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A fuzzy-MADM based approach for site selection of offshore wind farm in busy waterways in China

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Abstract: The offshore wind farm has developed fast as a type of abundant, clean, renewable energy sources. The offshore wind farm located close to the shore especially in busy waterways may have significantly impact on the maritime safety. This paper proposes a fuzzy-MADM (multiple attribute decision-making) method for site selection of the offshore wind farm by compressively considering the feasibility of installation (i.e. cost and production) and maritime safety. The kernel of this approach is to establish a three-layer decision-making framework after identifying the influencing factors from previous works, to derive the decision matrix by integrating the influencing factor and to obtain the weights of the attributes by using the Analytic Hierarchy Process. The proposed approach is applied to a real site selection of offshore wind farm in the Eastern China Sea. The result is reasonable because it agrees with the discussion of a workshop. Consequently, this paper provides a practical and quantitative tool for site selection of offshore wind farm.

Key words: offshore wind farm; decision-making; maritime safety; fuzzy-MADM

1 Introduction

1.1 Background of offshore wind farm development

As a clean environmental energy, the offshore wind farm has developed fast in recent years worldwide (Bilgili et al., 2011; Guedes Soares et al., 2014; Sun et al., 2012; Esteban and Leary 2012; Kaplan, 2015). Compared with the onshore wind farm, the advantages of the offshore wind farm are that there is more available space and fewer complaints about noise and visual intrusion (Sun et al. 2012). Moreover, the offshore wind farm also has the advantages of higher wind speeds, less turbulence and lower wind-shear (Bilgili et al., 2011). Upon February 2018, there are around 37 offshore wind farms with at least 200 MW nameplate capacities under operational and some others under construction (Wikipedia, 2018). Table 1 lists the top eight largest operational offshore wind farms in the world.

Table 1 Top eight largest operational offshore wind farms in the world (Wikipedia, 2018)

Offshore wind farm	Capacity (MW)	Country	Number of turbines	Commissioned
London Array	630	UK	175	2012
Gemini Wind Farm	600	Netherland	150	2017
Gode Wind (phases 1+2)	582	Germany	97	2017
Gwynt y Môr	576	UK	160	2015
Race Bank	573	UK	91	2018
Greater Gabbard	504	UK	140	2012
Dudgeon	402	UK	67	2017
Veja Mate	402	Germany	67	2017

Although the offshore wind farm has many advantages, some disadvantages also exist. Specifically, the offshore wind turbines are expensive and difficult to install due to rough sea conditions (Sun et al., 2012), and the expensive integration in to the electrical network (Bilgili et al., 2011). Therefore, many previous studies focused on the cost reduction and nameplate capacities maximization in every stage of development, manufacture, installation and operation.

Specifically, Snyder and Kaiser (2009) analysed the costs and benefits of offshore wind farm and they stressed the importance of maritime safety. Castro-Santos and Diaz-Casas (2015) proposed the location influence of the cost in lifecycle of floating offshore wind farm, and moreover, an extended work was carried out using Galicia as a case study (Castro-Santos, 2016). Studies on installation process (Barlow et al., 2015) as well as installation vessels (Paterson et al., 2017; Dalgic et al., 2015b; Sperstad, et al., 2017) are also carried out to reduce the cost for offshore wind farm. Operation and maintenance are conducted for optimized planning, routing and scheduling (Dalgic et al., 2015a; Irawan et al., 2017; Rinaldi et al., 2017; Pillai et al., 2017). Moreover, the maximization of overall production is another way by optimizing the offshore wind farm layout (Chowdhury et al., 2012; González et al., 2015).

1.2 Site selection of offshore wind farm

Different from development, manufacture, installation and operation, site selection is conducted at an early-stage to determine the feasibility of wind farm by considering the environmental issues, economic feasibility, and other factors. This site selection has been widely carried out both onshore (Höfer et al., 2016; Noorollahi et al., 2016; Latinopoulos and Kechagia 2015) and offshore wind farm planning (Chaouachi et al., 2017; Fetanat and Khorasaninejad 2015; Wu et al. 2016b).

Regarding the site selection of offshore wind farm, Chaouachi et al. (2017) used multiple attribute decision-making method (MADM) by considering security aspects, economic investment, operation costs and capacity performances. Fetanat and Khorasaninejad (2015) defined six criteria (i.e. depth and height, environmental issues, proximity to facilities, economic aspects, resource technical, and culture) together with related sub-criteria for this site selection. Wu et al. (2016b) selected the best offshore wind power station under intuitionistic fuzzy environment, and defined the wind resources, construction and maintenance conditions, supporting conditions onshore. Table 2 summarizes the method used for site selection of offshore wind farm. This table shows that the MADM method (also known as multiple criteria decision-making), which uses multiple attribute to obtain a comprehensive evaluation result, has been widely used for site selection of offshore wind farm.

Table 2 Overview of studies on site selection of offshore wind farm

Study	Technique applied	Case study region	Main results
Chaouachi et al. 2017	MADM & AHP	Baltic States	The optimal wind sites reflects the characteristics of market design, regulatory aspects or renewable integrating targets

Fetanat and Khorasaninejad 2015	MADM & fuzzy DEMATEL	Iran	The best site can be selected among four alternatives and the robustness of the method is verified
Wu et al. 2016b	MCDM-ELECTRE-III	China	The site selection methodology is valid and practical
Kim et al. 2013	MCDM-GIS	South Korea	Construction costs associated with the substructure and grid connection are crucial in determining the location of the offshore wind farm
Kim et al. 2016	GIS	South Korea	The offshore wind farms can be located along a wide range of the eastern and western coasts of Jeju Island by considering energy resources and economics.
Cradden et al. 2016	MADM & GIS	Europe	The main potential for combined technologies in Europe is focused to the north and west due to strong resources and acceptable depth conditions.
Vasileiou et al. 2017	GIS & AHP	Greece	The result demonstrates the potential for deploying offshore wind and wave energy in Greece, especially in the offshore areas of Crete and in a lengthwise zone extended from North-central to central Aegean.

Moreover, from previous works, the influencing factors are considered from different perspectives and are summarised in Table 3. From this table, it can be seen that few research focused on maritime safety in site selection of offshore wind farm. However, the risk analysis of offshore wind farm has attracted some attention recently (Kang et al., 2017; Shafiee et al., 2015; Abaei et al., 2017; Wu et al., 2017d). In fact, this is a significant concern of offshore wind farm especially the collision with the offshore wind farm turbine foundations (Moulas et al., 2017). Hence, the maritime safety should be considered in the stage of site selection.

Table 3 summary of criteria considered from the literature reviewed

Criteria	Chaouachi et al. 2017	Fetanat and Khorasaninejad 2015	Wu et al. 2016b	Kim et al. 2013	Kim et al. 2016	Cradden et al. 2016	Vasileiou et al. 2017
Wind resources	√	√	√	√	√	√	√
Water depth	√	√	√	√	√	√	√
Sea state	×	√	√	√	×	×	×
Distance to shore	√	√	√	√	√	√	√
Environmental protection	√	√	√	√	√	√	×
Shipping traffic	×	×	×	×	×	√	√
Logistics	×	×	√	√	×	√	×
Electricity networks	√	√	√	×	×	√	√
Population served	×	×	×	×	×	×	√
Culture	×	√	×	×	×	×	×
Social benefits	×	×	√	×	×	×	×

Although some existing works have conducted to consider the risk of offshore wind farm when looking at the literature (BMT, 2005; Moulas et al., 2017), few studies can be found to select the best offshore wind farm in the busy waterway by addressing the problem of maritime safety. However, this is a predominant issue from the previous works (Mou et al., 2010; Yip, 2008; Zhang et al., 2016; Wu et al., 2015). Moreover, some previous works used the qualitative assessment on the criteria, which makes the model hard to quantified and implemented. Therefore, the motivation of this paper is to propose a fuzzy-MADM approach for site selection of offshore wind farm by comprehensive considering the cost, production and safety. From this perspective, the proposed method develops a three-layer decision-making approach by treating the wind resources, natural environment, traffic environment and conditions for wind turbine as the attributes, and the associated influencing factors are identified and quantified from the previous works in order to obtain a convincing result.

The remainder of this paper is organized as follows. Section 2 develops a three-layer decision-making approach for site selection of offshore wind farm, where the influencing factors are identified and quantified from the previous works by considering the cost, production and maritime safety. In order to verify the proposed decision-making approach, Section 3 applies this proposed approach to Eastern China Sea as a Case Study and the result demonstrates that this approach is practical and useful for site selection of offshore wind farm. Limitations of the proposed approach are discussed in Section 4, and the conclusions are drawn in Section 5.

2 Development of decision-making model for site selection of offshore wind farm

2.1 Establish a generic decision-making framework for offshore wind farm

The site selection of offshore wind farm is influenced by several factors, and the MADM method is widely used for such problem from Table 2. Without loss of generality, $X = \{x_1, x_2, \ldots, x_t\} (t \geq 2)$ is defined as a set of candidates sites for offshore wind farms. $Y = (y_1, y_2, \ldots, y_s)(s \geq 2)$ is defined as a set of attributes. Let $A = (a_{ij})_{s \times t}$ be the decision matrix, where a_{ij} is the attribute value. $w_i = (w_1, w_2, \ldots, w_s)$ are the weights of the attributes, note that the weight should be greater than zero and the summation of weights should be equal to one, and this is written as $w_i \geq 0 \; (i = 1, 2, \ldots, s)$ and $\sum_{i=1}^{s} w_i = 1$. Define V_j as the overall assessment on the j *th* site of offshore wind farm, this can be written as Eq. (1).

$$V_j = \sum_{i=1}^{s} w_i a_{ij} \tag{1}$$

It can be seen that the greater value V_j is, the better the j *th* site of offshore wind farm is. In order to obtain the overall assessment on the multiple sites of offshore wind farms, the decision-making framework is established in the following three steps.

First, the three-layer decision-making framework is established after identifying the attributes and influencing factors, moreover, the decision matrix is obtained by using fuzzy logic method.

Second, the weights of the attributes are derived by using AHP method, and the expert judgements are introduced in this process.

Third, final decision-making is carried out after acquisition of the weights and values of decision attributes, and the best site of the offshore wind farms are selected.

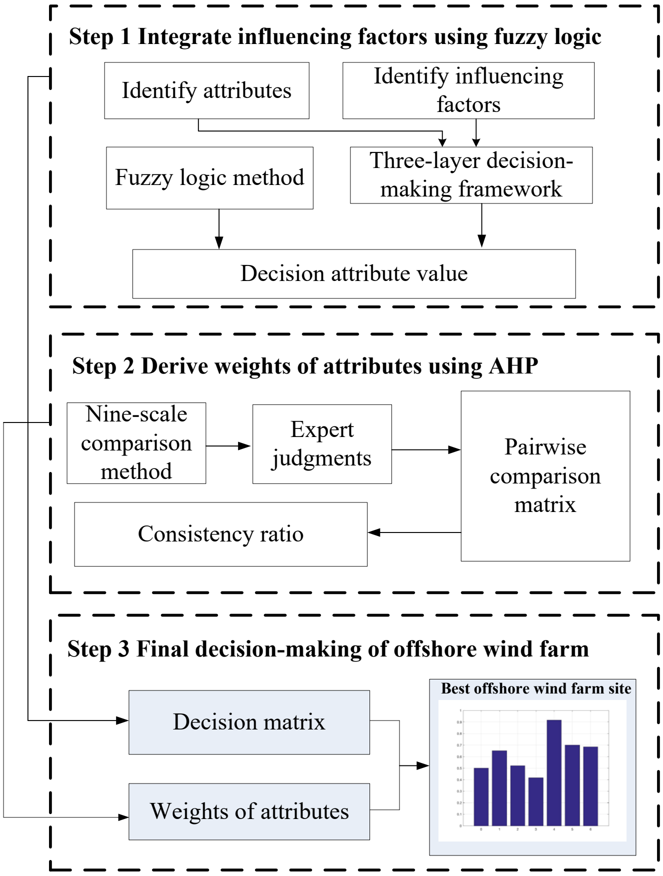


Fig. 1 Generic decision-making framework for site selection of offshore wind farm

2.2 Identify influencing factors to obtain the hierarchical decision-making framework

In order to make an overall assessment on the candidate sites, the influencing factors of the offshore wind farms should be identified from the previous works in the decision-making problem (Wu et al., 2017c). Similar with other site selections of offshore wind farms (Hofer et al., 2016; Kim et al., 2016; Wu et al., 2016b), the annual mean wind speed, wind duration, and mean wind power density should be considered as they are key factors to describe the wind resources of wind farms. Water depth is a distinguishing factor for the site selection of offshore wind farm owing to the offshore nature, and this factor will have impact on the installation of the wind turbine and finally influence the cost of installation (Fetanat and Khorasaninejad 2015; Wu et al., 2016b). Moreover, the Chinese government also have related policies for this factor (NEB and SOA 2011). Wave height will influence the offshore wind farm design (Fetanat and Khorasaninejad 2015; Sulaiman et al., 2013). Maritime safety is the key issue for offshore wind farm in the busy waterway. As there are many ships navigating in the channel, anchoring in the anchorage and also fishing in the fishing area, the construction of offshore wind farm will occupy the navigable waterways and also have impact on the radar and very high frequency, which is used for communication of collision avoidance for the ships (Chauvin et al., 2013). Moreover, the distance from the shore will have impact on the eclectic and grid connection (Lee et al., 2009), this is why the Chinese government have taken financial support for development of the offshore wind farm far from the shore (NEB and SOA 2011). The nameplate capacity is the factor to describe the power production capacity. The explanations of these factors are summarized and shown in Table 4.

Table 4 Explanations of influencing factors for site selection of offshore wind farm

Influencing factors	Explanation
Annual mean wind speed (m/s)	A key factor to describe the wind resources
Wind duration (h)	A key factor to describe the wind resources
Mean wind power density (W/m^2)	A key factor to describe the wind resources
Water depth (m)	Influence the installation of the wind turbine
Wave height (m)	Influence the offshore wind farm design
Distance from the fairway (nm)	Influence the safety of the ships navigating in this area
Distance from the anchorage (nm)	Influence the safety of the ships navigating in this area
Distance from the fishing area (nm)	Influence the safety of the ships navigating in this area
Distance from the shore (km)	Influence the eclectic and grid connection
Nameplate capacity (MW)	The power production capacity influences the outputs of wind farm

After identifying the influencing factors of these influencing factors, the attributes should then be defined in order to facilitate the decision-making process. The four attributes, which are wind resources, natural environment, traffic environment and conditions for wind turbine, are defined as the parent criteria of the influencing factors.

Therefore, the hierarchical decision-making framework for site selection of offshore wind farm is established and shown in Fig.2.

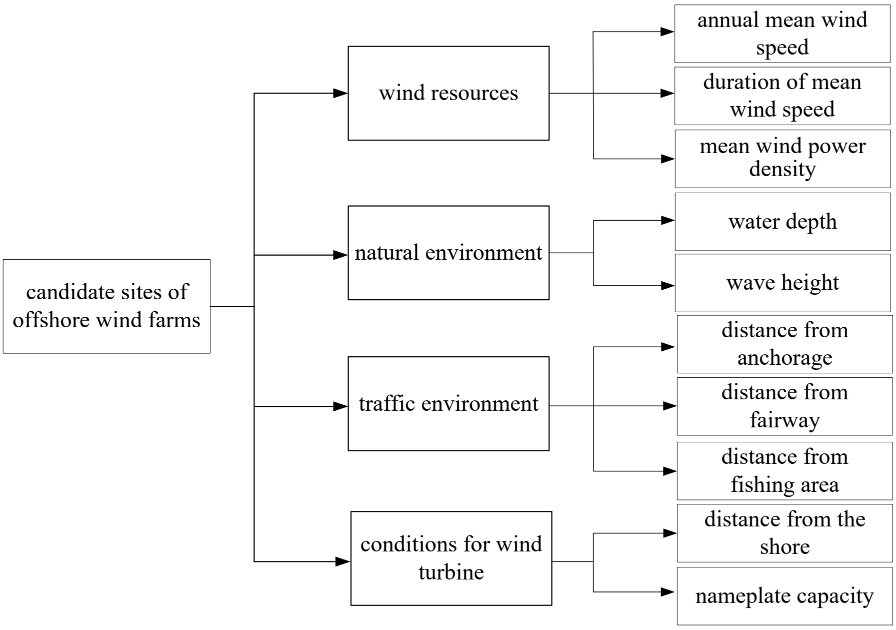


Fig. 2 Hierarchical decision-making framework for site selection of offshore wind farm

2.3 Fuzzify the input and output variables for offshore wind farms

The fuzzy logic method is widely used for risk analysis (Cullum et al., 2018; Ung, 2018) and decision-making (Sahin and Yip 2017; Wu et al., 2016a) for maritime transportation. The process of using fuzzy logic is as follows. First, the influencing factors and attributes are fuzzified. Second, membership functions and IF-THEN rules are established to develop the fuzzy logic boxes, and the attribute values (expressed by linguistic variables) after fuzzy rule based reasoning method can be derived. Third, the crisp values of the attributes are obtained after defuzzification using the centre of gravity method. This process is shown in Fig.3.

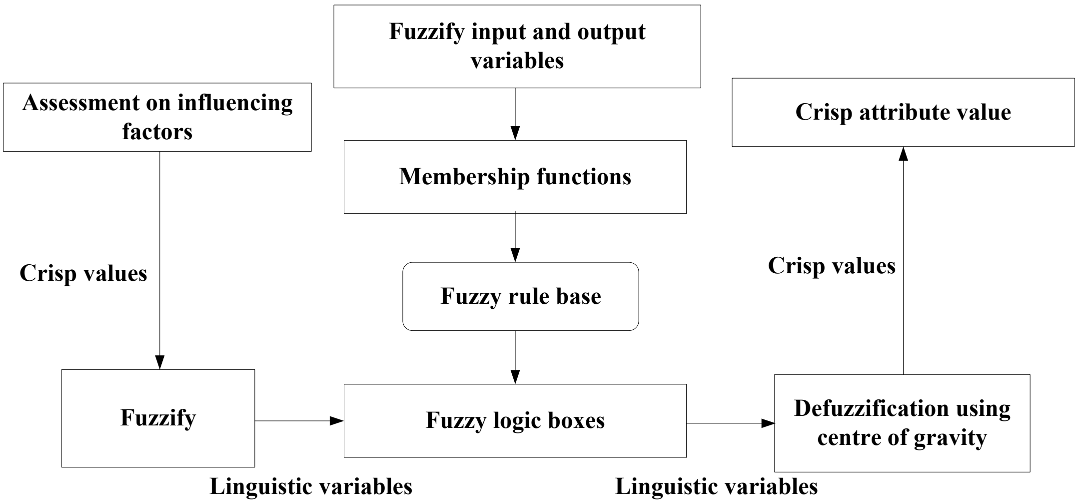


Fig. 3 Fuzzy rule based reasoning process for site selection of offshore wind farm

The input and output variables need to be fuzzifed. Expert judgments and membership functions are two widely used in the previous works (Pam et al., 2013; Yang et al., 2013). The former method needs to invite the experts to make judgments on each influencing factor by using several linguistic variables with several categories, which makes the experts will be confused and the result not to be convincing. For example, if there are five alternatives and five linguistic variables in five categories, the experts have to make 1250 judgments ($5\times5\times5\times10=1250$). Hence, membership function method will be introduced in this paper.

The triangular membership function, which is widely used in the previous works (Wu et al., 2016a; Cosgun et al., 2014), is shown in Fig. 3. For the input variables, as all the influencing factors are identified from the previous works and field investigation, it is also easy to use these existing researches to fuzzify the influencing factors. Five linguistic terms, which are “very bad”, “bad”, “moderate”, “good” and “very good”, are introduced in this paper. Note that less than seven linguistic variables should be used as it may be difficult to distinguish the difference among the linguistic variables, moreover, more than three linguistic variables should be used to achieve a comprehensive result (Wu et al., 2017b). Fuzzification of these factors are described in detail in the following.

(1) Annual mean wind speed. As the traditional wind turbine is 10m height, the data of the wind resources, includes annual mean wind speed, wind duration and mean wind power density, are collected at this height. From the field investigation in Eastern China Sea, the lowest annual mean wind speed is 2.5m/s, while the highest speed

is around 7 m/s. Therefore, 7 m/s is assumed to be “very high” with a probability of one, while 2.5m/s is treated as “very low” with a probability of one, and the result is shown in Table 3.

(2) Wind duration. By using the same investigation, the longest duration is 8000 hours in the coastal area. Hence, 8000 and 0 are assumed to be “very long” and “very short” with a probability of 1.0, respectively.

(3) Mean wind power density. The highest mean wind power density is 300 w/m^2 and this is assumed to be very high with a probability of 1.0.

(4) Water depth. The water depth will influence the foundation cost (Dicorato et al., 2011). Although in some researches the foundation cost, includes manufacturing cost and cost of transport and installation, is assumed to be constant (Lundberg 2003). However, the water depth is highly related with the foundation cost for further research. For example, in a study within OWFLO project (Elkinton et al., 2005), the monopile foundation cost has a liner relationship with the water depth, and another research discovered that the cost increased by 2% for each meter of further depth with a basic water depth equal to 8 m (Nielsen 2003). As the National Energy Administration and National Bureau of Oceanography has issued a joint policy that the water depth should be more than 10m for offshore wind farm in China (NEB and SOA 2011), the 10m is assumed to be very good and 40m is treated as very bad as the cost increases a lot.

(5) Wave height. From the previous research (Sulaiman et al., 2013), the wind turbine will be greatly influenced with a wave height of more than 10m, and 10m is assumed to very bad in Table 5.

(6) Distance from the fairway, anchorage and fishing area. These three factors are related with maritime safety and are similar but a little difference. In the channel and anchorage, the ships have to avoid collision by using visual sight and radar to detect other ships. From some field test in Donghai Bridge, while it is the first offshore wind farm in China, the wind farm has slight impacts on radar when it is installed 3nm far from the anchorage and channel. However, the fishing area is different as the fishing boat may be fishing using trawl,

which will influence the cabin line of the wind farm, and the wind farm should be farer from the fishing area than the anchorage and channel.

(7) Distance from the shore. Distance from the shore will influence the maintenance cost (Sarker and Faiz 2016) and transportation and installation costs (Sarker and Faiz 2017). Moreover, according to the policy of Chinese Government, the distance from the shore should be more than 10km, and this is assumed to be very good in this study. Moreover, different from the distance from the channel and anchorage, the farer the distance from shore, the better alternative is.

(8) Nameplate capacity. The nameplate capacity influences the production of the wind farm, as it is hard to earn money in the current stage, many countries have fiscal policy of the Government subsidy. In this regard, it is better to develop a wind farm with nameplate capacity of 100 kW, and this is assumed as moderate in this paper.

Table 5 Fuzzified input variables of offshore wind farms

Input variables	Very bad	Bad	Moderate	Good	Very good
Annual mean wind speed (m/s)	Very low (1.34,2.5,3.63)	low (2.5,3.63,4.75)	Moderate (3.63,4.75,5.88)	high (4.75,5.88,7)	Very high (5.88,7,8.13)
Wind duration (h)	Very short (0,0,75)	Short (0,75,150)	Moderate (75,150,225)	Long (150,225,300)	Very long (225,300,375)
Mean wind power density (W/m^2)	Very low (0,0,2k)	low (0,2k,4k)	Normal (2k,4k,6k)	High (4k,6k,8k)	Very high (6k,8k,10k)
Water depth (m)	Very deep (32.5,40,47.5)	Deep (25,32.5,40)	Normal (17.5,25,32.5)	Shallow (10,17.5,25)	Very shallow (2.5,10,17.5)
Wave height (m)	Very heavy (7.5,10,12.5)	Heavy (5,7.5,10)	Moderate (2.5,5,7.5)	Light (0,2.5,5)	Very light (0,0,2.5)
Distance from the fairway (nm)	Very close (0,0,1.5)	Close (0,1.5,3)	Moderate (1.5,3,4.5)	Far (3,4.5,6)	Very far (4.5,6,7.5)
Distance from the anchorage (nm)	Very close (0,0,1.5)	Close (0,1.5,3)	Moderate (1.5,3,4.5)	Far (3,4.5,6)	Very far (4.5,6,7.5)
Distance from the fishing area (nm)	Very close (0.5,2,3.5)	Close (2,3.5,5)	Moderate (3.5,5,6.5)	Far (5,6.5,8)	Very far (6.5,8,9.5)
Distance from the shore (km)	Very far (40,50,60)	Far (30,40,50)	Moderate (20,30,40)	Close (10, 20,30)	Very close (0, 10,20)
Nameplate capacity (MW)	Very small (0,0,25)	Small (0,25,50)	Normal (25,50,75)	Large (50,75,100)	Very large (75,100,125)

While for the output variables, which are wind resources, natural environment, traffic environment and conditions for wind turbine, they are all fuzzified by using the triangular fuzzy numbers shown in Fig. 4. Similar with the description proposed by Godaliyadde et al. (2011), the meanings of each linguistic variable are adapted and shown in Table 6 (wind resources as an example).

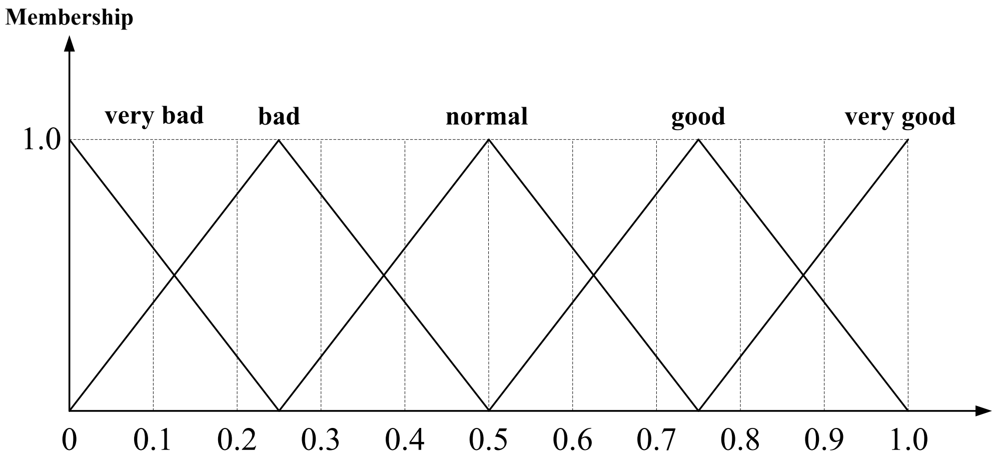


Fig. 4 Standard triangular fuzzy numbers for fuzzification

Table 6 Description of linguistic terms of output variables (wind resources as example)

Linguistic variables	Description
Very bad	The wind resources is very bad for offshore wind farm installation
Bad	The wind resources is bad for offshore wind farm installation
Normal	The wind resources is normal for offshore wind farm installation
Good	The wind resources is good for offshore wind farm installation
Very good	The wind resources is very good for offshore wind farm installation

2.4 Use of fuzzy rule based reasoning to derive the decision matrix

After fuzzification of the input and output variables, the fuzzy logic boxes should be established. The multiple-input single-output fuzzy logic box is introduced in this paper, which is also used by Balmat et al. (2011). Specifically, the influencing factors are treated as input variables and the corresponding attribute is treated as output variable. As shown in Fig. 4, four fuzzy logic boxes are established, namely wind resources, natural environment, traffic environment, and conditions for wind turbine.

The fuzzy rule base, an important component of fuzzy rule based reasoning, is constructed by using the IF-THEN rules in Eq.(2).

$$R_k^l : IF\ x_{1k}\ is\ A_{1k}^l\ and \cdots x_{nk}\ is\ A_{nk}^l\ THEN\ y_k\ is\ B_k^l \tag{2}$$

where $A_{nk}(n=1,2\cdots N)$ and B_k are the fuzzy sets of input variable and output variable of the k th fuzzy logic box, respectively. $n=1,2\cdots N$ is the k th input variable, in this paper, it can be easy discovered from Fig. 4 that

N is equal to 2 or 3. $x_k = (x_{1k}, x_{2k}, \ldots, x_{nk})^T \in U$ and $y \in V$ are the linguistic terms. L is the lth (l=1,2$\cdots L$) rule for the associated decision attribute.

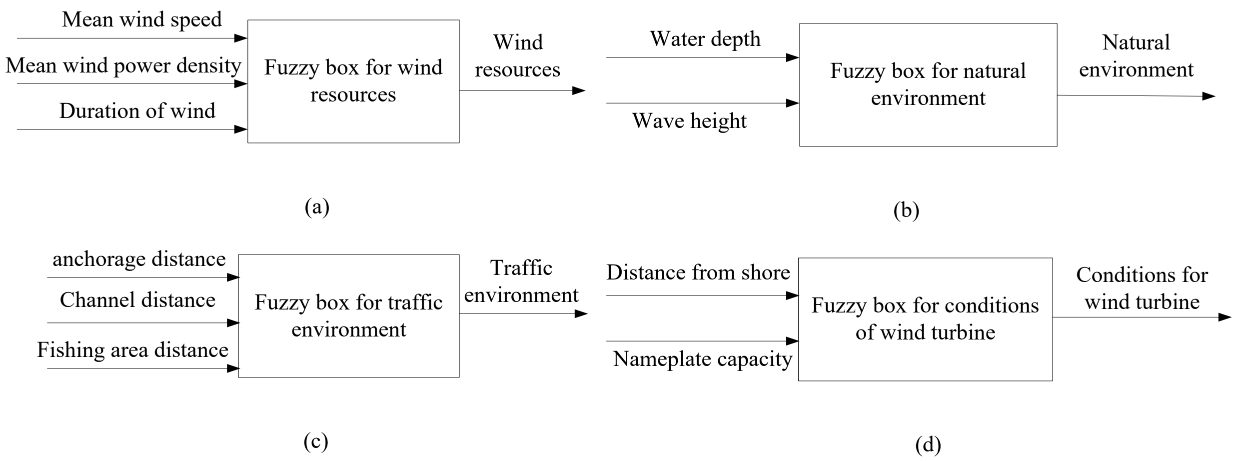


Fig. 4 Fuzzy box for attributes of site selection of offshore wind farm

By introducing this IF-THEN scheme, the fuzzy rule base can be established. Take the wind for example, as there are three input variables and each with five linguistic terms, there are 125 ($5 \times 5 \times 5$=125) rules for this fuzzy logic box. For sake of space, only a few rules are given by using IF-THEN rules, and they are shown in Table 7. Moreover, the surface figure of fuzzy rule base for wind resources can also be derived and is shown in Fig.5.

Table 7 Fuzzy rule base for wind resources

rule #	Annual mean wind speed	Mean wind power density	Duration of wind	Wind resources
1	Very low	Very low	Very short	Very bad
…	…	…	…	…
7	Very low	Low	Low	Low
…	…	…	…	…
33	Low	low	Moderate	Normal
…	…	…	…	…
52	Moderate	Very low	Low	Low
…	…	…	…	…
90	High	Normal	Very long	Very good
…	…	…	…	…
111	Very high	Normal	Very short	Normal
…	…	…	…	…
119	Very high	High	Long	Good

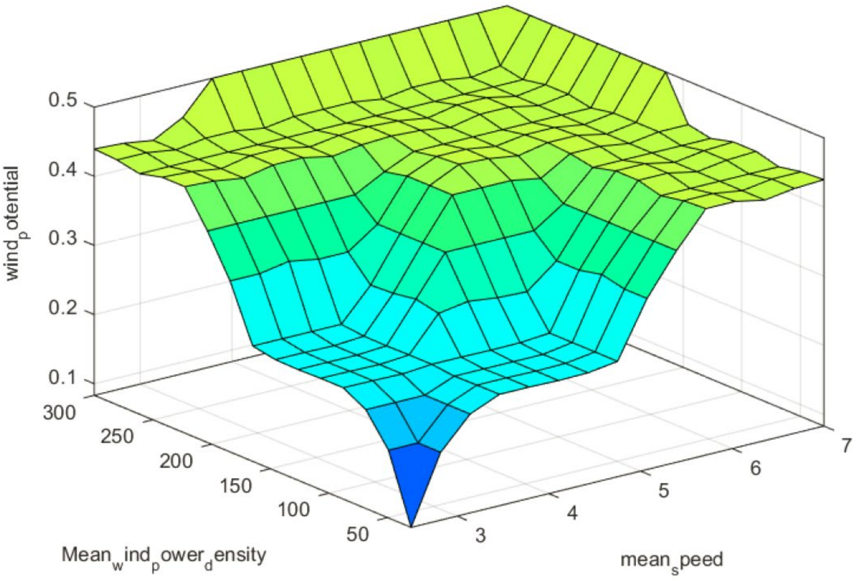


Fig. 5 Surface figure of fuzzy rule base for wind resources

The fuzzy rule base for other attributes (i.e. natural environment, traffic environment and conditions for wind turbine) can also be constructed in this way. For sake of space, they are not given in this paper. Another important component of fuzzy rule based reasoning, fuzzy inference engine is also developed for further reasoning. There are two widely used inference types (i.e. Mamdani and Sugeno) in the fuzzy logic system. The Mamdani type, which is intuitive and has widespread acceptance, is used in this paper. The principle of Mamdani type is to use the Min-Max method, which can be achieved by using Eq.(3) .

$$\mu_{B_k^l}(y) = \max_{l=1}^{L}(\sup \min \mu_{A_{1k}^l}(x_1), \mu_{A_{2k}^l}(x_2) \cdots \mu_{A_{Nk}^l}(x_N), \mu_{B_k^l}(y)) \tag{3}$$

In order to have a better understanding of the Mamdani method, a multiple-input multiple-rule case is used as an example, which is shown in Fig. 6. The principle of this process is first integrate two inputs by using the Min-Max method in the top left corner of this figure, and finally integrate all the results.

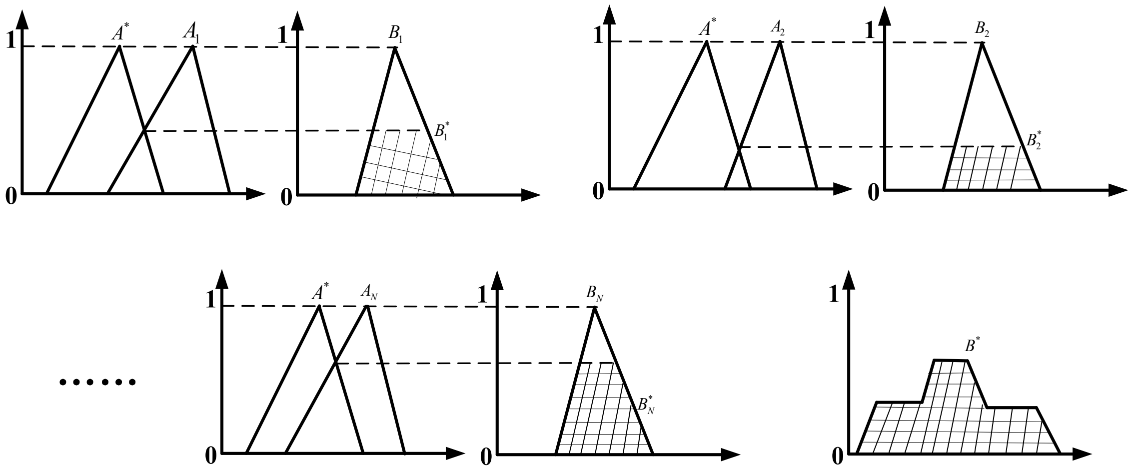
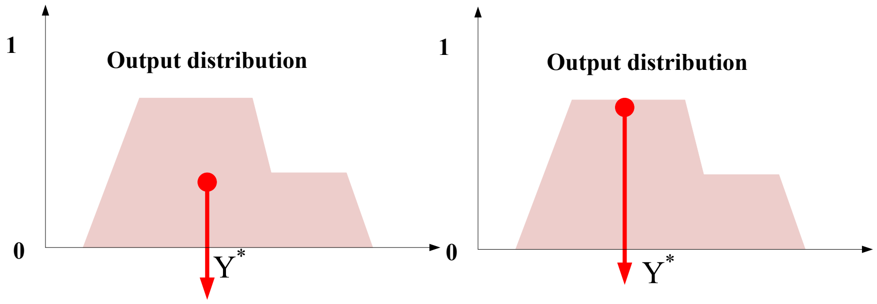


Fig. 6 Multiple-input multiple-rule example of Min-Max method

After derivation of the output (expressed by using linguistic terms), the final results are defuzzified. There are two common techniques for defuzzifying, which are centre of mass and mean of maximum. The comparison of these two methods can be shown in Fig. 7.



(a) center of gravity

(b) mean of maximum

Fig. 7 Comparison of two defuzzification methods

It can be seen from Fig. 7 that the former method uses the centre of mass to come up with one crisp number, while the latter method uses mean of maxima to come up with one crisp number. As the former considers the total output distribution into consideration, this paper uses the former method in order to gain a comprehensive evaluation result of the offshore wind farm sites. This method is achieved by using Eq. (4).

$$Y* = \frac{\int_Z \mu_B(Y)YdY}{\int \mu_B(Y)dY} \tag{4}$$

2.5 Determine the weights of attributes using AHP method

After using the fuzzy rule based reasoning method to integrate the influencing factors, the attribute values can be derived. As the importance four decision attributes (wind resources, natural environment, traffic environment, and conditions for wind turbine) are different for site selection of offshore wind farm. In order to select the best offshore wind farm using Eq.(1), the weights of these attributes should be obtained before making final decisions of site selection.

The most widely used method (Wu et al., 2017a) to derive the weights of different attributes is Analytic Hierarchy Process (AHP) proposed by Saaty (1977) in 1977. There are three steps to achieve this AHP method. First, develop the hierarchical structure of the four attributes, as this paper intends to obtain the weights of the four decision attributes, they are treated as in the same level. Second, obtain the pairwise comparison matrix by using a nine rank scales comparison method given by expert judgements. The process is to compare them to each other two at a time. Third, calculate the weights of the four attributes by using Eq. (5).

$$GW = \lambda_{\max} w_i, \quad w_i = (w_1, w_2, w_3, w_4)^T \tag{5}$$

where G is the comparison matrix among four attributes w_j. $\lambda_{\max}$ is the largest eigenvalue of comparison matrix, and w_j is the associated eigenvector of $\lambda_{\max}$.

The consistency index (CI) is used to examine the consistency of the expert judgments, which is defined as Eq. (6).

$$CI = \frac{\lambda_{\max} - 1}{n - 1} \tag{6}$$

Afterwards, the consistency ratio (CR), which is equal to CI divided by the random consistency index (RI), is used to judge the consistency of expert judgments. The value of RI is related to the dimension of comparison matrix, in this study, the RI is a predefined number (i.e. equal to 0.90) since there are four decision attributes.

$$CR = \frac{CI}{RI} \tag{7}$$

If $CR > 0.1$, the comparison matrix is assumed to inconsistency and the experts are requested to make adjustment on their judgments until the comparison matrix meet the requirement on CR. This is especially useful to judge whether the experts have reasonable judgments or not and the unreasonable judgements can be avoided by defining this threshold.

3Application of the proposed model for site selectin of offshore wind farm in the East China Sea

3.1 Scenario description of site selection in the Eastern China Sea

In the Eastern China Sea, where the first offshore wind farm (i.e. Dong Hai Bridge), the construction of another offshore wind farm is under consideration. Different from the offshore wind farm constructed in the Dong Hai Bridge, this wind farm intends to be developed in the Changjiangkou waterway area, which is a typical busy waterway area in the world and the traffic separation scheme (TSS) has been developed. First, all ships travel between southern ports (e.g. Guangzhou, Shenzhen) and northern ports (e.g. Dalian, Tianjin) have to use this TSS. Traditionally, the ships with dead weight tonnage (DWT) less than 10000t use the internal route while the ship larger than that size use the outer route, which is shown in Fig. 8. Second, the ships that call at Shanghai Port have to use this TSS as it connects the fairways for Shanghai Port. Specifically, the Nancao Fairway for the small-sized ships with draught less than 7.0m, and the Beicao Fairway for the large-sized ships. As the Shanghai Port is a very busy port in the word, there are always many ships navigating in this waterway. Third, there are several anchorages for the ships waiting for the tide in this waterway. Last, there are also many fishing ships as this place is a ten-thousand-nautical-miles fishing ground.

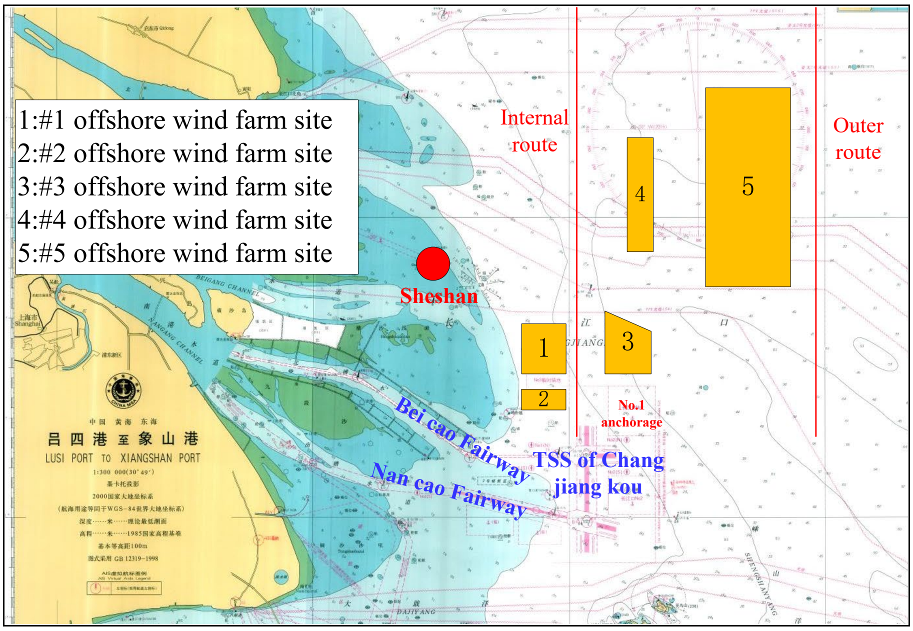


Fig. 8 Candidate sites of offshore wind farm in the Eastern China Sea

As shown in Fig.8, there are five candidate sites of offshore wind farm in the eastern China Sea. The five candidate sites are determined by a workshop with the attendance of Maritime Safety Administration, State Oceanic Administration, Traffic Planning Committee, and the wind farm company. The detailed information of the influencing factors for site selection of offshore wind farm is shown in Table 8. The information is defined from different sources. The three factors of wind resources, which are annual mean wind speed, wind duration, and mean wind power density, are derived from the field investigation. Water depth is obtained from the nautical chart provided by the maritime safety administration. Wave height is also obtained from the historical data. Distance from the fairway, anchorage, fishing area and shore (i.e. Sheshan) is calculated by using data of the nautical chart. The value of nameplate capacity is estimated by the wind farm company.

Table 8 Detailed information of influencing factors for wind farm sites

Influencing factors	1#	2#	3#	4#	5#
Annual mean wind speed (m/s)	6	6	6	7	7
Wind duration (h)	280	280	300	330	300
Mean wind power density (W/m^2)	6000	6500	7000	8000	8000
Water depth (m)	10	10	10	25	30
Wave height (m)	1.5	1.5	2.5	2.5	3
Distance from the fairway (nm)	1	1	1.3	2.5	3
Distance from the anchorage (nm)	2.7	2.7	1	5	5
Distance from the fishing area (nm)	2.5	2.5	2	3	4
Distance from the shore (km)	10	10	37	39	50
Nameplate capacity (MW)	25	25	35	50	230

3.2 Derivation of the attribute value using fuzzy rule based reasoning

By introducing the membership functions shown in Table 5, the influencing factors can be fuzzified and the results are shown in Table 9.

Table 9 Fuzzified distribution of the influencing factors

Influencing factors	1#	2#	3#	4#	5#
Annual mean wind speed (m/s)	(*high*,0.89; *very high*,0.11)	(*high*,0.89; *very high*,0.11)	(*high*,0.89; *very high*,0.11)	(*high*,1.00)	(*high*,1.00)
Wind duration (h)	(*long*,0.27; *very long*,0.73)	(*long*,0.27; *very long*,0.73)	(*long*,1.00; *very long*,0.00)	(*very long*,0.73)	(*long*,1.00)
Mean wind power density (W/m^2)	(*normal*, 1.00)	(*high*,0.75; *very high*,0.25)	(*high*,0.50; *very high*,0.50)	(*very high*,1.00)	(*very high*,1.00)
Water depth (m)	(*very shallow*, 1.00)	(*very shallow*, 1.00)	(*very shallow*, 1.00)	(*normal*, 1.00)	(*normal*, 0.33; *deep*, 0.67)
Wave height (m)	(*light*, 0.60; *very light,*0.40)	(*light*, 0.60; *very light,*0.40)	(*light*, 0.80; *very light,*0.20)	(*light*, 0.80; *very light,*0.20)	(*moderate,0.20;* *light*, 0.80)

Distance from the fairway (nm)	(*very close*, 0.33; *close,*0.67)	(*very close*, 0.33; *close,*0.67)	(*very close*, 0.13; *close,*0.87)	(*close*, 0.33; *moderate,*0.67)	(*moderate,*1.00)
Distance from the anchorage (nm)	(*close*, 0.20; *moderate,*0.80)	(*close*, 0.20; *moderate,*0.80)	(*very close*, 0.33; *close,*0.67)	(*close*, 0.13; *moderate,*0.87)	(*close*, 0.13; *moderate,*0.87)
Distance from the fishing area (nm)	(*very close*, 0.67; *close,*0.33)	(*very close*, 0.67; *close,*0.33)	(*very close*, 1.00)	(*very close*, 0.67; *close,*0.33)	(*very close*, 0.33; *close,*0.67)
Distance from the shore (km)	(*close*, 1.00)	(*moderate*, 0.90; *close,*0.10)	(*far*, 0.70; *moderate,*0.30)	(*far*, 0.90; *moderate,*0.10)	(*very far*, 1.00)
Nameplate capacity (MW)	(*small*, 1.00)	(*small*, 1.00)	(*small*, 0.60; *normal*, 0.40)	(*moderate*, 1.00)	(*very large*, 1.00)

As the fuzzy rule base has been developed in Subsection 2.4, the inference method will be introduced to integrate the influencing factors. The attribute value of wind resources for #1 candidate of wind farm is used here to illustrate the integration process by using Min-Max compositional rule.

First, the fuzzy AND operator is used to obtain the linguistic terms of the wind resources. It can be seen from Table 7 that only four rules are activated, the activated rules and the result of the wind resources after using fuzzy AND operator is shown in Table 10.

Table 10 Mamdani inference process using fuzzy AND operator (wind resources of No.1 site)

Activated rules	Wind speed	Duration	Power density	Min	Wind resources
R_{11}^{93}	0.89 *high*	0.27 *long*	1.00 *normal*	0.27	*good*
R_{11}^{118}	0.11 *very high*	0.27 *long*	1.00 *normal*	0.11	*good*
R_{11}^{98}	0.89 *high*	0.73 *very long*	1.00 *normal*	0.73	*good*
R_{11}^{123}	0.11 *very high*	0.73 *very long*	1.00 *normal*	0.11	*very good*

Second, the output (wind resources) is aggregated by using the Max method as follows.

$$wind\ potential=\begin{Bmatrix} \max(0,0,0,0), very\ bad; \max(0,0,0,0), bad; \max(0,0,0,0), normal; \\ \max(0.27,0.11,0.73,0), good; \max(0,0,0,0.11), very\ good \end{Bmatrix}$$

Therefore, $wind\ potential = (0\ very\ bad; 0\ bad; 0\ normal; 0.73\ good; 0.11\ very\ good)$. This result can be interpreted as the wind resources is good with a probability of 0.73 and is very good with a probability of 0.11.

Last, the defuzzification can be achieved by using the centre of gravity method, and the results (i.e. decision attribute values) are shown in Table 9.

Table 11 Decision attribute values for site selection of offshore wind farm

Candidate site	Wind resources	Natural environment	Traffic environment	Conditions for wind turbine
# 1	0.752	0.910	0.244	0.625

# 2	0.759	0.910	0.244	0.625
# 3	0.782	0.917	0.235	0.250
# 4	0.920	0.750	0.409	0.250
# 5	0.920	0.591	0.591	0.500

It can be seen from Table 9 that the #4 and #5 candidate sites have the best wind resources and the candidate site (e.g. #1) has worse wind resources as it is very close to the shore. This is why the Chinese government intend to develop the offshore wind farm in recent years. Moreover, if the candidate site is far from the shore, this candidate site will have few impacts on the traffic flow in both the fairway and the anchorage, this can also be seen from Table 11 that the #5 candidate site has the best performance of traffic environment. However, the farer candidate has worse performance on the natural environment than the closer one, this is because the wave height and water depth will have impact on the wind turbine design and make it hard to be reliable in the heavy sea. Moreover, it is very hard to install the wind turbine in the site with large water depth. Another attribute with worse performance is condition for wind turbine when the candidate site is far from the shore. In Table 11, the candidate 5# has good performance on nameplate capacity but with bad performance on the distance from the shore as it is hard for eclectic and grid connection. However, #1 and #2 has best performance though the nameplate capacity is small but they are close to the shore.

From the above analysis, it can be summarized that the #4 and #5 candidate sites have the best wind resources while #1 has the worst performance on this attribute. #3 has the best natural environment while #5 has the worst performance on this attribute. #5 has the best traffic environment while #1 and #2 have the worst performance on this attribute. #1 and 2# have the best conditions for wind turbine while #3 and #4 have the worst performance. This makes it hard to select the best offshore wind farm as they have their best performance on one or two attributes but also with worst performance on other attributes. Therefore, the weights of the attributes should be introduced to have a comprehensive assessment on these candidate sites.

3.3 Site Selection of the best site for offshore wind farm

By introducing the AHP method, the weights of the decision attributes can be obtained. In order to derive a reasonable result of the weights, the experts, who attended the mentioned workshop (i.e. Maritime Safety Administration, State Oceanic Administration, Traffic Planning Committee, and the wind farm company), are invited to make judgments on these attributes. The results are shown in Table 12, by using Eq. (5)-(6), the weights of the attributes can be obtained. Moreover, the consistency ratio is also calculated by using Eq. (7), and the result is 0.0538. As it is smaller than 0.10, this means the expert judgements are consistent.

Table 12 Pairwise comparison matrix for decision attributes

Decision attributes	Wind potential	Natural environment	Traffic environment	Conditions for wind turbine	Weights
Wind resources	1.00	0.33	0.33	0.33	0.10
Natural environment	3.00	1.00	1.00	0.33	0.22
Traffic environment	3.00	1.00	1.00	1.00	0.29
Conditions for wind turbine	3.00	3.00	1.00	1.00	0.39

Consistency ratio CR=5.38×10^{-2}.

From Table 10, the weight of conditions for wind turbine is assigned most, and the wind resources is assigned least. This is reasonable as the conditions for wind turbine is predominate for wind turbine installation. Otherwise, even though the wind resources is very good but it is impossible to install the wind turbine and the nameplate capacity is too less to generate electricity, this site should not be taken into consideration. Moreover, the natural environment and traffic environment are also two significant factors. This is because this paper intends to select the wind farm far from the shore, and the maritime safety should be considered to ensure the offshore wind farm will not significantly influence the traffic flow.

After obtaining the weights of decision attributes and decision matrix, the utility value of each candidate site can be derived by using Eq. (1). The results of final decision-making are shown in Table 13.

Table 13 Final decision-making of offshore wind farm

Candidate site	Utility value	Ranking
# 1	0.590	2
# 2	0.591	1
# 3	0.446	5
# 4	0.529	4
# 5	0.588	3

From Table 13, it can be seen that the best offshore wind farm is #2, and the worst site is #3. This is because the # 2 wind farm site has best performance of natural environment and conditions for wind turbine among all candidate sites, moreover, the performance of wind resources also ranks third though the traffic environment is the worst. However, the # 3 candidate site is the worst as this site has the worst performance on traffic environment and conditions of wind turbine, moreover, as these two attributes has larger weights than the other two attributes, this candidate should be the worst owing to the significant impacts on the traffic flow and far from the shore. Although the result is acceptable, from Table 9, it can be seen that the distance from the shore of #5 is very far, which is the only total negative factor with the probability of 1.0 for all candidate sites. Moreover, from the discussion of the workshop, this negative influence can be reduced and an optimized alternative is discussed in the following subsection.

3.4 Optimization of the selected site of offshore wind farm

The optimization is carried out in order to be easier to connect the power grid. The proposed alternative is to add a 220kV relay station between the offshore wind farm and the shore (i.e. Sheshan) to boost voyage. The optimized alternative is shown in Fig. 9.

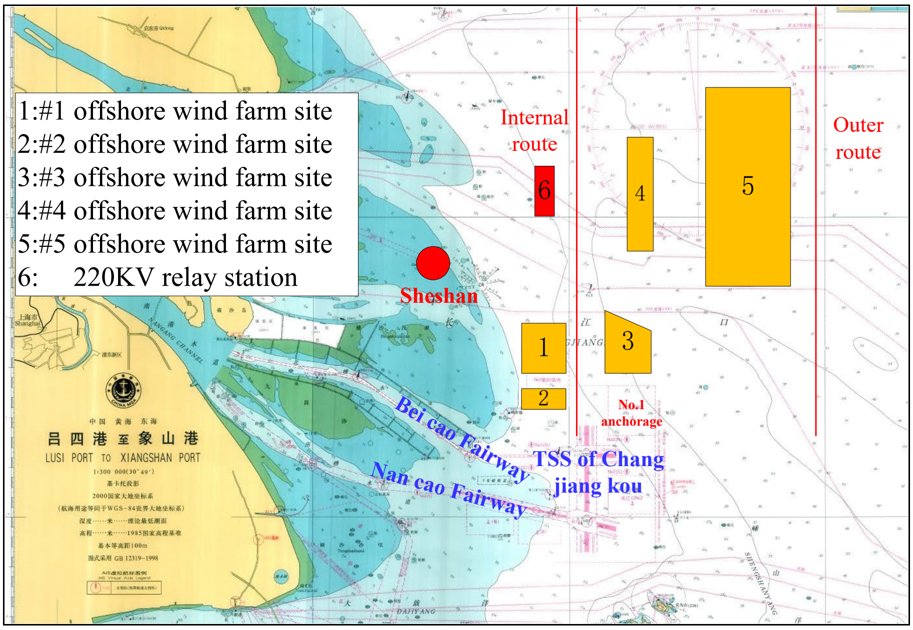


Fig. 9 Optimized alternative for offshore wind farm

From Fig. 9, the candidate site from shore (i.e. Sheshan) is closer than the original alternative. By introducing this relay station, the # 4 site from the relay station is around 24 km, while the # 4 site from the relay station is around 35 km. Therefore, the fuzzified distribution of distance from the shore for # 4 wind farm have changed from $(far, 0.90; moderate, 0.1)$ to $(moderate, 0.40; close, 0.60)$, and the distribution for # 5 wind farm changes from $(very\ far, 1.00)$ to $(far, 0.50; moderate, 0.50)$. After this optimization, the conditions for wind turbine of # 4 changes from 0.250 to 0.395, while this attribute value of #5 changes from 0.500 to 0.625. Based on this adjustment, the final decision-making of optimized offshore wind farm by introducing the weights using AHP method is shown in Table 14.

Table 14 Final decision-making of optimized offshore wind farm

Candidate site	Utility value	Ranking
# 1	0.590	3
# 2	0.591	2
# 3	0.446	5
# 4	0.585	4
# 5	0.637	1

From Table 14, the best offshore wind farm is # 5 after introducing the relay station. This is reasonable as the impact of the distance from shore has been largely reduced, and this alternative has the best performance of wind resources, traffic environment and conditions for wind turbine. Moreover, the utility value of # 4 has also increased though it also ranks No.4 after this adjustment. The result is the same with the result discussed on the workshop, which means the proposed model is beneficial for site selection of offshore wind farm.

4 Discussion

In this paper, five offshore wind farm sites have been given after a discussion of the attendance (i.e. Maritime Safety Administration, State Oceanic Administration, Traffic Planning Committee, and the wind farm company) on the workshop. This means these five sites are feasible though some deficiencies may exist and the objective of this proposed model is to select the best candidate site. Moreover, as this paper focuses on the site selection of offshore wind farm in a busy waterway, the influencing factors are identified from the perspective of tradeoffs between the economic feasibility and maritime safety. However, some other factors such as the effect on animals and birds, climate change and noise and visual impact (Leung and Yang 2012; Dai et al., 2015; Snyder and Kaiser 2009) are not taken into consideration. Therefore, when applying this proposed model for site selection of offshore wind farm, some influencing factors should be adjusted according to the distinguishing features of the new scenario.

The total negative influencing factors should be carefully handled in the site selection of offshore wind farm by using fuzzy logic method. This is because this may significantly influence the result. Take the factor of distance from the shore example, in this paper, the # 5 site is 50 km far from the shore, which is negative with probability of 1.0. It can be deduced that if the distance is 80 km, the result will be the same with the distance from 50 km. While in practice, this candidate site is impossible because it is too hard to connect the power grid. Therefore, when using the fuzzy logic method, if there is a negative factor with the probability of 1.0, this influence should be reduced in order to have a reasonable result. However, if the factor is positive with the probability of 1.0, this can be ignored because it cannot influence the result of other factors. Therefore, in practice, if the factor is total negative, this impact should be carefully treated and some discussion should be carried out to evaluate this influence, moreover, if this impact cannot be estimated or reduced, this offshore wind site should not be selected.

5 Concluding remarks

The main contribution of this paper is to propose a fuzzy-MADM method for site selection of offshore wind farm in the busy waterway, the proposed model considers both the economic feasibility and maritime safety in the modelling process. Specifically, the influencing factors are identified from previous works, and are integrated to obtain the decision matrix by using the fuzzy logic method, while the weights of the attributes are derived from the expert judgements. The result demonstrates that this proposed method is useful for site selection of offshore wind farm and can be applied to other busy waterways for site selection of offshore wind farm.

However, when applying this proposed method to other waterways, the influencing factors should be adjusted as this paper only considers the economic and maritime safety, which are the main distinguishing features of this waterway for offshore wind farm installation. However, in other waterways, the traffic may not so busy but the impact on the environmental issues may be the predominate problem, therefore, this factor should be taken into consideration. Moreover, when applying the fuzzy logic method to site selection of offshore wind farm, the total negative factor should be carefully treated, and the decision-maker should try to reduce the influence if possible, otherwise, this candidate site should not be selected because it is unfeasible though the performance of other factors are very good.

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