizes the vector of weights. Empirical applications suggest that this pairwise comparison method is one of the most effective techniques for spatial decision-making approaches based on GIS (Díaz and Guedes Soares, 2021; Vagiona and Kamilakis, 2018; Vagiona and Karanikolas, 2012). There exist many well-documented examples of the application of this method with success (Díaz and Guedes Soares, 2020a; Mahdy and Bahaj, 2018).

It is well known that the input data to the multicriteria evaluation procedures usually present the property of inaccuracy, imprecision, and ambiguity. Despite this knowledge, the methods typically assume that the input data are precise and accurate. Some efforts have been made to deal with this problem by combining the GIS multicriteria procedures with a sensitivity analysis (Seyr and Muskulus, 2019). Another approach is to use other methods based upon other families of MCDM (Mahdy and Bahaj, 2018).

It is hard to choose the input values for multicriteria analysis procedures in many situations since the criteria values for the different alternatives usually do not have a single realization but can obtain a range of possible values. Performing a multicriteria analysis with the mean values produces a mean result, but the uncertainty in either the input values or the result cannot be quantified. A solution to this dead-end is a stochastic approach, which utilizes probability distributions for the input parameters instead of single values. A stochastic multicriteria analysis implies that the analysis is performed multiple times with varying input values for the criteria involved. According to their low outcome probabilities, such an approach uses the whole range of possible criteria value outcomes, and extreme events are, according to their low outcome probabilities, realistically represented as rare events (Seyr and Muskulus, 2019).

Constraints depict the areas where the turbines will not be allowed. These restrictions are generally characterized by other maritime uses (e.g., hydrocarbons and minerals), the protection of natural areas and technical aspects. The main restrictions are as follows:

- *Military areas:* Areas for military operations (exercises and manoeuvres). These marine sites are considered unsuitable for the offshore wind farms deployment since space is conditioned to periodical and special military operations.
- *Exploration and exploitation of hydrocarbons and minerals*: The areas for the public tender of marine regions cannot be considered eligible for the deployment of floating farms.
- *Extraction of marine sand and gravel*: Marine aggregates licenses similarly to previous criteria excluded other activities from the area of interest.
- *Aquaculture and fishing banks:* The possibility to share the oceanic space between offshore wind and these activities is currently under study (Díaz et al., 2019). Also, fishing trawls could break the power lines.
- *Marine renewable energies pilot zones:* These maritime zones are considered inadequate for implementing commercial concepts projects (e.g., wave farms, tidal farms, offshore wind farms, etc.) since they only have the permit to deploy pilot or pre-commercial installations.
- *Environmental protected areas:* The protected areas correspond to added value natural zones, where the biodiversity defence and survivability are ensured through local, national, or European legislation. Natura 2000 Special Protection Areas (SPAs), migration corridors and refuges for wildlife have been selected as protected areas in the European Atlantic Area marine environment.

- *Underwater lines and pipelines:* The underwater grids are selected as an exclusion criterion due to the regulatory framework that protects these installations.
- *Maritime traffic:* The revised maps show the shipping lanes, shipping density, anchoring areas, precautionary areas, and clearways.
- *Heritage areas:* The archaeological monuments, shipwrecks and historical places located in the National and European Geographic Information Systems.
- *Wind Velocity:* The maritime zones with mean wind velocity smaller than 4 m/s (average cut-in wind speed) at 10 m height.
- *Water Depth:* The bathymetry supposes a spatial constraint on the site selection. This constraint is strongly dependent on the installation characteristics of the supporting platform structure.
- *Distance from the Shore:* The deployment of wind turbines in the proximity of the shoreline leads to negative impacts (visual impact, noise). Moreover, the distance may affect several human activities (fishing, recreational activities) existing nearshore.

Both methodologies are designed by the reality of the region of application. Based on that, the number of criteria and the treatment of them has some differences.

Weights for criteria are assigned with the help of the AHP (Saaty, 1977). An AHP extension was specifically developed for the Python environment at the Centre for Marine Technology and Ocean Engineering (Díaz et al., 2019; Díaz and Guedes Soares, 2021, 2020), while the Liverpool John Moores University implemented the AHP+ER MADA technique (Loughney et al., 2021, 2020; Loughney and Wang, 2020). During the development of both methodologies, different approaches were used by the researchers to determine sites under restrictions and unsuitable for further quantitative analysis.

Table 2. Criteria used by both methodologies.

AHP Methodology			
Type	No.	Criteria	Units
Metocean	C1	Wind velocity	m/s
	C2	Wind potential	h/year
	C3	Water depth	m
	C4	Wave conditions	m
	C5	Marine currents	m/s
	C6	Temperature	^{o}C
Viability	C7	Technical feasibility	density
	C8	Sufficient study times	density
Logistics	C9	Distance to local electrical grid	km
	C10	Distance from coastal facilities	Km

Facilities	C11	Distance from shore	Km
	C12	Distance from residential areas	km
	C13	Distance from maritime routes	km
	C14	Distance from underwater lines	km
	C15	Distance to marine recreational activities	km
	C16	Distance from airport	km
Marine environment	C17	Distance from protected areas	km
	C18	Proximity to migratory birds' paths	density
	C19	Proximity to migratory marine life paths	density
Techno-economic	C20	Area of the territory	Km^2
	C21	Proximity to the area of electricity demand	km
	C22	Population served	number
	C23	Multiple resources	density
MADA Methodology			
Metocean	C1	Wind Velocity	m/s
	C2	Potential Power Output (Max. capped at rated power of 10MW where possible)	MW
	C3	Wave Height (Significant Wave height)	m
	C4	Current Speed	m/s
	C5	Tidal Height	m
Logistics	C6	Vicinity to Substation (Grid Connection - only one grid connection available)	km
	C7	Distance from Ports for Installation	km
	C8	Distance from Ports for Maintenance Only	km
	C9	Water Depth	km
Facilities & Environment	C10	Proximity to Subsea Facilities	km
	C11	Proximity to Coast	km
	C12	Proximity to Fisheries	km
	C13	Proximity to Military Areas (only one Military area)	km
	C14	Proximity to Shipwrecks	km
	C15	Proximity to MPAs	km
	C16	Proximity to SACs (only one SAC)	km

3.1 Original AHP methodology developed for site selection in Portugal, Spain, and France

The main objective of a site selection analysis is the ranking of feasible alternatives. Generally, outranking methods, such as AHP, require pairwise or global comparisons, among other options. Here location alternatives are represented by wind farm areas, as defined by Díaz and Guedes Soares (2020a), which signify spaces for establishing floating farms. Geometrically, these alternatives represent a polygon each. A total of forty-two locations were evaluated for the site selection analysis. As alternatives are directly compared with their criteria values, the application of outranking methods does not require a transformation or standardization of criteria values. In some cases, the restrictions (constraints) and criteria are the same for the site search analysis.

Alternatives entirely located in restricted areas were eliminated from the analysis. However, some areas represent one alternative, partially affected by restricted areas, as these polygons are partially affected or boarded by an underwater connection or a navigation line. It has implied the inclusion of the constraints as an additional criterion in the decision process. The criterion representative of the used restrictions was then reclassified into two areas; areas where floating wind installation is forbidden or impossible due to other uses and locations where this use is permitted or feasible. It is important to define whether a higher value of a particular criterion leads to an improvement or a decrease in a location use suitability. In offshore wind farms development, an increase in the value of all criteria implies a suitability increase. For example, a higher wind potential value implies an increase in suitability to offshore wind use location. In contrast, a decrease in distance to environmental areas implies a reduction in wind farm use location suitability.

Geometrically, every alternative is a polygon so that within each polygon, a variety of criteria values are to be found. The question then arises as to which of the multiple criteria methods are used for the multicriteria analysis evaluation. Therefore, two sets of criteria are developed with site-specific values (mean) for the polygonal outline of a location alternative. In this methodology, twenty-three criteria are considered suitable for the application integration in the model and the application of MCDM. These criteria are selected based on the experts' opinions and sensitivity analysis. The sensitivity analysis guarantees the robustness of the model and consistency in the results (Díaz and Guedes Soares, 2021).

For the present analysis, the mean value was used for all criteria since this value better symbolizes all alternative values. Minimum and maximum values are usually rare events with a low probability of occurrence. The AHP methodology uses a comparison function, a function of the difference between two alternatives for any criterion. For more details on preference and functions, see (Ahn, 2017; Lai, 1995). The technique uses the "usual criterion" preference function based on the simple difference between alternatives. This function helps to discriminate best between available options to be achieved. The individual evaluation criteria are compared and ranked as weight function based on the expert's considerations. In the same way, the method is also applied to analyse the locations in each single criteria function.

3.1.1 AHP method and algorithm

The AHP is a pairwise comparison method developed by Saaty (1977). Each element is scored against the rest to evaluate its relative importance. This method divides a complex problem into parts as a hierarchy. The objective is at the top of the hierarchy. The rest of the criteria are on the other levels of the base.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix} = \begin{pmatrix} \frac{w_1}{w_1} & \cdots & \frac{w_1}{w_n} \\ \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \cdots & \frac{w_n}{w_n} \end{pmatrix} = \begin{pmatrix} 1 & \cdots & \frac{w_1}{w_n} \\ \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \cdots & 1 \end{pmatrix} \tag{1}$$

Thereby, a matrix with several columns and rows proportional to the criteria number is created.

A series of successive steps are followed to calculate the values. First, the matrix with the pairwise comparisons is completed. Then, the sum of elements in each column is determined. Each matrix component is divided by the sum of its column. Each row's mean value is calculated and noted in a new column. This column collects the priority vector of the criteria. Moreover, the methodology AHP provides mathematical tools to measure the consistency of the comparison (Saaty, 2008). This allows checking the objectivity of the process - the consistency index calculation following the next steps:

- The sum of the matrix elements is multiplied by the relative weight of the respective criterion.
- The products for all columns are added and defining the result as λmax. Then, the Consistency Index (CI) is defined through Eq. (1) given by (Takeda and Yu, 1995):

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

where n is the number of criteria (matrix order).

The comparison matrix inputs are randomly selected. The results are obtained through a simulation with Eq. (1). Complementary, the results level of consistency is obtained from the Consistency Ratio (CR) (see Eq. (2)). The CR should have a value no larger than 0.1 (Takeda and Yu, 1995):

$$CR = \frac{CI}{RI} \tag{3}$$

The Random Index (RI) is correlated with the number of matrix elements. The RI used was proposed by (Alonso and Lamata, 2006). The RI is related to the order of the matrix in Eq. (1) as shown in Table 3.

Table 3. Saaty's Random Index values.

Matrix	***RI***

Order (n)	
1	0
2	0
3	0.5245
4	0.8815
5	1.1086
6	1.2479
7	1.3417
8	1.4056
9	1.4499
10	1.4854
11	1.5141
12	1.5365
13	1.5551
14	1.5713
15	1.5838
16	1.5978
17	1.6086
18	1.6181
19	1.6265
20	1.6341
21	1.6409
22	1.6470
23	1.6526
24	1.6577
25	1.6624
…	…

The paired comparison of alternatives produces a preference matrix for each criterion. Having calculated the preference matrices and each criterion, a first aggregation is performed by multiplying each preference value by a weighting factor (expressing the weight or importance of a criterion) and building the sum of these products. This allows determining relative weights between each of the alternatives to be evaluated and established to calculate the numerical probability of each alternative. This probability determines the likelihood that the alternative must fulfil the expected goal. The higher the probability, the better the chances the alternative must satisfy the project's final goal. These calculations result in a preference index.

3.2 Original MADA methodology developed for site selection in UK and Ireland

There are several steps involved in the procedure for applying a MADA algorithm to a problem. Having several steps is key for maintaining consistency throughout the process and offers an element of confidence to the final analysis. There are key elements that the procedure must follow, and these elements shall be outlined in the following sections. Fig. 4 also outlines the methodological framework utilised in this research. In Fig. 4 each step of the methodology is outlined with further sub-steps also highlighted. For example, in Step 1 the main objective is to determine the scope and domain of the research application. The sub-steps further detail how this is to be done, i.e., defining a specific area for analysis, and identifying a set of exclusion criteria to exclude unsuitable sites to avoid an unnecessarily complex quantitative assessment. This methodology has been applied to Scotland and Ireland in (Loughney et al., 2021, 2020; Loughney and Wang, 2020).

3.2.1 Determine the Domain and the exclusion criteria.

The initial domain, used in the site selection analysis by Loughney et al. (2021) (Loughney et al., 2021) has been highlighted in Fig. 1 as the large area off the northern coast of Scotland, which is approximately 170 km East to West (3°–6° West) by 83 km North to South (58.75°–59.5° North). This area was divided into 450 individual grid squares of 5.5km × 5.5km. Similarly, the exclusion criteria have also been outlined in Section 3. These exclusion criteria were applied to the large region in Fig. 1. This resulted in 45 sites being outlined as suitable for further quantitative analysis as they were not impacted by any exclusions or restrictions to Floating Offshore Wind (FOW) implementation. The methodology outlined in the following sections was applied to these 45 sites to rank the most suitable areas for FOW implementation. Subsequently, a number of these 5.5km × 5.5km were utilised in the previously outlined AHP analysis as part of the comparative case study (see Fig. 2).

3.2.2 Identify individual criteria for quantitative analysis.

This section of the methodology involves filtering possible criteria that are relative to the description and the objective. For this problem, the criteria were devised from literature studies based upon the key requirements of FOW implementation. These have been previously outlined, in part, in Table 2.

3.2.3 Develop the evaluation hierarchy.

Once the criteria have been established, a hierarchy must be determined to coherently develop a solution to the problem. This hierarchy groups certain criteria under one general criterion. This allows for a smaller number of criteria to be aggregated gradually to reduce the calculation complexity of the decision-making (Guo et al., 2009; Liu et al., 2005; Sadeghi et al., 2018; Yang, 2001).

3.2.4 Outline suitable evaluation grades.

Subjective judgements may be used to distinguish one alternative from another in terms of qualitative criteria. However, in this research, it is possible to use objective data to determine the belief degrees. For example, evaluating data may suggest that the logistics of a site is *poor, indifferent, average, good* or *Excellent* (Ren et al., 2005; Yang and Xu, 2002). These five evaluation terms have been outlined, with H_n denoting the n^{th} evaluation grade. This is demonstrated by Eq. (4):

$$H_n = \{Poor\ (H_1), Indifferent\ (H_2), Average\ (H_3), Good\ (H_4), Excellent\ (H_5)\} \tag{4}$$

3.2.5 Develop the belief degrees and criteria weights for MADA analysis.

The weights of the criteria are calculated through PC and AHP and are determined by qualitative assessment from expert judgement, using questionnaires. PC and AHP are selected, as they are efficient methods of applying a qualitative data gathering mechanism to a quantitative methodology. The method of utilising PC and AHP to determine subjective quantitative data for application in a relative weighting system is exceptionally useful in filling gaps in data for additional analysis techniques, such as the ER approach (see Fig. 4).

It is supposed that there is a simple two-level hierarchy. Suppose there are L basic criteria e_j $(j=1\ldots L)$ associated with general criterion E. Similarly, suppose the normalised weights of each general criterion are given as $\omega_1, \omega_2 \ldots \omega_i \ldots \omega_L$ $(i=1\ldots L)$ where, ω_i is the relative weight of the i^{th} general criterion (E_i) with $0 \leq \omega_i \leq 1$ and ω_{ij} is the weight of the basic criterion (e_i) $0 \leq \omega_{ij} \leq 1$, where j represents the j^{th} basic criterion under the i^{th} general criterion. For example, the weighing of general criterion, Logistics, is represented by ω_1 and the weight of the 3rd basic criterion under logistics, (Depth, e_3) is represented by ω_{13}. See Table 4 which outlines the evaluation hierarchy and contains the allocated notation related to the weighting of criteria. Furthermore, let $\beta_{n,i}$ denote the belief degree of the basic criterion e_i to the evaluation grade H_n, where $\beta_{n,i} \geq 0$ and $\sum_{n=1}^{N} \beta_{n,i} = 1$ Finally, $S(e_i)$ is the assessment of an alternative under criterion e_i,. This assessment can be represented by Eq. (5) (Li and Liao, 2007; Loughney et al., 2021; Ren et al., 2005; Yang and Xu, 2002).

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1, \ldots, N\}\ \ i = 1, \ldots, L \tag{5}$$

The assessment of a criterion, $S(e_i)$ is complete if the sum of the belief degrees is equal to 1, *i.e.* $\sum_{n=1}^{N} \beta_{n,i} = 1$.

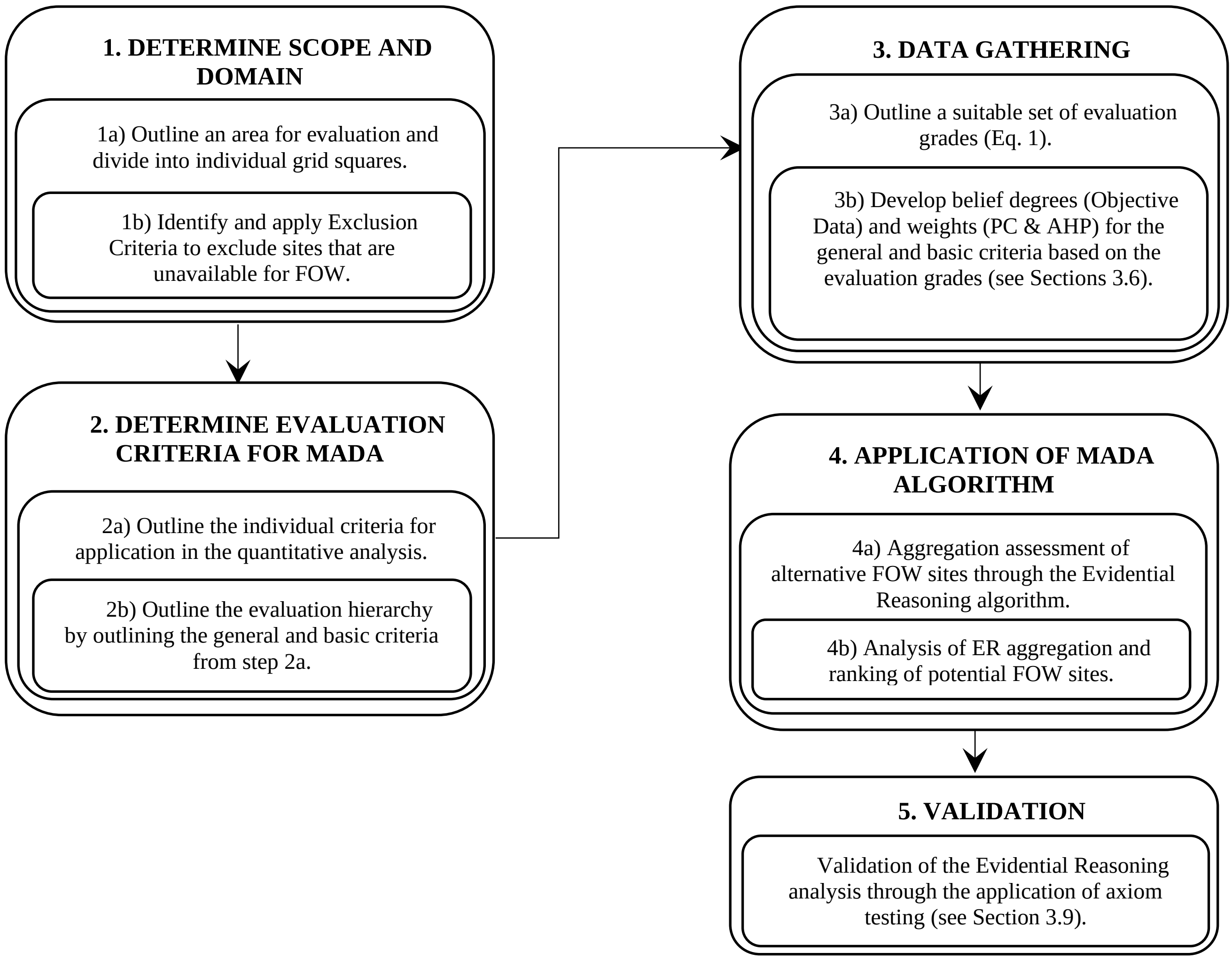

Fig. 4. Methodological framework for FOW site selection using Evidential Reasoning.

3.2.6 Evidential Reasoning Algorithm and Data Aggregation

Suppose $m_{n,i}$ is the probability mass representing the degree to which e_i supports the hypothesis that the general criterion E is assessed to H_n, and is calculated by Eq. (6) (Li and Liao, 2007; Loughney et al., 2021; Yang and Xu, 2002).

$$m_{n,i} = \omega_i \beta_{n,i} \quad n = 1, \dots, N \tag{6}$$

Similarly, for basic criteria, Eq. (6) is rewritten as Eq. (7):

$$m_{n,j} = \omega_{ij} \beta_{n,i} \quad n = 1, \dots, N \tag{7}$$

where, $m_{n,j}$ is the probability mass of the basic criteria e_j assessed to Hn. Also, $E_{I(j)}$ must be defined as the subset of the j basic criteria under the I^{th} general criterion, as given by Eq. (8).

$$E_{I(j)} = \{e_1 \quad e_2 \dots\ e_j\} \tag{8}$$

$m_{n,I(i)}$ is the probability mass defined as the degree to which all criteria in $E_{I(i)}$ support the hypothesis that E is assessed to the grade H_n. Similarly, $m_{H,\ I(i)}$ is the remaining probability mass which is unassigned to individual grades after all the basic criteria in $E_{I(i)}$ have been assessed. The terms $m_{n,\ I(i)}$ and $m_{H,\ I(i)}$ can be determined by combining the basic probability masses $m_{n,}$ and $m_{H,j}$ for all values of $n=1,\ \dots,\ N$ and $j=1,\ \dots,\ i$ (Li and Liao, 2007; Loughney et al., 2021; Yang and Xu, 2002). Thus, the Evidential Reasoning algorithm is expressed through Eqs. (9-12).

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{\substack{z=1 \\ z\neq t}}^{N} m_{t,I(i)} m_{z,i+1}\right]^{-1} i = 1, \dots, L-1 \tag{9}$$

$$m_{n,I(i+1)} = K_{I(i+1)} \begin{pmatrix} m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} \\ + m_{H,I(i)} m_{n,i+1} \end{pmatrix} \qquad n = 1, \dots, N \tag{10}$$

$$m_{H,I(i+1)} = K_{I(i+1)} m_{H,I(i)} m_{H,i+1} \tag{11}$$

$$\beta_n = \frac{m_{n,I(L)}}{1 - m_{H,I(L)}}, \qquad n = 1, \dots, N,\ i = 1, \dots, L \tag{12}$$

where $K_{I(i+1)}$ is a normalising factor so that $\sum_{n=1}^{N} m_{n,I(i+1)} + m_{H,I(i+1)} = 1$ and β_n is the combined belief degree of the aggregated assessment for the criteria (Li and Liao, 2007; Loughney et al., 2021; Yang and Xu, 2002).

3.2.7 Utility Assessment and Ranking

The criteria must be ranked based upon their aggregated belief degrees from the ER algorithm. Suppose the utility of an evaluation grade, H_n, is denoted by $u(H_n)$. The utility of the evaluation grades is assumed to be equidistant as follows, with $u(H_1)=0$, $u(H_2)=0.25$, $u(H_3)=0.5$, $u(H_4)=0.75$ and $u(H_5)=1$ (Yang, 2001). The estimated utility for the general and basic criteria, $S(e_i)$, is given by Eq. (13) (Loughney et al., 2021; Yang and Xu, 2002).

$$u\big(S(e_i)\big) = \sum_{n=1}^{N} u(H_n) \beta_n\, (e_i) \tag{13}$$

3.2.8 Validation of the decision-making process.

Validation is a key aspect of the methodology, as it provides a reasonable amount of confidence to the results. In current literature, there is an axiom-based validation procedure, which is useful for the validation of the process. The aggregation process may not be rational or meaningful if it does not follow certain axioms. The application of four axioms is consistent with the partial validation procedure applied to the ER approach and is heavily utilised in literature (Durbach, 2012; Loughney et al., 2021; Yang and Xu, 2002). The four axioms assessed are as follows:

- *Axiom 1.*

  A general criterion must not be assessed to H_n if the basic criteria are not assessed to H_n.
- *Axiom 2.*

  The general criterion should be precisely assessed to H_n, provided all basic criteria are assessed to H_n.
- *Axiom 3.*

  If all basic criteria, under a general criterion, are completely assessed to a given subset of evaluation grades, then the general criterion should be assessed to the same subset of grades.
- *Axiom 4.*

  If an assessment for basic criteria is incomplete, then the assessment for the general criterion should be incomplete to a certain degree.

4 Adaptation of both methodologies

The objective of the methods comparison is due to the differences in the use and application of geographical tools to map and visualise maritime uses data. The purpose of this paper is to adapt both MCDM methodologies and their application in a region previously studied by each one. The comparison of both methodologies is performed with the application of MCDM. The comparison of both methods is performed in three steps, (i) evaluation criteria and the data format, (ii) experts weighting of criteria, and (iii) MCDM methodologies results. The Scottish and Madeira regions are proposed as case studies for comparison.

4.1 Methodology adaptation from MADA to AHP for the case of Scotland

The results obtained through the MADA method are consistent with the sixteen criteria used and their application in the Multicriteria model (Alonso and Lamata, 2006; Loughney and Wang, 2020). To adapt the AHP method (Díaz and Guedes Soares, 2022a) to the MADA method (Loughney et al., 2021, 2020), the AHP methodology changed from the original twenty-three criteria (Díaz and Guedes Soares, 2020a) to the sixteen proposed. The experts weighting of criteria is also obtained from the same experts' AHP initial evaluation (Díaz and Guedes Soares, 2021, 2022a, 2022b) with the same AHP methodology previously presented.

The criteria preference values have been assigned by the industry experts involved in the Arcwind project after discussions and completing a questionnaire adequately developed for this specific case. The highest preference values (and therefore the highest weights) were given to the met ocean data and environmentally high-value areas (Table 4). Other environmental and logistics criteria were considered less important as some encountered hazards (proximity to military regions and proximity to shipwrecks) can be mitigated or avoided by applying more suitable wind farm design techniques.

Table 4. Criteria used in MADA method and adapted to AHP method with different experts' evaluation.

No.	Criteria	Original MADA	New AHP
C1	Wind Velocity	0.115	0.097
C2	Potential Power Output (Max. capped at rated power of 10MW where possible)	0.104	0.126
C3	Wave Height (Significant Wave height)	0.076	0.069
C4	Current Speed	0.022	0.038
C5	Tidal Height	0.016	0.038
C6	Vicinity to SubStation (Grid Connection - only one grid connection available)	0.079	0.071
C7	Distance from Ports for Installation	0.054	0.065
C8	Distance from Ports for Maintenance Only	0.053	0.065
C9	Water Depth	0.147	0.051
C10	Proximity to Subsea Facilities	0.026	0.057
C11	Proximity to Coast	0.022	0.045
C12	Proximity to Fisheries	0.023	0.041
C13	Proximity to Military Areas (only one Military area)	0.081	0.041
C14	Proximity to ShipWrecks	0.014	0.057
C15	Proximity to MPAs	0.078	0.085
C16	Proximity to SACs (only one SAC)	0.089	0.056

The validation of a model consists of checking whether the model's structure is suitable for the purpose and if it achieves an acceptable level of accuracy in the results. In quantitative MCDM models, validation is usually carried out by checking the degree of agreement between the data produced by both models. In the present study, the validation of the models has been made by verifying that the result follows the preferences in the assignation of the weights to the criteria. The Pearson coefficient (r) of 0.535 as the correlation between the criteria weight in both methodologies shows an important variability associated mostly with the expert's opinions where an *r-value* of greater than 0.5 indicates a large or strong correlation.

4.2 Methodology adaptation from AHP to MADA for the case of Madeira

As outlined in Section 3.2, Steps 1 and 2 of the AHP to MADA analysis has already been outlined due to the similar nature of the two decision-making methodologies. The following sections will apply the input data from the AHP methodology (outlined in Section 3.1) to the MADA methodology (outlined in Section 3.2)

4.2.1 Criteria for Quantitative analysis and Evaluation Hierarchy

Both the AHP and MADA methodologies utilised similar criteria to conduct site selection for floating offshore wind farms. However, they are different in terms of the geographical locations of the proposed sites and so the criteria for the methodologies are slightly different. For example, the AHP methodology considers proximity to airports whereas the MADA methodology has not due to the difference in locations and the lack of an airport within any range of the sites in Scotland. Given that some criteria were different, the most applicable criteria were utilised for the adaptation of the AHP methodology in Madeira to the developed MADA methodology. Similarly, given that both methodologies were applied to numerous sites, it was determined that a finite number of sites would be utilised to compare the methodologies.

Table 5 outlines the criteria utilised for the adaptation from AHP to MADA as well as the initial data values for each criterion for each site. Twelve criteria were similar for Madeira, out of the original 16 criteria applied in the MADA methodology for Scotland. Furthermore, the criteria outlined (e_1 to e_{12}) represent the basic criteria in the Evaluation Hierarchy. Thus, these basic criteria are grouped based upon similarity into the General Criteria (X, Y and Z). The General Criteria are the same as the General Criteria utilised in the MADA methodology applied to the Scotland FOW sites and are also shown in Table 5.

Table 5. Evaluation hierarchy showing the general and basic criteria for ER analysis as well as average values or input data for each criterion for each site.

General Criteria (With Notation)		Basic Criteria (with notation)		Units	Sao Vicente	Porto da Cruz	Porto Santo
X	Metocean	e1	Wind Speed	m/s	8.32	8.3	8.33
		e2	Wind Power	MW	3.77	3.74	3.78
		e3	significant wave height	m	2.58	2.54	2.6
		e4	Current Speed	m/s	0.3	0.3	0.3
Y	Logistics	e5	Water Depth	m	500	200	80
		e6	Proximity to Ports for Installation and Maintenance	km	38	17.4	13
Z	Facilities & Environment	e7	Proximity to Sub Station	km	3.5	6.1	3
		e8	Proximity to nearest Land/Coast	km	1.8	2.8	1
		e9	Proximity to Shipping Lanes	km	28	4.7	10
		e10	Proximity to MPAs	km	0	0	0
		e11	Proximity to Habitats (Birds & Marine Life)	km	1	1	1
				km	4	4	4
		e12	Proximity to Subsea Facilities	km	1.5	1.5	10

4.2.2 Criteria Weights and Belief Degrees.

As stated in Section 3.2.3, the evaluation grades for the analysis shall be *Poor, Indifferent, Average, Good* and *Excellent* (see Eq. (4)). Data for each criterion shall be gathered to ensure that each site is assessed under each criterion with a set of data covering all possible evaluation grades. The next step is to determine the relative weights of the general and basic criteria for aggregation in the ER algorithm. The weights of the criteria are calculated through PC and AHP and are determined by qualitative assessment from expert judgement, using questionnaires.

Nine experts and their judgements were used to complete the qualitative questionnaire across the discipline of offshore wind structure and farm development within the industry. The nine experts are to remain anonymous, however, all experts are currently employed by companies, which develop and implement fixed and floating offshore wind structures. All experts have a MSc or PhD degree qualification and have 5 or more years of experience within the offshore renewable energy industry. Further explanation of this is demonstrated in (Loughney et al., 2021, 2020; Loughney and Wang, 2020). Utilising the PC and AHP methods, the weights for all the basic and general criteria are calculated and are demonstrated in Table 6.

Table 6. Comparison of the criteria weights used for the initial AHP methodology and the comparative MADA methodology.

General Criteria	Basic Criteria		AHP Weights	MADA Weights
Met-Ocean (X)	e1	Wind	0.29	0.36
	e2	Power	0.38	0.33
	e3	Wave	0.21	0.24
	e4	Current	0.13	0.07
		Total Met-Ocean	1	1
Logistics (Y)	e5	Depth	0.29	0.44
	e6	Ports	0.36	0.32
	e7	Sub Station	0.36	0.24
		Total Logistics	1	1
Facilities & Environment (Z)	e8	Land/Coast	0.15	0.07
	e9	Shipping Lanes	0.15	0.28
	e10	MPAs	0.30	0.29
	e11	Habitats	0.20	0.28
	e12	Subsea Facilities	0.20	0.08
		Total Facilities & Environment	1	1

Table 7. Belief degrees for the MADA analysis for the sites under investigation.

Evaluation Grades			Poor	Indifferent	Average	Good	Excellent
General Criteria	Basic Criteria	Site A Site B Site C	Sao Vicente Porto da Cruz Porto Santo				
Metocean	Wind	A	0	1	0	0	0
		B	0	1	0	0	0
		C	0	1	0	0	0
	Power	A	0	1	0	0	0
		B	0	1	0	0	0
		C	0	1	0	0	0
	Wave	A	0	0	0	1	0
		B	0	0	0	1	0
		C	0	0	0	1	0
	Current	A	0	0	0	1	0
		B	0	0	0	1	0
		C	0	0	0	1	0
Logistics	Depth	A	0	0	0	0	1
		B	0	0	0	1	0
		C	0	1	0	0	0
	Ports	A	0	0	0	0	1
		B	0	0	0	0	1
		C	0	0	0	0	1
	Sub Station	A	0	0	0	0	1
		B	0	0	0	0	1
		C	0	0	0	0	1
Facilities & Environment	Land/Coast	A	1	0	0	0	0
		B	1	0	0	0	0
		C	1	0	0	0	0
		A	0	1	0	0	0

Shipping	B	1	0	0	0	0
Lanes	C	1	0	0	0	0
MPAs	A	1	0	0	0	0
	B	1	0	0	0	0
	C	1	0	0	0	0
Habitats	A	1	0	0	0	0
	B	1	0	0	0	0
	C	1	0	0	0	0
Subsea	A	1	0	0	0	0
Facilities	B	1	0	0	0	0
	C	1	0	0	0	0

The AHP methodology utilised to calculate the weights in the MADA analysis has been outlined in Section 3.1. As the number of criteria is different between the AHP and MADA methodologies, normalisation has been used to demonstrate the relationship of the weights from both methodologies. The Pearson coefficient of correlation was used to determine the correlation between the two sets of weights. The *r-value* was found to be 0.795, which indicates a strong correlation with the weights. While this value is greater than 0.5 indicating a strong correlation, it is not exceptionally close to one. This indicates some variation in the values given that these are expert judgements. Table 7 demonstrates the belief degrees for the ER analysis for each set of 16 basic criteria, for the three sites in the analysis. This data is developed by data provided by IST and Ifermer for the original AHP site selection methodology.

4.3 Scotland case study

Table 8 shows the results of the floating wind farms suitability analysis for new development. The left-hand side of Table 8 shows the suitability ranking under the criteria proposed (see Table 4). The right-hand side indicates the weight of the area extracted from experts' opinions.

Although the suitability analysis sometimes presents good values to all locations evaluated, the specific characteristics of each site imply that certain areas are more attractive than others. The most suitable locations for offshore wind development are areas A14, A15 and B15 (Table 8). The least suitable sites are E12, F12 and F1, where the characteristics of these locations are very similar and are less susceptible to floating turbines development.

Table 8. Scotland ranking of locations and locations weights.

	MADA		AHP	
Ranking	Location	Weight	Location	Weight
1	A15	0.7565	A14	0.9984
2	A14	0.7461	A15	0.9981
3	A13	0.7337	B15	0.9975
4	B15	0.733	A13	0.9974
5	B14	0.733	B14	0.9972
6	B13	0.7228	C15	0.9964
7	C15	0.7002	B13	0.9962
8	D14	0.6981	C14	0.9957
9	D13	0.697	C13	0.9950
10	D12	0.6953	D15	0.9947
11	C14	0.6918	D14	0.9942
12	C13	0.6894	D13	0.9934
13	E13	0.6834	D12	0.9931
14	E14	0.6834	E15	0.9924
15	E12	0.6764	E14	0.9919
16	F14	0.6571	E13	0.9909
17	F15	0.6551	E12	0.9904
18	D15	0.6513	F15	0.9896
19	F13	0.6487	F14	0.9890
20	F11	0.6466	F13	0.9881
21	F12	0.6439	F12	0.9875
22	E15	0.6325	F11	0.9866

The variability between models and experts' opinions allows testing the robustness of the results, more than a sensitivity analysis of a model. The combination and adaptation of both methodologies will enable one to recognize the vulnerabilities and strengths of results. The highest proximity of areas and the similarity of data might cause inaccuracies and variations in the final ranking of locations. Table 4 shows the results of this study where the best areas for floating wind farms in Scotland were identified. The least favourable locations are the ones that predominantly lie further from the coast, where other criteria show higher values. To measure the correlation between both results, the Pearson coefficient of correlation (r) between both data has been calculated, giving a value of 0.971, significant at a 0.001 level, implying a high agreement between both results.

4.4 Madeira case study

Table 9 shows the ranking order and values of the comparative analysis for sites in Madeira. The left side of Table 8 demonstrates the original AHP ranking order of the sites in terms of suitability for floating wind farm implementation. Whereas the right-hand side shows the utility values and ranking order of the sites when the ER method is applied, with the input data from the AHP methodology.

The location of Porto Santo ranks as the most suitable in both methodologies. However, the other two sites are ranked inversely across the two analyses. There are a few possible reasons for this difference in the ranking. The number of criteria utilised across the two methodologies is slightly different given the original geographical applications of the methodology. Furthermore, average objective values have been utilised to develop the belief degrees resulting in a binary situation where the beliefs in the evaluation grades are 1 or 0. This means that one evaluation grade is at 1 while the rest are at 0. This is not necessarily a glaring problem in the analysis, as even with more data these beliefs may remain the same. This is because each evaluation grade has a scale related to the performance of the sites to allocate an evaluation grade using the available data. Nevertheless, more input data may show some variation in the input data (for example, *Poor(0), Indifferent(0.2), Average(0.5), Good (0.3), Excellent (0)*).

What can be stated is that with both methodologies and the input data used, the most suitable site remains the same for Madeira. This shows a level of consistency across both methodologies. Furthermore, the ER algorithm is assessed against four axioms for some partial validation. In this instance, the analysis conforms to all four axioms outlined in Section 3.2.7. Finally, the correlation between both sets of results is also determined. The Pearson coefficient of correlation (r) is utilised, as with the comparison analysis in Section 4.3, and produced a value of 0.895, indicating a strong correlation between the two results.

Table 9: Madeira ranking of locations and locations weights.

	AHP		**MADA**	
Ranking	Location	Weight	Location	Weight
1	Porto Santo	0.392	Porto Santo	0.697
2	São Vicente	0.308	Porto da Cruz	0.634
3	Porto da Cruz	0.300	São Vicente	0.567

5 Discussion and conclusions

The floating wind farm locations suitability map developed with the AHP and MADA methods integrated into a GIS for the maritime surroundings of the European Atlantic coast is a substantial aid in the land-use management of these waters. Similarly, an additional benefit is achieved by integrating geoscientific aspects in the land-use decision process, as demanded by the 2030 Agenda for Sustainable Development.

A fundamental problem of decision theory is how to derive weights of criteria. One disadvantage of the AHP method is the inherent subjectivity of assigning preference values between criteria. The weights derived from these preference values usually have a profound effect on the results of the suitability analysis. However, in this particular case, there are no substantial differences between both methodologies in the location suitability analysis. The results of the site search analysis performed under the original AHP and MADA methodologies are robust enough. The adaptation between both methods has added some uncertainties and imbalances to the results. This imbalance is related mainly to the axioms and algorithms and the experts' involved opinion. The original methodologies and criteria were selected to achieve robust results. Nevertheless, the differences created in this adaptation of methods influence the results. These variations are more present in locations with similar characterisation values.

After some discussions with different experts in the decision support systems and following the original and the new results, the present results suggest that the best locations for floating wind turbines deployment remain equal on Madeira and Scotland's marine areas. The secondary locations or the least favourable locations change concerning the original methodologies due to previously mentioned aspects. The weights obtained for the location's ranking are very similar, so the ranking is susceptible to minor alterations. This variability makes it impossible to consider that the adaptation of both compared methods may be possible for future applications since the principles of robustness are not guaranteed in the results.

An advantage of value/utility-based methods as AHP is that criteria do not need standardization or transformation processes, reducing subjectivity. However, using AHP, more decisions need to be made regarding the selection of the preference function and which set of criteria weights to use. On the other hand, MADA transforms the values in different degrees of suitability, adding some subjectivity by manipulating data. However, this approach only requires analyzing in detail the criteria by the methodology developer side to pre-assign a value reducing the times needed by experts involved. Some differences can be observed in alternatives located in areas of Scotland. This is the case of alternative location A14, which presented a high mean value in the MADA methodology but presented a rank 2 in the AHP approach. In this case, the weight assigned to the criteria in AHP adapted approach was not enough to rank this alternative in the first position. Thus, higher importance should be given to the requirements in the site selection approaches.

Performing AHP with the mean values of MADA and experts’ evaluation and vice versa produce meaningful results. Still, the uncertainty in either the input values or the result cannot be quantified.

However, it can be seen that there are levels of consistency across both methodologies and optimisation of the methodologies can be achieved. Similarly, further analysis can be conducted with a larger data sample to determine if this has attributed to the differences in results or if it the aggregation of the data within the decision-making techniques themselves.

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Appendix A. Case studies location data

1) Scotland locations

Criteria		Wind Velocity	Power Output	Significant Wave height	Current Speed	Tidal Height	Vicinity to Substation	Distance from Ports (Installation)	Distance from Ports (Maintenance)	Water Depth	Proximity to Subsea Facilities	Proximity to Coast	Proximity to Fisheries	Proximity to Military Areas	Proximity to Shipwrecks	Proximity to MPAs	Proximity to SACs
		m/s	MW	m	m/s	m	km	km	km	km	km	km	km	km	km	km	km
A15	Min	8.5	4.0	1.7	0.2	3.0	154.5	100.0	474.5	100.0	16.9	56.3	11.8	61.1	28.5	49.2	31.9
	Max	16.3	10.0	3.7	0.2	3.9		609.3	516.0	200.0	17.4	169.1	66.4		98.5	117.6	
	Ave	12.4	7.0	2.7	0.2	3.5		354.6	495.2	150.0	17.2	112.7	39.1		63.5	83.4	
B15	Min	8.5	4.0	1.7	0.2	3.0	148.9	107.8	482.3	100.0	22.5	50.7	11.8	55.5	22.9	49.2	26.4
	Max	16.3	10.0	3.7	0.2	3.9		617.2	523.9	200.0	23.0	163.5	60.9		93.1	112.5	
	Ave	12.4	7.0	2.7	0.2	3.5		362.5	503.1	150.0	22.8	107.1	36.4		58.0	80.8	
C15	Min	8.5	4.0	1.7	0.2	3.0	143.2	112.4	486.9	100.0	28.2	45.1	11.8	50.0	17.3	49.2	20.9
	Max	16.3	10.0	3.7	0.2	3.9		621.7	528.4	200.0	28.7	157.8	55.5		87.7	107.3	
	Ave	12.4	7.0	2.7	0.2	3.5		367.1	507.7	150.0	28.4	101.4	33.6		52.5	78.3	
D15	Min	8.3	3.8	1.7	0.2	3.1	137.6	117.5	492.0	70.0	33.8	39.4	17.4	44.4	11.7	49.2	15.5
	Max	16.0	10.0	3.8	0.2	4.0		626.9	533.6	200.0	34.3	152.2	50.0		82.3	102.2	
	Ave	12.2	6.9	2.7	0.2	3.6		372.2	512.8	135.0	34.1	95.8	33.7		47.0	75.7	
E15	Min	8.3	3.8	1.7	0.2	3.1	132.0	122.9	497.4	70.0	39.4	37.7	17.4	38.9	6.1	43.6	10.2
	Max	16.0	10.0	3.8	0.2	4.0		632.2	538.9	200.0	39.9	146.6	44.5		77.0	97.2	
	Ave	12.2	6.9	2.7	0.2	3.6		377.5	518.2	135.0	39.7	92.1	31.0		41.5	70.4	
F15	Min	8.3	3.8	1.7	0.3	3.2	126.4	128.3	502.8	70.0	45.1	28.7	23.0	33.3	0.5	38.0	5.0
	Max	16.0	10.0	3.8	0.3	4.1		637.6	544.4	200.0	45.6	140.9	39.0		71.7	92.2	
	Ave	12.2	6.9	2.7	0.3	3.7		383.0	523.6	135.0	45.3	84.8	31.0		36.1	65.1	
A14	Min	8.5	4.0	1.7	0.2	3.0	154.8	133.8	508.3	100.0	16.9	56.3	6.1	61.1	29.2	43.6	31.9
	Max	16.3	10.0	3.7	0.2	3.9		643.1	549.8	200.0	17.4	169.1	68.1		97.1	115.7	
	Ave	12.4	7.0	2.7	0.2	3.5		388.4	529.0	150.0	17.2	112.7	37.1		63.1	79.6	
B14	Min	8.5	4.0	1.7	0.2	3.0	149.2	112.4	486.9	100.0	22.5	50.7	6.1	55.5	23.6	43.6	26.4
	Max	16.3	10.0	3.7	0.2	3.9		621.7	528.4	200.0	23.0	163.5	62.5		91.6	110.4	
	Ave	12.4	7.0	2.7	0.2	3.5		367.1	507.7	150.0	22.8	107.1	34.3		57.6	77.0	
C14	Min	8.5	4.0	1.7	0.2	3.0	143.6	115.7	490.2	70.0	28.2	45.1	6.1	50.0	18.1	43.6	20.9
	Max	16.3	10.0	3.7	0.2	3.9		625.0	531.7	200.0	28.7	157.8	56.8		86.2	105.2	
	Ave	12.4	7.0	2.7	0.2	3.5		370.4	511.0	135.0	28.4	101.4	31.5		52.1	74.4	
D14	Min	8.3	3.8	1.7	0.2	3.1	138.0	120.0	494.5	70.0	33.8	39.4	11.8	44.4	12.6	43.6	15.5
	Max	16.0	10.0	3.8	0.2	4.0		629.3	536.1	200.0	34.3	152.2	51.2		80.7	100.0	
	Ave	12.2	6.9	2.7	0.2	3.6		374.7	515.3	135.0	34.1	95.8	31.5		46.7	71.8	
E14	Min	8.3	3.8	1.7	0.2	3.1	132.4	124.8	499.3	70.0	39.4	40.4	11.8	38.9	7.1	38.0	10.2
	Max	16.0	10.0	3.8	0.2	4.0		634.2	540.9	200.0	39.9	146.6	45.6		75.3	94.9	
	Ave	12.2	6.9	2.7	0.2	3.6		379.5	520.1	135.0	39.7	93.5	28.7		41.2	66.4	
F14	Min	8.3	3.8	1.7	0.3	3.2	126.8	129.9	504.4	70.0	45.1	30.3	17.4	33.3	1.6	32.4	5.0
	Max	16.0	10.0	3.8	0.3	4.1		639.2	545.9	200.0	45.6	140.9	39.9		69.9	89.8	
	Ave	12.2	6.9	2.7	0.3	3.7		384.6	525.2	135.0	45.3	85.6	28.7		35.8	61.1	
A13	Min	8.5	4.0	1.7	0.2	3.0	155.4	135.1	509.6	70.0	16.9	56.3	0.5	61.1	30.3	38.0	31.9
	Max	16.3	10.0	3.7	0.2	3.9		644.4	551.2	200.0	17.4	169.1	56.8		96.0	114.0	
	Ave	12.4	7.0	2.7	0.2	3.5		389.8	530.4	135.0	17.2	112.7	28.7		63.1	76.0	
B13	Min	8.5	4.0	1.7	0.2	3.0	149.8	117.5	492.0	70.0	22.5	50.7	0.5	55.5	24.8	38.0	26.4
	Max	16.3	10.0	3.7	0.2	3.9		626.9	533.6	200.0	23.0	163.5	51.2		90.4	108.7	
	Ave	12.4	7.0	2.7	0.2	3.5		372.2	512.8	135.0	22.8	107.1	25.9		57.6	73.3	
C13	Min	8.5	4.0	1.7	0.2	3.0	144.2	120.0	494.5	70.0	28.2	45.1	0.5	50.0	19.4	38.0	20.9
	Max	16.3	10.0	3.7	0.2	3.9		629.3	536.1	200.0	28.7	157.8	45.6		84.9	103.4	
	Ave	12.4	7.0	2.7	0.2	3.5		374.7	515.3	135.0	28.4	101.4	23.0		52.2	70.7	

D13	Min	8.3	3.8	1.7	0.2	3.1	138.6	123.5	498.0	70.0	33.8	39.4	6.1	44.4	14.0	38.0	15.5
	Max	16.0	10.0	3.8	0.2	4.0		632.9	539.6	200.0	34.3	152.2	39.9		79.4	98.1	
	Ave	12.2	6.9	2.7	0.2	3.6		378.2	518.8	135.0	34.1	95.8	23.0		46.7	68.1	
E13	Min	8.3	3.8	1.7	0.2	3.1	133.1	127.8	502.3	70.0	39.4	33.8	6.1	38.9	8.7	32.4	10.2
	Max	16.0	10.0	3.8	0.2	4.0		637.1	543.8	200.0	39.9	146.6	34.3		73.9	92.9	
	Ave	12.2	6.9	2.7	0.2	3.6		382.4	523.0	135.0	39.7	90.2	20.2		41.3	62.6	
F13	Min	8.3	3.8	1.7	0.3	3.2	127.5	132.4	506.9	70.0	45.1	32.7	11.8	33.3	3.5	26.8	5.0
	Max	16.0	10.0	3.8	0.3	4.1		641.7	548.4	200.0	45.6	140.9	28.7		68.4	87.7	
	Ave	12.2	6.9	2.7	0.3	3.7		387.0	527.6	135.0	45.3	86.8	20.2		36.0	57.2	
D12	Min	8.3	3.8	1.7	0.2	3.1	139.5	137.2	511.7	70.0	33.8	39.4	0.5	44.4	16.0	32.4	15.5
	Max	16.0	10.0	3.8	0.2	4.0		646.6	553.3	200.0	34.3	152.2	39.9		78.4	96.4	
	Ave	12.2	6.9	2.7	0.2	3.6		391.9	532.5	135.0	34.1	95.8	20.2		47.2	64.4	
E12	Min	8.3	3.8	1.7	0.2	3.1	134.0	131.4	505.9	70.0	39.4	33.8	0.5	38.9	10.9	26.8	10.2
	Max	16.0	10.0	3.8	0.2	4.0		640.7	547.4	200.0	39.9	146.6	34.3		72.8	91.1	
	Ave	12.2	6.9	2.7	0.2	3.6		386.1	526.7	135.0	39.7	90.2	17.4		41.9	59.0	
F12	Min	8.3	3.8	1.7	0.3	3.2	128.5	135.5	510.0	70.0	45.1	35.9	6.1	33.3	5.9	21.3	5.0
	Max	16.0	10.0	3.8	0.3	4.1		644.9	551.6	200.0	45.6	140.9	28.7		67.3	85.8	
	Ave	12.2	6.9	2.7	0.3	3.7		390.2	530.8	135.0	45.3	88.4	17.4		36.6	53.5	
F11	Min	8.3	3.8	1.7	0.3	3.2	129.8	140.0	514.5	70.0	45.1	39.6	0.5	33.3	8.2	15.8	5.0
	Max	16.0	10.0	3.8	0.3	4.1		649.4	556.1	200.0	45.6	140.9	23.0		66.4	84.3	
	Ave	12.2	6.9	2.7	0.3	3.7		394.7	535.3	135.0	45.3	90.2	11.8		37.3	50.0	

2) Madeira region locations

Criteria	Units	Sao Vicente - Santana	Porto da Cruz - Caniçal	Porto Santo
Wind velocity	m/s	8.32	8.3	8.33
Wind potential	h/year	4281	4299	4301
Water depth	m	500	200	80
Wave conditions	m	2.58	2.54	2.6
Marine currents	m/s	0.3	0.3	0.3
Temperature	º C	21.6	21.6	21.5
Technical feasibility	density	1	1	1
Sufficient study times	density	1	1	1
Distance to local electrical grid	km	3.5	6.1	3
Distance from coastal facilities	Km	38	17.4	13
Distance from shore	Km	1.8	2.8	1
Distance from residential areas	km	1.8	2.8	3
Distance from maritime routes	km	28	4.7	10
Distance from underwater lines	km	1.5	1.5	10
Distance to marine recreational activities	km	0	0	0
Distance from airport	km	21.9	9.6	3
Distance from protected areas	km	0	0	0
Proximity to migratory birds' paths	density	1	1	1
Proximity to migratory marine life paths	density	4	4	4
Area of the territory	km^2	51	57.5	87
Proximity to the area of electricity demand	km	22.9	18.8	6
Population served	number	262302	262302	5483
Multiple resources	density	3	3	1