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A novel fuzzy Bayesian network-based MADM model for offshore wind turbine selection in busy waterways: An application to a case in China

Jie Xue [a, c, d, e, f], Tsz Leung Yip [b], Bing Wu [c, d, e, *], Chaozhong Wu [c, d, e], P.H.A.J.M. van Gelder [a]

[a] Safety and Security Science Group (S3G), Faculty of Technology, Policy and Management, Delft University of Technology, Delft, the Netherlands
[b] Department of Logistics and Maritime Studies, Hong Kong Polytechnic University, Hong Kong, China
[c] Intelligent Transport Systems Research Center (ITSC), Wuhan University of Technology, Wuhan, China
[d] National Engineering Research Center for Water Transport Safety (WTSC), Wuhan University of Technology, Wuhan, China
[e] Engineering Research Center for Transportation Safety, Ministry of Education, Wuhan, China
[f] School of Energy and Power Engineering, Wuhan University of Technology, Wuhan, China

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ABSTRACT

Offshore wind power is an important renewable energy source and plays an essential role in optimizing the energy structure worldwide. Simultaneously, offshore wind turbine (OWT) selection is a complicated process since it concerning various variables and optimization scenarios. In this paper, a novel fuzzy Bayesian network-based model for multiple-attribute decision-making (MADM) is proposed. First of all, a three-layer decision-making framework for OWT selection is established through systematically combing previous studies, expert knowledge, and the principal component analysis (PCA) results by treating the wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety as the attributes, and the corresponding 11 influencing factors are identified and quantified. Moreover, a triangular fuzzy number is introduced to fuzzify each influencing factor, and the belief degree for different linguistic variables corresponding to the specific influencing factor is employed in the fuzzy *IF-THEN* rule system. Then, the belief rule base is transformed into the Bayesian network as the conditional probability tables (CPTs), which can directly express the influence relationship of various factors and realize the integration of various influence factors to obtain the optimal scheme. Finally, the proposed model is validated by taking a case study in busy waterways in the Eastern China Sea as an example. This research provides an intuitive, feasible, and practical way for OWT selection.

1. Introduction

Energy is an inexhaustible impetus for all countries' economic development and an essential cornerstone for human survival and progress. However, the current energy and environmental problems are becoming increasingly severe, and traditional oil and other resources are gradually depleted. Thus, people are beginning to look for alternative energy and paying more and more attention to renewable energy, especially wind energy. As shown in Fig. 1(a), for some time, wind energy has been the fastest growing renewable energy source worldwide [1], and many countries take wind energy as an essential option to improve their energy structure and mitigate climate change, and promote energy saving and emission reduction. For the statistics shown in Fig. 1(b), renewable energy (including biofuels but excluding hydro) posted a record increase in consumption in energy terms (2805.5 TWh), and this was the largest increment for any source of energy in 2019. In addition, wind provided the enormous contribution to renewables growth (1429.6 TWh, accounting for 50.96% of the renewable energy and 5.29% of the global energy) followed closely by solar (724.1 TWh) [2].

* Corresponding author. Intelligent Transportation Systems Research Center (ITSC), Wuhan University of Technology, 1040 Heping Avenue, Wuhan, Hubei 430063, China.
E-mail addresses: J.Xue@tudelft.nl (J. Xue), t.l.yip@polyu.edu.hk (T.L. Yip), bing.wu@whut.edu.cn (B. Wu), wucz@whut.edu.cn (C. Wu), P.H.A.J.M.vanGelder@tudelft.nl (P.H.A.J.M. van Gelder).

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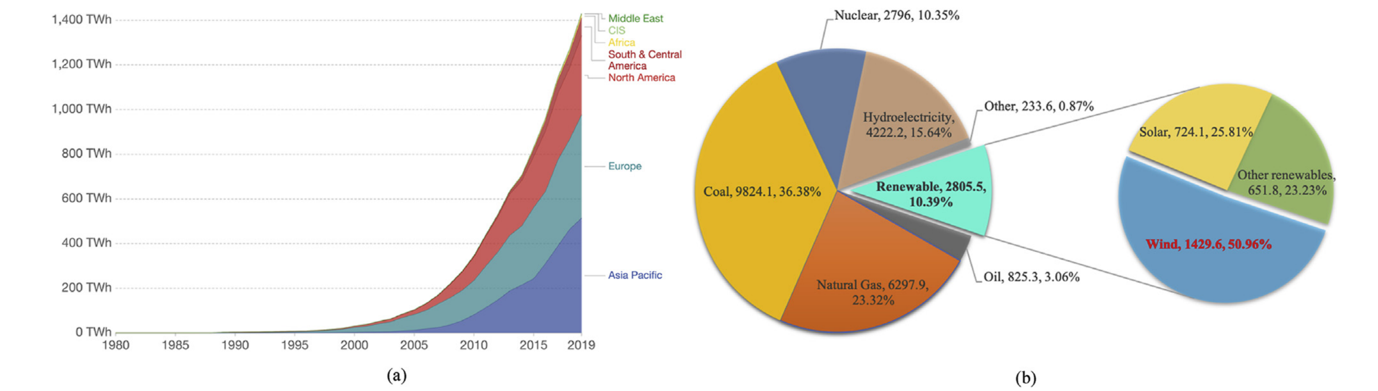

Fig. 1. (a) Wind energy generation by region for both onshore and offshore wind sources [6]. (b) The statistic of the global energy distribution by energy type in 2019. Data source: BP [2]. Note: The energy generation is measured in terawatt-hours (TWh) per year.

Table 1
Top ten largest operational offshore wind farms worldwide [4].

No.	Name	Country	Capacity (MW)	Number of turbines	Commissioned
1	Hornsea 1	United Kingdom	1218	174	2019
2	East Anglia ONE	United Kingdom	714	102	2020
3	Walney Extension	United Kingdom	659	87	2018
4	London Array	United Kingdom	630	175	2013
5	Gemini Wind Farm	Netherlands	600	150	2017
6	Beatrice	United Kingdom	588	84	2019
7	Gode Wind	Germany	582	97	2017
8	Gwynt y Môr	United Kingdom	576	160	2015
9	Race Bank	United Kingdom	573	91	2018
10	Greater Gabbard	United Kingdom	504	140	2012

Offshore wind power is an important renewable energy source. Its development plays a vital role in promoting the technological progress of the entire wind power industry and can play a role in continuously optimizing the national energy structure. Compared with onshore wind power, offshore wind power, as a new energy source, has the advantages of wide applicable space, low noise and light visual intrusion, and abundant wind energy resources [3]. Global offshore wind power maintains a strong growth trend. In terms of regions, Europe is still the global leader in the offshore wind power industry, and countries such as the United Kingdom, Germany, Denmark, Sweden, Belgium, and the Netherlands are developing rapidly [2,4]. Table 1 lists the top ten largest operational offshore wind farms with at least 200 MW nameplate capacities worldwide.

The research for offshore wind power began in the early 1990s. In recent years, offshore wind power technology has become increasingly mature and has started to be applied on an extensive scale development [1]. According to the “Offshore Wind Outlook 2019” report released by the International Energy Agency (IEA), since 2010, offshore wind power has grown at an annual rate of about 30%. At the same time, the single-unit capacity of offshore wind turbine (OWT) will increase from 3 MW in 2010 to 15–20 MW in 2030 (predicted value), and the turbine height will also develop from 90 m to 230–250 m [5].

In the past few years, the idea of large-scale utilize of wind power has received widespread attention, mainly in four research areas [7]. The first area is mainly focused on the sensors and instrumentation applied for wind measurements [8]. The second area is concerned with the evaluation and assessment of wind energy potential for a specific region and the applications of wind energy [9]. The third area is the design and characterization of wind turbines [10]. The fourth area deals with the development and design of wind farm [11]. In addition, an optimal, practical, and efficient wind farm design depends on various design constraints and objectives. It is related to several influencing factors/aspects such as the wind farm layout, site selection, and wind turbine selection. Each of these aspects could be regarded as a comprehensive and complex optimization and decision-making issue [12,13].

With the improvement of OWT technology, wind turbines are gradually developing to the tendency of a large scale. Large wind turbines can make better use of wind energy, but the difficulty of construction and maintenance will also increase accordingly. At the same time, the problem of whether different types of wind turbines can adapt to the navigation environment of its nearby waters is also a crucial issue that needs to be concerned. Therefore, the wind turbine selection for the wind farm has widely attracted the attention of academia. Specifically, Lee, Hung, Kang and Pearn [14] proposed a multi-criteria decision-making method for OWT selection, taking four aspects of wind turbine characteristics, economic factors, environmental impact, and technical level for comprehensive evaluation. Rehman and Khan [13] developed a decision turbine selection strategy based on a fuzzy decision-making approach and indicated that the important criteria such as the turbine's power rating, turbine height, and impeller diameter need to be considered. Paul and Rather [15] presented a new method that considers economy, reliability, resilience, and environmental aspects to select a suitable wind turbine for a wind farm site. Zhao, Su, Zhao and Yin [16] utilized the two-parameter Weibull distribution approach to assessing wind power resource for various islands in the South China Sea into to give an optimal scheme for wind turbine selection. Pantaleo, Pellerano, Ruggiero and Trovato [17] and Stockton [18] carried out the study on turbine selection from an economic point of view. They indicated that the selection and installation of wind turbines, and the construction of ancillary electrical equipment, etc., and in terms of the entire life cycle of a wind farm, it will eventually return to the problem of economic feasibility. Additionally, the wake effect is an important influencing factor for the OWT positioning choice for wind farm area, the same type of OWT could result in various wind farm layout optimization schemes with specific optimization model, and the optimization problem, especially focusing on the influence of wake effect, is a comprehensive and complicated research topic [11,15,19–21]. Moreover, in some studies for wind farm site selection, factors affecting the OWT selection are taken into consideration as well [22,23].

Multiple-attribute decision-making (MADM) is commonly used in economics, military, and engineering technology [23]. Also, in the research area of offshore wind farms [24,25]. The OWT selection problem can be defined as a complex MADM which has attracted substantial attention for the academia and stakeholders. The problem could be solved by using the automated decision-making techniques-computational intelligence techniques, due to computational intelligence techniques that could conduct this kind of problems systematically and efficiently [11,26], and replace the human-based decision making which is sometimes prone to inefficient and somewhat wrong decisions [13]. A variety of computational intelligence based MADM techniques, for instance, fuzzy logic [27], weighted aggregation [28], and Pareto ranking [29], have been utilized by researchers in different sub-domains for wind farm design.

Moreover, due to the complexity and uncertainty of decision problems, the problems of MADM are always combined with the characteristic of uncertain and fuzzy matters [30], so fuzziness is an important factor involved in the real-world decision-making problems [31]. Fuzzy logic is commonly used to conduct uncertainties caused by the scarcity of data and could describe both the quantitative and qualitative influencing factors effectively [22,23]. Nevertheless, it also may lose some useful information when describing the relationship between input variables and output variables due to the utilization of the traditional *IF-THEN* rules with a 100% belief degree [32]. However, this is unrealistic in practice because the problem often has uncertainty. Thus, various belief degrees that can represent the output variables precisely may be more suitable for OWT selection. In addition, Bayesian network (BN) is the most commonly used approach for risk analysis due to its flexible and intuitive structure and the ability to express the quantitative relationships from the perspective of probabilistic [33]; BN can indicate uncertainty relationship between consequences and causes for an event/problem [34,35] and solve the problem of difficulty in describing the output variables accurately as well as intuitively represent the development process. Furthermore, it can describe the relationship between various influencing factors of OWT selection. Thus, the decision-making process for OWT selection can be converted to a MADM framework utilizing BN. In addition, after obtaining the belief rule base, its results can be converted into conditional probability tables (CPTs); thereby a complete BN structure can be established. Thus, using the BN, the reasoning process for overall assessment and evaluation for each wind turbine candidate's final performance can be conducted.

The overviewed literature indicates that some studies have been conducted on the selection of OWT. Still, most of them only considered from a specific aspect and utilized the qualitative assessment on the criteria. Moreover, research on the selection of OWT in the busy waterway, especially against comprehensively consider the influences of wind turbine parameters, economy, reliability, and navigation safety, are still scanty. Therefore, this study focus on the problem of wind turbine selection, established a novel fuzzy Bayesian network-based multiple-attribute decision-making (MADM) model. First of all, a three-layer decision-making framework for OWT selection is established by systematically combing previous studies, expert knowledge as well as the results of the principal component analysis (PCA) by treating the wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety as the attributes, and the corresponding 11 influencing factors are identified and quantified. Secondly, considering the lack of quantitative data or description on the main influencing factors when conducting selecting OWT selection, and some data are ambiguous, a triangular fuzzy number is introduced to fuzzify each influencing factor. At the same time, considering that the traditional *IF-THEN* rule is difficult to describe the output variable accurately, the belief degree for different linguistic variables corresponding to the specific influencing factor is employed into the fuzzy *IF-THEN* rule system. Then, we transform the belief rule base into the Bayesian network as the CPTs, which can directly express the influence relationship of various factors and realize the integration of various influence factors, so as to obtain the optimal scheme for OWT selection. Finally, the proposed model is validated by taking a case study in busy waterways in China as an example. This research is of great significance to the OWT selection and the construction of wind farms.

The remainder of this paper is structured as follows. First, a fuzzy Bayesian network-based decision-making model for OWT selection by considering the wind turbine parameters, economy, reliability, and navigation safety is proposed in Section 2. Second, an application to a case of China is conducted to verify the developed model in Section 3. Third, Section 4 details our experiment results, and the discussions for the results are presented. Finally, the conclusions are drawn in Section 5.

2. Proposed novel fuzzy Bayesian network-based decision-making model for offshore wind turbine selection

Offshore wind turbine selection is a complicated process. The contribution and innovation of the proposed model are mainly threefold: a) A novel feasible and applicable three-layer MADM framework for OWT selection BN model, including the influencing factor layer, the decision-making criterion layer, and the target layer for OWT selection, is designed; b) The model

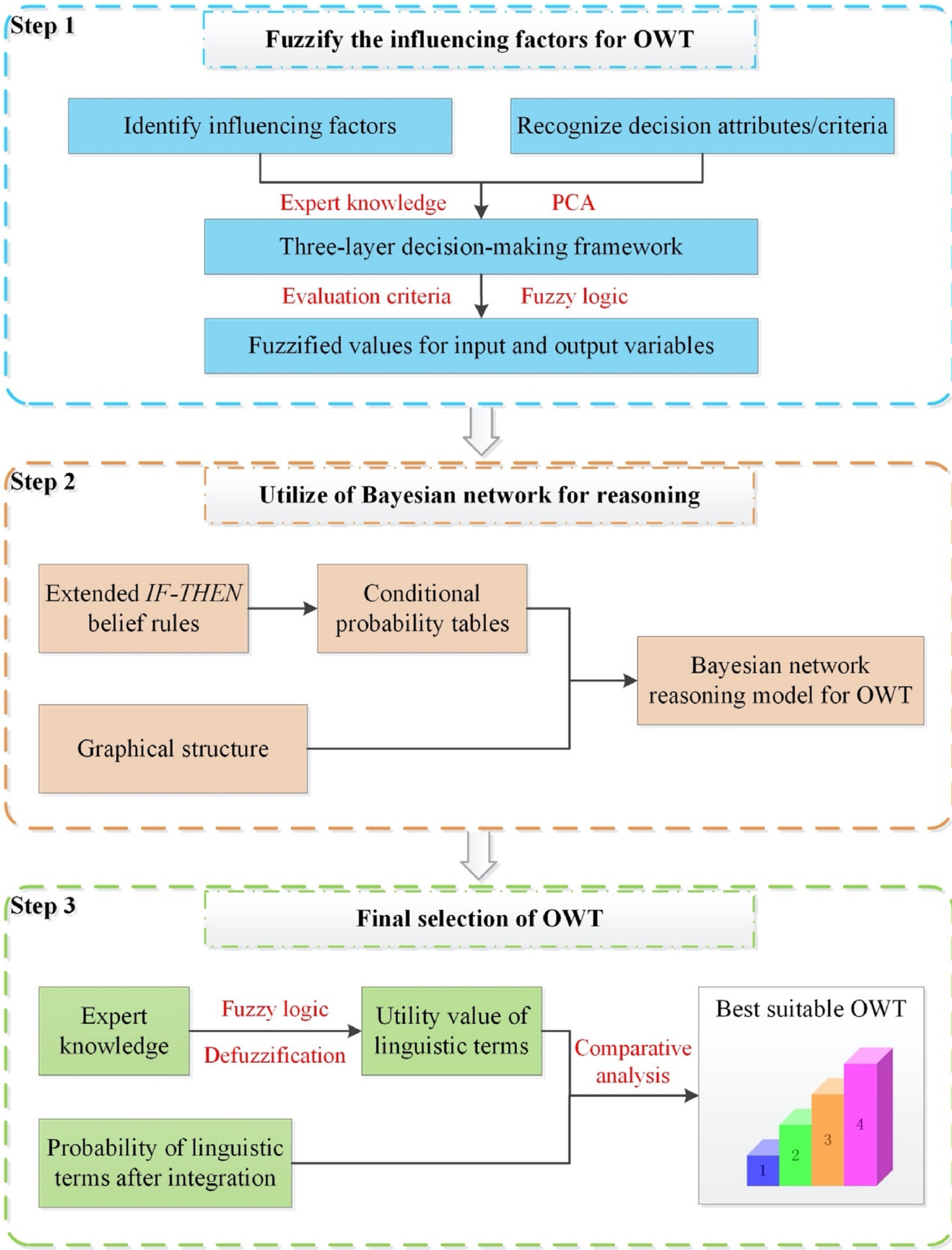

Fig. 2. A generic decision-making framework for offshore wind turbine selection.

comprehensively employed the essential influencing factors under complicated busy waterways, in aspects of the wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety; c) The proposed model and framework are not only concerned with a standard BN model; it comprehensively combined the principal component analysis, fuzzy logic, experts knowledge, and belief rule theory with traditional BN. A detailed description of the proposed model and the material which be utilized in this study are presented in this section.

2.1. Establish a three-step decision-making framework for offshore wind turbine

The selection of offshore wind turbine is influenced by several factors; in a fuzzy Bayesian network-based MADM approach is developed in this paper. In order to select the best suitable OWT by comprehensively consider the influencing factors, a generic three-step decision-making framework is established as follows (Fig. 2).

First, the influencing factors and attitudes are identified and

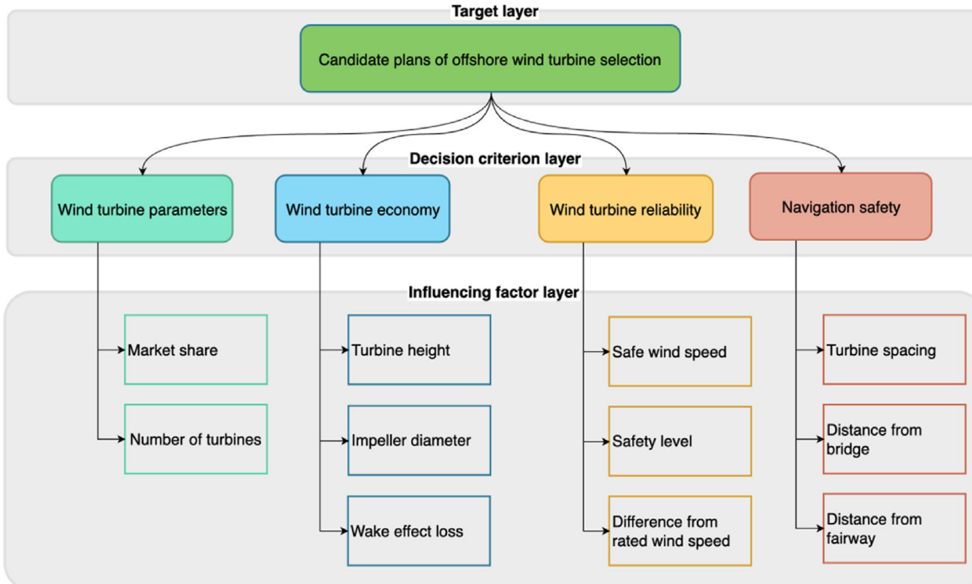

Fig. 3. Proposed three-layer decision-making framework for offshore wind turbine selection.

recognized from previous studies and expert knowledge, then analyzed and determined by utilizing the principal component analysis; thus, a three-layer hierarchical decision-making framework for the selection of OWT, including the influencing factor layer, decision attribute/criterion layer, and target layer (overall performance of the candidate plans of OWT selection), is developed (Fig. 3). Then, the influencing factors are fuzzified by establishing the evaluation criteria and utilizing fuzzy logic theory.

Second, the extended *IF-THEN* rules are introduced to precisely describe the relationships between influencing factors and decision attributes, and these rules are transformed to conditional probability tables (CPTs) for Bayesian Network, while the graphical structure is derived by using the three-layer decision-making framework.

Third, combined with the expert knowledge and fuzzy logic theory, the best suitable candidate OWT is selected by multiplying the utility values with the associated probability for the linguistic terms after comprehensive comparative analysis.

2.2. Identify influencing factors to develop a hierarchical decision-making framework for offshore wind turbine selection

The offshore wind turbine selection problem is complex since it concerning various variables and optimization scenarios. In this situation, it is impractical to develop a model containing all the relevant influencing factors directly. In this case, to make a comprehensive and overall analysis of the candidate OWT, the main influencing factors of the OWT selection should be recognized and identified from previous studies/reports/expert knowledge in the decision-making problems [33].

Existing research on OWT selection mainly include 11 influencing factors such as market share, number of turbines, turbine height, and impeller diameter, etc. The reasons for the selection of various influencing factors are explained and shown in Table 2.

After identifying the influencing factors of OWT selection, to facilitate the decision-making process, it is necessary to define the parent criteria of the influencing factors for wind turbine selection.

Table 2
Explanation for the identified influencing factors for offshore wind turbine selection.

Influencing factors	Explanation
Market share [36,37]	The market share represents the market's recognition and preference for a specific type of OWT
Number of turbines [14]	The number of turbines affects the difficulty of construction/installation and maintenance of wind turbine
Turbine height [13]	The height of the turbine is closely related to the wind speed and ultimately affects the power generation of the wind turbine
Impeller diameter [38]	The wind power of OWT is proportional to the square of the impeller diameter
Wake effect loss [39,40]	The actual power generation needs to deduct the influence of the wake effect loss
Annual average wind speed [22]	An important factor in describing the wind resources
Wind power density [41,42]	An essential factor in describing the wind resources. It is the mean annual power available per square meter of the swept area of a turbine
Annual energy production [43,44]	The total amount of electrical energy the wind farm produces over a year. It is an important factor for site selection and wind turbine economy evaluation
Safe wind speed [38]	The higher the safe wind speed, the longer the wind turbine can work, and it is relatively more harmless for the turbine
Safety level [16]	The higher the safety level, the better the reliability of the wind turbine
Rated wind speed [38]	The wind power of the OWT is proportional to the cube of the wind speed
Turbine spacing [22,23]	Influence the installation and maintenance of wind turbine and the safety of the ships navigating in this area (including the safety of maintenance ship)
Distance from bridge [22,23]	It is an important factor for site selection of offshore wind farm, influence the safety of the ships navigating in this area
Distance from fairway [22,23]	It is an important factor for site selection of offshore wind farm, influence the safety of the ships navigating in this area, also to avoid damage to turbine by ships in channels

According to the characteristics of the influencing factors, they are classified into four attributes of wind turbine parameters (market share number of turbines), wind turbine economy (turbine height, impeller diameter, wake effect loss, annual average wind speed, wind power density, annual energy production), wind turbine reliability (safe wind speed, safety level, rated wind speed), and navigation safety (turbine spacing, distance from bridge, distance from fairway).

Principal component analysis (PCA) is a mathematical method used to reduce the dimensionality of data; simultaneously, most of the characteristics of the variation in the data are retained [45]. In addition, PCA has also proved to be a feasible method to recognize the influential variables and an efficient way to identify the relationships among various variables [46]. The basic equations for the calculation of principal components are described as follows:

Assume there are m samples and each sample has n variables/indicators; the sample dataset could be expressed as a matrix:

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

To eliminate the dimension and order of magnitude of the data in the principal component analysis, it is usually necessary to standardize the original data, convert it into dimensionless data, thus standardize the matrix.

$$x'_{ij} = \frac{x_{ij} - \bar{x}_j}{\sqrt{\mathrm{var}(x_j)}} \tag{2}$$

$$\bar{x}_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{3}$$

$$\sqrt{\mathrm{var}(x_j)} = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(x_{ij} - \bar{x}_j\right)^2} \tag{4}$$

where $\bar{x}_j$ is the average value and $\sqrt{\mathrm{var}(x_j)}$ is the standard deviation of the j-th variables (i = $1,2,3, \ldots,m$; j = $1,2,3, \ldots,n$).

Then the correlation matrix $R = (r_{jk})_{n\times n}$ could be built, the correlation coefficient for variables j and k, i.e., the elements of the correlation matrix, could be obtained as:

$$r_{jk} = \frac{1}{m-1}\sum_{i=1}^{m} x'_{ij}x'_{ik} = \frac{1}{m-1}\sum_{i=1}^{m}\left[\left(x_{ij}-\bar{x}_j\right)\Big/\sqrt{\mathrm{var}(x_j)}\right]\left[\left(x_{ik}-\bar{x}_k\right)\Big/\sqrt{\mathrm{var}(x_k)}\right] = \frac{\sum_{i=1}^{m}\left(x_{ij}-\bar{x}_j\right)\left(x_{ik}-\bar{x}_k\right)}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}-\bar{x}_j\right)^2 \sum_{i=1}^{m}\left(x_{ik}-\bar{x}_k\right)^2}} \tag{5}$$

where i = $1,2,3, \ldots,m$; j = $1,2,3, \ldots,n$; k = $1,2,3, \ldots,n$. The initial eigenvalues $(\lambda_1, \lambda_2, \cdots, \lambda_n)$ are obtained based on the characteristic equation $|R - \lambda E| = 0$ (E is the identity matrix) and the corresponding eigenvectors $\vec{\mu}_k = (u_{k1}, u_{k2}, \cdots, u_{kn})^T$, $(k = 1,2,3,\cdots,n)$ are derived from $R\vec{\mu}_k = \lambda\vec{\mu}_k$, and $\vec{\mu}_k$ should satisfy the condition $\vec{\mu}_k^{\,T}\vec{\mu}_k = 1$. Thus, the k-th principal component (k = $1,2,3, \ldots,n$) could be represented as:

$$\begin{aligned} F_k &= u_{k1}x'_1 + u_{k2}x'_2 + \cdots + u_{kn}x'_n \\ &= u_{k1}\left(\frac{x_1 - \bar{x}_1}{\sqrt{\mathrm{var}(x_1)}}\right) + u_{k2}\left(\frac{x_2 - \bar{x}_2}{\sqrt{\mathrm{var}(x_2)}}\right) + \cdots + u_{kn}\left(\frac{x_n - \bar{x}_n}{\sqrt{\mathrm{var}(x_n)}}\right) \end{aligned} \tag{6}$$

The principal components are required to explain and represent the original data's variation characteristics as much as possible. The number of principal components determined for representing the original influencing factors dataset of OWT selection could be computed by

$$ACR = \left(\sum_{j=1}^{p}\lambda_j \Big/ \sum_{k=1}^{n}\lambda_k\right) \times 100\% \tag{7}$$

Where j = $1,2,3, \ldots,p$; k = $1,2,3, \ldots,n$, and p ($p \le n$) is the recognized number of principal components. Generally, the accumulative contribution ratio (ACR) is more than 80% [47].

In this paper, to reduce the subjectivity of identifying the influencing factors and simplify model calculations, instead of using all the original influencing factors of the wind turbine economy attribute, the PCA is employed to better address the choice of the influencing factors. First, the identified six influencing factors (variables) for the six plans (samples) are standardized based on Eqs. (2)–(4) (Tables A1 and A2), then the correlation coefficient matrix of the variables is obtained through Eq. (5) (Table A3). It can be seen that there are several significant correlations among variables (i.e., the six influencing factors of wind turbine economy). For instance, there is a high positive correlation among turbine height, annual average wind speed, and wind power density; the impeller diameter is highly negatively correlated with wake effect loss; the annual energy production is highly positively correlated with wake effect loss, etc. Moreover, the PCA results are shown in Table A4; the results indicate that about 72.11% of the total variation could be explained by the first principal component and about 96.79% by the first two principal components. In other words, about 96.79% of the total variance (i.e., ACR) in the six considered variables can be condensed into two new variables (i.e., two new principal components). Table A5 presents the essential variables for the first two principal components. The component loading values represent the correlations between the principal components and the original variables; the greater the absolute value of the load value is, the stronger the correlation happens [48]. Thus, the first principal component could be defined and represented by turbine height, impeller diameter, wake effect loss, annual average wind speed, and wind power density. In addition, the second principal component could be mainly characterized by annual energy production and wake effect loss.

Overall, considering the high positive correlation among turbine height, annual average wind speed, and wind power density, their influencing characteristics for the proposed model are similar. Thus, the most important variable, turbine height, with the biggest component loading value, is identified in our case. In addition, considering the high percentage of the first principal component (72.11%), and the low contribution of annual energy production in the first principal component (Table A5), as well as the high positive correlation between annual energy production and wake effect loss (Table A3), the annual energy production is not included in our model. Thus, the turbine height, impeller diameter, wake effect loss are identified and recognized as the main influencing factors for the attribute wind turbine economy.

Therefore, combined with the previous studies/reports/expert knowledge as well as the principal component analysis for specific influencing factors for OWT selection, a hierarchical three-layer decision-making framework for OWT selection is established, as shown in Fig. 3. Note that the different items included in the decision criterion layer or influencing factor layer can be adjusted according to different scenarios and actual situation in practical applications.

2.3. Fuzzify the input and output variables for offshore wind turbine

Fuzzy logic is always used to conduct inaccurate and uncertain data [49]. A membership function assigns a value between 0 and 1 to each element of the discourse. The assigned value (i.e., degree of membership) determines the degree to which a given element belongs to the fuzzy set, noted that any fuzzy set could be uniquely determined by its membership [50].

Fuzzy numbers are a case of fuzzy set, and the most widely utilized fuzzy numbers are triangular and trapezoidal fuzzy numbers [51]. Besides, due to the computational simplicity of the triangular fuzzy numbers, it has the advantage of processing imprecise information [52]. Moreover, in the practical applications of quantitative evaluation, fuzzy membership functions are always

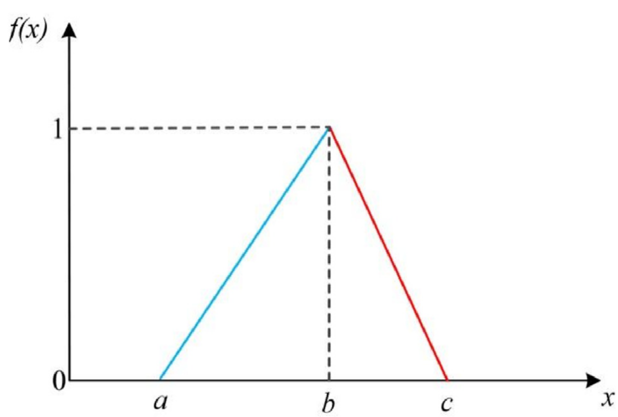

Fig. 4. Triangular membership functions.

used to convert the linguistic estimations/terms into fuzzy numbers. Therefore, triangular membership functions will be utilized in this paper. The triangular membership functions are defined as follows (Eq. (8) and Fig. 4):

$$f(x) = \begin{cases} 0, & x < a \\ (x-a)/(b-a), & a \le x \le b \\ (c-x)/(c-a), & b \le x \le c \\ 0, & x > c \end{cases} \tag{8}$$

The input variables and output variables should be fuzzified before to facilitate the process of MADM. For the input variables, quantitative and qualitative influencing factors are fuzzified by utilizing different methods. Among them, the safety level is a qualitative influencing factor; it has two certain options: IEC I and IEC S, thus the safety level is directly described and defined by linguistic variables (moderate for IEC I, and good for IEC S). Moreover, for the other influencing factors, they are all quantitative influencing factors; therefore, the triangle membership function, which is commonly utilized in previous studies [36,53], is applied to fuzzify the quantitative influencing factors.

Considering the number of language variables will affect the accuracy of the description of influencing factors: too many language variables will significantly increase the number of inference rules, while too few language variables will result in increasing the difficulty to accurately describe and distinguish the degree of influence of influencing factors [37]. Note that more than three linguistic variables should be utilized to obtain comprehensive results. At the same time, less than seven linguistic variables should generally be applied, as this will make it difficult for decision-makers to distinguish the differences of multiple linguistic variables [54]. Thus, four linguistic terms, which are “Bad”, “Moderate”, “Good” and “Very Good”, are introduced in this paper. The criteria for the input variables’ fuzzification are derived based on the specific conditions and relevant regulations. Fuzzification for these factors is detailed as follows, and the fuzzification results are shown in Table 3.

In addition, for the output variables, which are wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety, are all fuzzified by applying the standard triangular fuzzy numbers (the meanings of each linguistic variable’s meanings are similar with the description from Godaliyadde, Phylip-Jones, Yang, Batako, Wang and Godaliyadde [55], as shown in Fig. 5).

2.4. Establish inference rules for offshore wind turbine selection

After fuzzification of the influencing factors for the OWT, the results need to be converted to the decision criterion layer. In this process, specific reasoning *IF-THEN* rules need to be used to

Table 3
Fuzzify the identified influencing factors.

Input variables	Bad	Moderate	Good	Very Good
Market share (%)	Low (0,0,10)	Moderate (0,10,30)	High (10,30,60)	Very High (30,60,100)
Number of turbines	Many (80,70,60)	Normal (70,60,50)	Less (60,50,40)	Very Less (50,40,30)
Turbine height (m)	Low (90,80,70)	Moderate (100,90,80)	High (110,100,90)	Very High (120,110,100)
Impeller diameter (m)	Short (90,110,130)	Moderate (110,130,150)	Long (130,150,170)	Very Long (150,170,190)
Wake effect loss (%)	Very High (17,15,13)	Normal (15,13,11)	Low (13,11,9)	Very Low (11,9,7)
Safe wind speed (m/s)	Low (30,40,50)	Moderate (40,50,60)	High (50,60,70)	Very High (60,70,80)
Safety level	/	IEC I	IEC S	/
Difference from rated wind speed (m/s)	Large (9,7,5)	Normal (7,5,3)	Small (5,3,1)	Very Small (3,1,0)
Turbine spacing (km)	Close (0.3,0.6, 0.9)	Moderate (0.6,0.9,1.2)	Far (0.9,1.2,1.5)	Very Far (1.2,1.5,1.8)
Distance from bridge (NM)	Close (0,0.5,1)	Moderate (0.5,1,1.5)	Far (1,1.5,2)	Very Far (1.5,2,5)
Distance from fairway (NM)	Close (0,0.5,1)	Moderate (0.5,1,1.5)	Far (1,1.5,2)	Very Far (1.5,2,5)

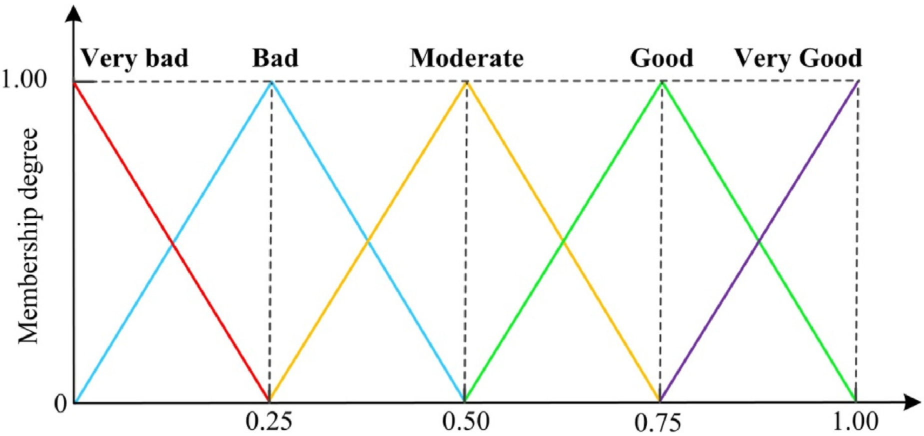

Fig. 5. Standard triangular fuzzy numbers for fuzzification.

establish a connection between the input variables (i.e., the 11 influencing factors) and output variables (the corresponding attributes of the decision criterion layer, i.e., wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety). In traditional *IF-THEN* rules, influencing factors are always used as input variables, and decision criteria are used as output variables, and a 100% belief degree is adapted to describe the results. A traditional *IF-THEN* rule is defined as follows [32]:

$$R_k: \ IF \ A^k_{1J_1} \ and \ A^k_{2J_2} \ \ldots A^k_{nJ_n} \ THEN \ \left\{\left(\beta^i_k, B_i\right)\right\} \tag{9}$$

where R_k is the k-th ($k = 1,2, \cdots, K$) reasoning rule, $A^k_{nJ_n}$ represents the linguistic variables corresponding to the n-th ($n = 1,2, \cdots, N$) input variable (i.e., the specific influencing factor) utilized in the k-th rule. B_i means the linguistic variables corresponding to the output variables (i.e., the corresponding attributes), β^i_k is the belief degree assigned to B_i, which corresponding to the consequent of the output variables for the input of $A^k_{nJ_n}$.

Take the wind turbine parameter attribute as an example; the *IF-THEN* reasoning rule could be expressed as follows:

R_1: *IF* the market share is “Low” *and* the number of turbines is “Many”, *THEN* the wind turbine parameter is (1, Bad), (0, Moderate), (0, Good), (0, Very Good).

It can be seen from the above *IF-THEN* rule that the results are described with 100% belief degree. Nevertheless, in practice, an event/situation usually does not have 100% certainty but is always combined with complexity/uncertainty. The classical fuzzy *IF-THEN* rule is commonly utilized in the marine safety and security research domain [22,32]. Therefore, in this paper, we employ various belief degrees for different linguistic variables corresponding to the specific influencing factor into the fuzzy *IF-THEN* rule system [40]. Thus, the traditional *IF-THEN* scheme is extended into a more specific and realistic scheme. Note that N is the number of input variables; it can be seen from Fig. 3 that N is equal to 2 or 3. Since four linguistic variables are used for all influencing factors, thus J_n ($n = 1,2,3,4$), B_i ($i = 1,2,3,4$), and $\beta^i_k (i = 1, 2, 3, 4)$. The proposed generic *IF-THEN* scheme, combined with a belief structure, is established as follows:

$$R_k: \ IF \ A^k_{1J_1} \ and \ A^k_{2J_2} \ \ldots A^k_{nJ_n} \ THEN \\ \left\{\left(\beta^1_k, B_1\right), \left(\beta^2_k, B_2\right), \left(\beta^3_k, B_3\right), \left(\beta^4_k, B_4\right)\right\} \tag{10}$$

where the meaning of each parameter is the same as Eq. (9).

Thus, the above case of the description for the wind turbine parameter, which with the extended *IF-THEN* rule combined with belief degree, could be rewritten as follows:

R_1: *IF* the market share is “Low” *and* the number of turbines is “Many”, *THEN* the wind turbine parameter is (0.9, Bad), (0.1, Moderate), (0, Good), (0, Very Good).

The belief rule base can accurately reflect the link between the input variables (i.e., influencing factors) and output variables (i.e., the decision-making/corresponding attributes of the decision criterion layer with probabilistic uncertainty). Through introducing this *IF-THEN* scheme with belief structure, the specific *IF-THEN* rules could be developed to establish the fuzzy reasoning rule base. Note that there are two input variables, and each with four linguistic terms, so 16 ($2^4 = 16$) rules could be established to facilitate the process of belief reasoning. The belief rule base for the attributes of wind turbine economy ($3^4 = 81$ rules), wind turbine reliability ($3^4 = 81$ rules), and navigation safety ($3^4 = 81$ rules) could also be established in the same way. According to this reasoning rule, the established belief rule base for the wind turbine parameter is shown in Table 4 (for the sake of space, only the rules for the wind turbine parameter are given).

2.5. Conduct Bayesian network-based rule reasoning

Bayesian network (BN) is an inference approach expressed by a directed acyclic graph (DAG) [56], which indicates the uncertainty relationship between consequences and causes for an event/problem [34]. BN is mainly composed of nodes, directed arc and, conditional probability tables (CPTs) [57]; nodes represent the random variables, directed arcs represent the conditional dependencies between nodes, and CPTs represent the transition logic from parent nodes to child nodes [58]. The parent node acts as an independent variable with a prior probability distribution, while the child node acts as an independent variable with a conditional probability distribution under the condition of the corresponding parent node [57].

The joint probability distribution (JPD), which determines the conditional dependencies between different variables, could be specified by the CPTs for the nodes [59]. In a BN, suppose $Pa(A_i)$ as the parent set of variables A_i, the CPTs of A_i is represented by $P(A_i|Pa(A_i))$, then the $P(U)$ (JPD) of a set of variables $U = A$ ($A_1, A_2, A_3, \ldots, A_n$) could be described as Eq. (11) [33,56].

$$P(U) = \prod_{i=1}^{n} P(A_i|Pa(A_i)) \tag{11}$$

Table 4
Belief rule base for offshore wind turbine parameters.

Rule No.	Input variables		Output variables (Wind turbine parameters)			
	Market share	Number of turbines	Bad	Moderate	Good	Very Good
1	Low	Many	0.90	0.10	0	0
2	Low	Normal	0.80	0.20	0	0
3	Low	Less	0.20	0.40	0.30	0.10
4	Low	Very Less	0.10	0.10	0.50	0.30
5	Moderate	Many	0.20	0.40	0.30	0.10
6	Moderate	Normal	0.10	0.10	0.50	0.30
7	Moderate	Less	0	0.40	0.50	0
8	Moderate	Very Less	0	0.30	0.30	0.40
9	High	Many	0	0.40	0.40	0.20
10	High	Normal	0	0.30	0.50	0.20
11	High	Less	0	0.30	0.40	0.30
12	High	Very Less	0	0.20	0.20	0.60
13	Very High	Many	0	0.30	0.50	0.20
14	Very High	Normal	0	0.20	0.50	0.30
15	Very High	Less	0	0.20	0.20	0.60
16	Very High	Very Less	0	0	0.20	0.80

A feature of BN is that it can perform two-way reasoning (either from the causes to the consequences or from consequences to the causes). When a new evidence E is provided to any variable, accordingly, the prior probabilities of all other variables are updated in the BN model [33,60]. The posterior probabilities of variables can be calculated as Eq. (12).

$$P(U|E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \tag{12}$$

The decision-making framework for OWT selection in Fig. 3 can be converted to a three-layer decision-making framework utilizing BN, as shown in Fig. 6. In addition, after obtaining the belief rule base, its results can be converted into CPTs, thereby establishing a complete BN structure. Thus, by using the BN, the reasoning process can be conducted.

2.6. Make a final decision by utilizing utility value and expert knowledge

$X = \{x_1, x_2, \ldots, x_t\}(t \geq 2)$ is defined as a set of candidate turbines for offshore wind farms. $Y = (y_1, y_2, \ldots, y_s)(s \geq 2)$ is defined as a set of attributes. Let$H_n = \{H_1, H_2, H_3, H_4\}$ be the linguistic terms to describe the performance of the candidate turbines, $P_n = (P_1, P_2, P_3, P_4)$ are the probability values after integration of the influencing factors (probability value can be obtained from the evaluation result of Bayesian network). Define U_i as the overall performance on the i-th candidate turbine; this can be written as Eq. (13).

$$U_i = \sum_{n=1}^{4} P_i V_i \tag{13}$$

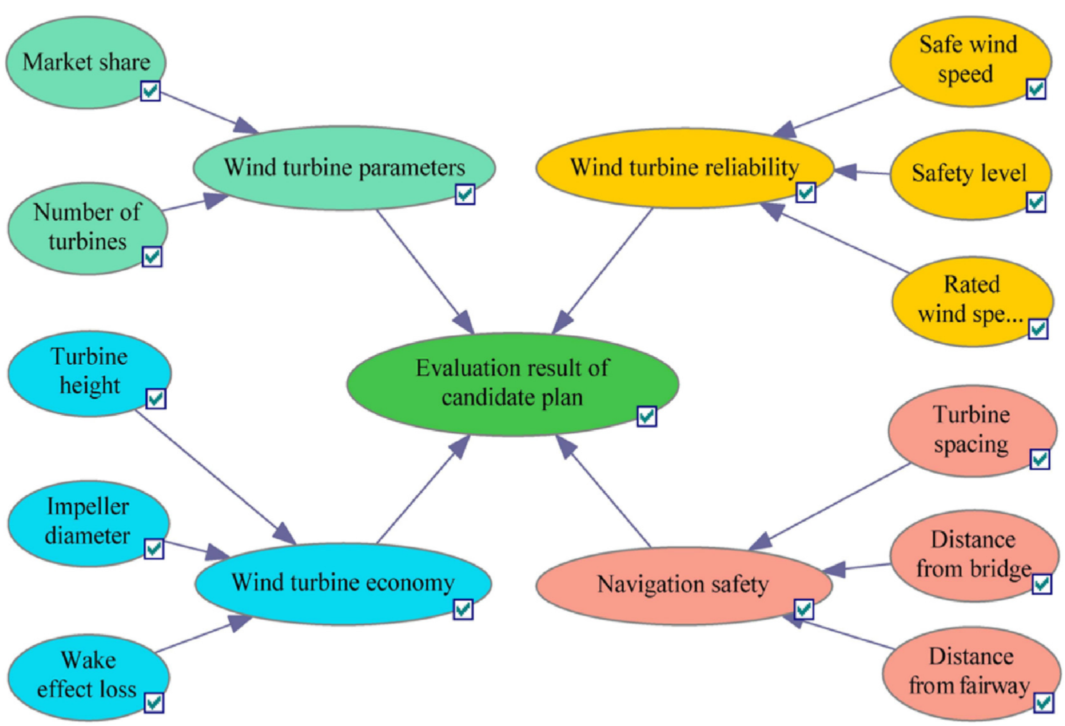

Fig. 6. Bayesian network's graphical relationships for offshore wind turbine selection.

Table 5
Triangular fuzzy numbers of different linguistic terms.

Experts	Weights(β_i)	Triangular fuzzy numbers of different linguistic terms				
		Very Bad (VB)	Bad (B)	Moderate (M)	Good (G)	Very Good (VG)
A	0.30	(0, 0, 0.30)	(0, 0.30, 0.50)	(0.30, 0.50, 0.80)	(0.50, 0.80, 1)	(0.80, 1, 1)
B	0.20	(0, 0, 0.20)	(0.10, 0.25, 0.45)	(0.25, 0.45, 0.60)	(0.40, 0.60,0.80)	(0.85, 1, 1)
C	0.20	(0, 0, 0.25)	(0.10, 0.30, 0.40)	(0.30, 0.45, 0.65)	(0.50, 0.80, 0.90)	(0.90, 1, 1)
D	0.30	(0, 0, 0.25)	(0.20, 0.35, 0.50)	(0.30, 0.50, 0.60)	(0.55, 0.75, 0.90)	(0.85, 1, 1)
Total	1	(0, 0, 0.26)	(0.10, 0.31, 0.47)	(0.29, 0.48, 0.67)	(0.50, 0.75, 0.91)	(0.85, 1, 1)

where V_i is the utility value for the i-th linguistic term, and they are predefined values. It can be seen that the greater the value U_i is, the better performance of the candidate turbine is.

2.6.1. Fuzzy membership functions of linguistic terms establishing

In many cases, the experts' expertise and information are always uncertain or vague. However, fussy sets can be applied with a mathematical tool combined with the linguistic terms in the analysis of reliability for the real-world problem [61,62], and it is better to employ fuzzy numbers to reflect human's real thoughts and in decision-making [63]. Thus, we use fuzzy numbers of the domain experts and consider the relative importance weights of different experts to optimize our proposed model. In order to derive a reasonable result of the proposed model, four domain experts are invited to make judgments on these linguistic terms. The backgrounds are detailed as follows:

- Expert A: A technical manager for wind turbine design and installation from a wind farm company.
- Expert B: An experienced chief officer with more than ten years of sailing experience.
- Expert C: A professor engaged in safety research for more than 15 years with specific reference to maritime traffic planning.
- Expert D: A staff in charge of safety management of the wind farm project from Shanghai Maritime Safety Administration.

Linguistic terms can be represented to the triangular fuzzy number and can be expressed from the knowledge of domain experts on the basis of the Delphi method [30,64]. Supposing that there have n experts, the i-th expert is assigned with the relative weight $\beta_i\,(i=1,\ldots,m)$, satisfying $\sum_{i=1}^{m}\beta_i=1$ and $\beta_i>0\,(i=1,\ldots,m)$. The linguistic term (according to the experts' judgment) for the specific variable is $x_i=(a_i,b_i,c_i)$; thus, the triangular fuzzy number $A=(a,b,c)$ corresponding to the fuzzy linguistic term for the variable could be defined as Eqs. (14)–(16).

$$a=\sum_{i=1}^{n}\beta_i a_i \tag{14}$$

$$b=\sum_{i=1}^{n}\beta_i b_i \tag{15}$$

$$c=\sum_{i=1}^{n}\beta_i c_i \tag{16}$$

This study represents the utility value using four linguistic terms: Bad (B), Moderate (M), Good (G), Very Good (VG). For standard triangular fuzzy numbers, each linguistic term is assigned in the same separation distance, for instance, the midpoint (i.e., b) in triangular fuzzy number A for each linguistic term Very Bad (VB), Bad (B), Moderate (M), Good (G), Very Good (VG) is 0, 0.25, 0.5, 0.75, 1, respectively [22,65]. However, in this paper, we comprehensively take the different evaluation criteria of each expert for each linguistic term into consideration, determine the triangular fuzzy number of different linguistic terms according to the knowledge of the domain experts, and employ the weight for each expert. Then Eqs. (14)–(16) are utilized to calculate the final triangular fuzzy numbers corresponding to different language terms (Table 5), thus representing the fuzzy membership function for the linguistic term more reasonably (Fig. 7).

2.6.2. Defuzzification for linguistic terms of the domain experts

The linguistic terms from domain experts need to be converted into crisp values before utilizing the utility value for further priority ranking and comparison. The transformation process is called defuzzification. Defuzzification can be conducted in different ways, such as the center of gravity (COG), max criterion, and mean of maximum (MOM) methods [66]. Among them, the center of gravity (COG) method (also named center of area (COA)) is the most widely

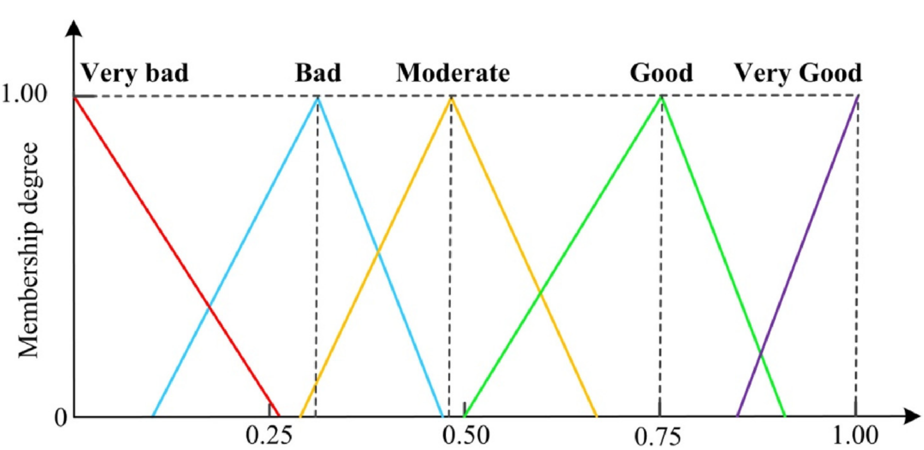

Fig. 7. Triangular membership functions for different linguistic terms.

Table 6
The crisp number of different linguistic terms.

Name	The triangular fuzzy number and crisp number of different linguistic terms				
Linguistic term	Very Bad (VB)	Bad (B)	Moderate (M)	Good (G)	Very Good (VG)
Fuzzy number	(0, 0, 0.26)	(0.10, 0.31, 0.47)	(0.29, 0.48, 0.67)	(0.50, 0.75, 0.91)	(0.85, 1, 1)
Crisp number	0.09	0.29	0.48	0.72	0.95

used technique proposed by Sugeno [67] as it considers the total output distribution and is more accurate [68].

The linguistic terms from the judgments of each domain expert can be defuzzified according to the proposed fuzzy membership function in Section 2.6.1, and the crisp number could be defined as follows:

$$A(X)=\frac{\int_X x\mu_A(x)dx}{\int_X \mu_A(x)dx} \tag{17}$$

Where *A(X)* represents the crisp value, x denotes the output variable, and $\mu_A(x)$ is the triangular membership function for linguistic terms from domain experts (Fig. 7). Specifically, the defuzzification for a triangular fuzzy number on the basis of Eq. (18) could be calculated as follows:

$$A(X)=\frac{\int_a^b x\frac{x-a}{b-a}dx+\int_b^c x\frac{c-x}{c-b}dx}{\int_a^b \frac{x-a}{b-a}dx+\int_b^c \frac{c-x}{c-b}dx}=\frac{1}{3}(a+b+c) \tag{18}$$

Then, the crisp number for different domain experts' linguistic terms could be expressed in Table 6.

3. Case study for the offshore wind turbine selection

3.1. Scenario description of offshore wind turbine selection

The wind farm project of the corporation of China General Nuclear Power Group (CGN) is located in the waters near the Donghai Bridge in the Eastern China Sea. Offshore wind farm sites 5# and 6# are selected and placed on both sides of the 5000 t navigation hole of the Donghai Bridge (shown in Fig. 8). In addition, the wind farm should meet the planned installed capacity of at least 282,000 KW. Through investigations, the options of 4 MW (including wind turbine generators WTG-1 and WTG-2 two options, in which the wake effect loss, rated wind speed, etc. have specific differences), 4.5 MW (WTG-3), 5.5 MW (WTG-4), 6 MW (WTG-5), and 6.45 MW (WTG-6) are selected. Due to the different powers of various turbines, to ensure the required installed capacity, thus, the number of turbines will be different in the specific offshore wind farm, which will also result in different spacing between different turbines.

As shown in Fig. 8, the offshore wind turbine candidate WTG-5 plan to build 47 wind turbines with a distance of 1.05 km between different wind turbines, a distance of 0.62 NM from the 5000 t navigation hole of the Donghai Bridge, and 0.68 NM from the Donghai Bridge. In addition, the turbine height of the 6 MW wind turbine is 110 m, and the impeller diameter is 172 m. According to the calculation result from the Wind Atlas Analysis and Application Program WAsP10.0 software, the wake effect loss is 11.30%, the safe wind speed is 70 m/s, the safety level is IEC S, and the rated wind speed difference is 4.5 m/s.

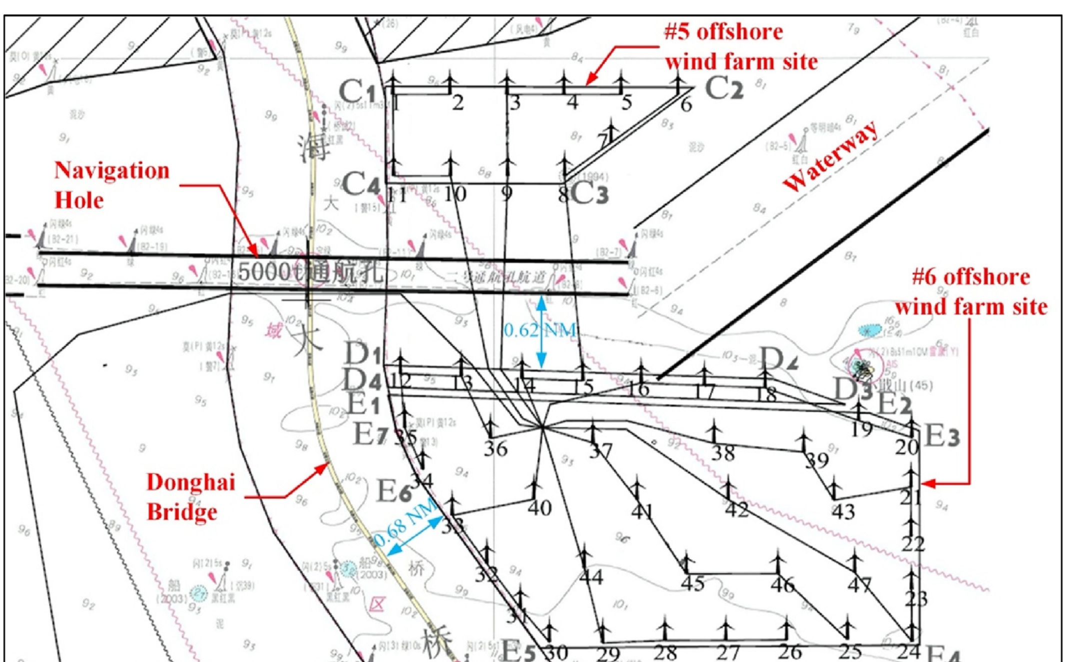

Fig. 8. An alternative construction plan for the 6 MW offshore wind turbines.

Moreover, the parameter values of the influencing factors for the other five schemes are shown in Table 7. It can be seen from Table 7 that there are individual differences in the values of the influencing factors under each OWT candidate. It should be noted that the values are defined from different sources. The market share is derived through the statistics of installed capacity in recent years. Besides, the turbine height, impeller diameter, safe wind speed, safety level, and rated wind speed difference are obtained through turbine parameters. The number of turbines and the turbine spacing are estimated by the wind farm company utilizing associated parameters based on the field of water area and installed capacity, etc. In addition, the wake effect loss is calculated by WAsP10.0 software, and the distance from the bridge and fairway are measured on the nautical chart.

3.2. *Obtain the fuzzified value of the influencing factors for offshore wind turbine*

By using the established fuzzy evaluation criteria for influencing factors of wind turbine selection in Table 3, the influencing factors under different OWT candidates in Table 7 are fuzzified, and the results are shown in Table 8. Specifically, take the market share of offshore wind turbine candidate WTG-1 for example, as the value is 55%, it belongs to *High* with a degree of 0.89, which can be calculated by utilizing the fuzzy evaluation criteria shown in Table 3, and the result is (60-55)/(60-30) = 0.17. In addition, the degree for it belongs to *Very High* is (55-30)/(60-30) = 0.83. Thus, the market share of OWT candidate WTG-1 can be represented as (*High*, 0.17; *Very High*, 0.83). Similarly, the fuzzification results of the other influencing factors for different OWT candidates could also be calculated and shown in Table 8.

As shown in Table 8, these six solutions for OWT selection have corresponding advantages and disadvantages. Among them, candidate WTG-1 has advantages in three aspects: market share, safe wind speed, and safety level. In addition, candidate WTG-2 has advantages in market share and safe wind speed. Moreover, candidate WTG-3 has advantages in safe wind speed and safety level. Besides, candidate WTG-4 has three advantages, such as safe wind speed, safety level, and rated wind speed difference. Also, candidate WTG-5 has advantages in four respects: turbine height, impeller diameter, safe wind speed, and safety level. What's more, candidate WTG-6 has advantages in terms of the number of turbines, wake effect loss, safety level, turbine spacing, distance from bridge, and distance from fairway. Although these six solutions for OWT candidates have advantages in different influencing factors, however, the importance of each influencing factor is different. Therefore, it is necessary to analyze and integrate these influencing factors further to obtain the optimal solution for OWT selection.

4. Results and discussion

The Bayesian network analysis involves amounts of calculations, especially when the Bayesian network is complicated and contains a lot of nodes and directed arcs. In the present paper, the

Table 7
Detailed information of the identified influencing factors for offshore wind turbine generators.

Input variables	WTG-1	WTG-2	WTG-3	WTG-4	WTG-5	WTG-6
Market share (%)	55	55	7	3	0	0
Number of turbines	71	71	63	51	47	44
Turbine height (m)	100	100	95	100	110	106
Impeller diameter (m)	146	140	148	158	172	168
Wake effect loss (%)	15.90	14.99	13.65	13.20	11.30	10.98
Safe wind speed (m/s)	70	70	70	70	70	52.5
Safety level	IEC S	IEC I	IEC S	IEC S	IEC S	IEC S
Difference from rated wind speed (m/s)	7	5	2.8	2.1	4.5	3.2
Turbine spacing (km)	0.6	0.6	0.6	0.9	1.05	1.25
Distance from bridge (NM)	0.43	0.50	0.64	0.65	0.68	0.81
Distance from fairway (NM)	0.50	0.50	0.50	0.50	0.62	0.65

Table 8
Fuzzified values of the identified influencing factors for various offshore wind turbine selection schemes.

Input variables	WTG-1	WTG-2	WTG-3	WTG-4	WTG-5	WTG-6
Market share (%)	(High,0.17; Very High,0.83)	(High,0.17; Very High,0.83)	(Low,0.30; Moderate,0.70)	(Low,0.70; Moderate,0.30)	(Low,1.00)	(Low,1.00)
Number of turbines	(Many,0.90; Normal,0.10)	(Many,0.90; Normal,0.10)	(Normal,0.70; Less,0.30)	(Normal,0.10; Less,0.90)	(Less,0.70; Very Less,0.30)	(Less,0.40; Very Less,0.60)
Turbine height (m)	(High,1.00)	(High,1.00)	(Moderate,0.50; High,0.50)	(High,1.00)	(Very High,1.00)	(High,0.40; Very High,0.60)
Impeller diameter (m)	(Long,0.80; Moderate,0.20)	(Long,0.50; Moderate,0.50)	(Long,0.90; Moderate,0.10)	(Long,0.60; Very Long,0.40)	(Very Long,1.00)	(Long,0.10; Very Long,0.90)
Wake effect loss (%)	(High,0.55; Normal,0.45)	(High,1.00)	(High,0.325; Normal,0.675)	(High,0.10; Normal,0.90)	(Normal,0.15; Low,0.85)	(Low,0.99; Very Low,0.01)
Safe wind speed (m/s)	(Very High,1.00)	(Very High,1.00)	(Very High,1.00)	(Very High,1.00)	(Very High,1.00)	(Moderate,0.75; High,0.25)
Safety level	(Good,1.00)	(Moderate,1.00)	(Good,1.00)	(Good,1.00)	(Good,1.00)	(Good,1.00)
Difference from rated wind speed (m/s)	(Large,1.00)	(Normal,1.00)	(Small,0.90; Very Small,0.10)	(Small,0.05; Very Small,0.95)	(Normal,0.50; Small,0.50)	(Normal,0.10; Small,0.90)
Turbine spacing (km)	(Close,1.00)	(Close,1.00)	(Close,1.00)	(Moderate ,1.00)	(Moderate,0.50; Far,0.50)	(Far,0.83; Very Far,0.17)
Distance from bridge (NM)	(Close,1.00)	(Close,1.00)	(Close,0.72; Moderate,0.28)	(Close,0.70; Moderate,0.30)	(Close,0.64; Moderate,0.36)	(Close,0.38; Moderate,0.62)
Distance from fairway (NM)	(Close,1.00)	(Close,1.00)	(Close,1.00)	(Close,1.00)	(Close,0.76; Moderate,0.24)	(Close,0.70; Moderate,0.30)

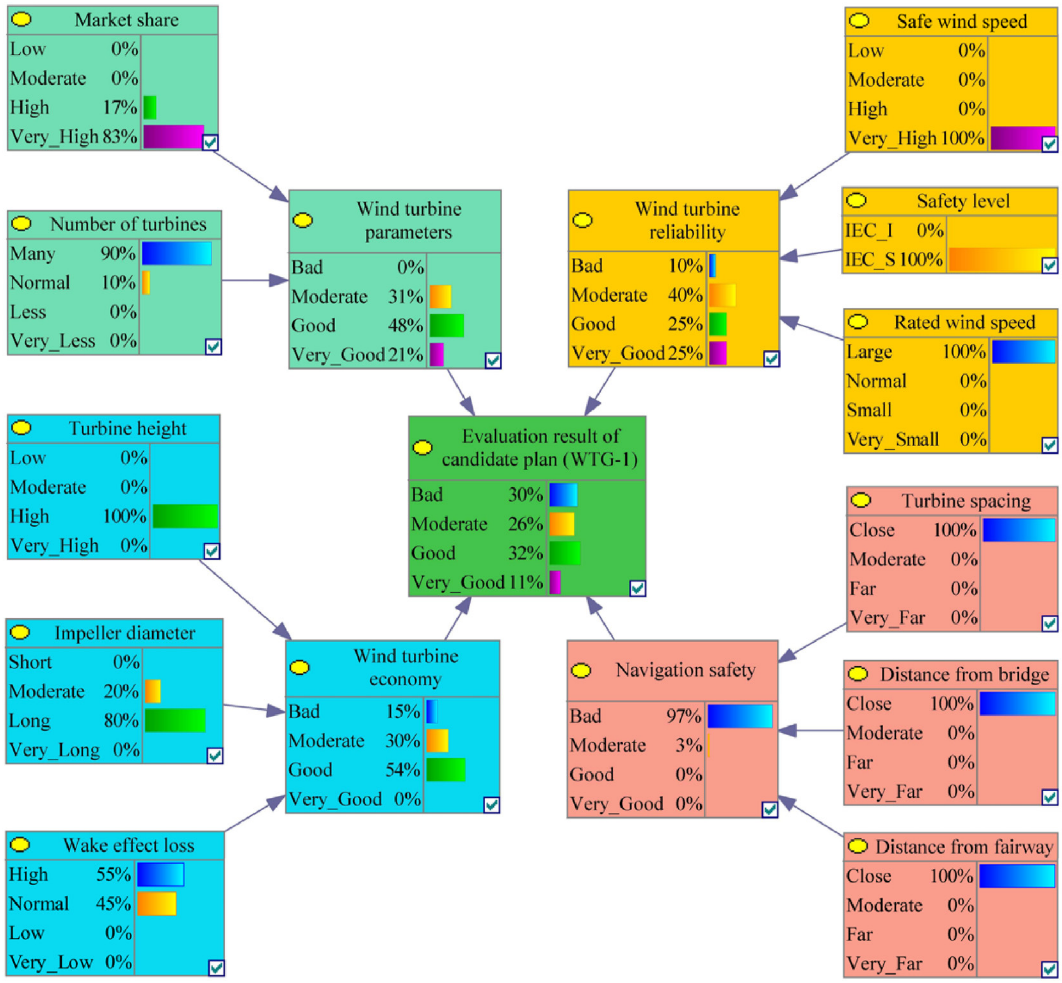

Fig. 9. Evaluation results of candidate plan WTG-1.

professional and widely used Bayesian network modelling software GeNIe, especially in the safety and reliability research domain [69–72], is utilized to calculate the evaluation results of each candidate plan based on above mentioned four perspectives of wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety from the proposed three-layer decision-making framework for offshore wind turbine selection.

Fig. 9 demonstrates the evaluation results of candidate plan WTG-1. Section 3.2 details the process and criteria for the fuzzification of the 11 influencing factors of each candidate plan in Table 7. Then, the fuzzification results of the 11 influencing factors for wind turbine generator WTG-1 shown in Table 8 are input into the software GeNIe. For instance, based on the data of wind turbine parameters for OWT candidate WTG-1: market share (High, 0.17; Very High, 0.83) and the number of turbines (Many, 0.90; Normal, 0.10). The Bayesian network reasoning results for the decision attribute value of wind turbine parameters are calculated and presented as (Moderate, 0.31; Good, 0.48; Very Good, 0.21). Similarly, the decision attribute values of other three levels of attributes could be represented as wind turbine economy (Bad, 0.15; Moderate, 0.30; Good, 0.54), wind turbine reliability (Bad, 0.10; Moderate, 0.40; Good, 0.25; Very Good, 0.25), and navigation safety (Bad, 0.97; Moderate, 0.03) (Table 9). Then the comprehensive Bayesian network reasoning results considering the comprehensive influences of 11 factors in terms of wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety for the final evaluation value of candidate plan WTG-1 could be presented as (Bad, 0.30; Moderate, 0.26; Good, 0.32; Very Good, 0.11) (Table 10). Note that the result is not listed above if the probability of the specific linguistic terms is zero and the sum of the

Table 9
Evaluation results for the four decision attributes of each offshore wind turbine candidate.

Candidate turbine	Wind turbine parameters	Wind turbine economy	Wind turbine reliability	Navigation safety
WTG-1	(0.00,0.31,0.48,0.21)	(0.15,0.30,0.54,0.00)	(0.10,0.40,0.25,0.25)	(0.97,0.03,0.00,0.00)
WTG-2	(0.00,0.31,0.48,0.21)	(0.26,0.27,0.46,0.00)	(0.00,0.50,0.25,0.25)	(0.97,0.03,0.00,0.00)
WTG-3	(0.24,0.41,0.28,0.08)	(0.10,0.45,0.45,0.00)	(0.00,0.00,0.64,0.36)	(0.91,0.09,0.00,0.00)
WTG-4	(0.19,0.39,0.33,0.09)	(0.02,0.33,0.53,0.13)	(0.00,0.00,0.35,**0.65**)	(0.57,0.43,0.00,0.00)
WTG-5	(0.17,0.31,0.36,0.16)	(0.00,0.03,0.31,**0.66**)	(0.00,0.17,0.51,0.33)	(0.44,0.43,0.13,0.00)
WTG-6	(0.14,0.22,0.42,**0.22**)	(0.00,0.00,0.50,0.50)	(0.00,0.28,0.71,0.00)	(0.34,0.38,0.25,**0.04**)

Table 10
Overall performance and ranking for offshore wind turbine candidates.

Candidate turbine	Evaluation value	Overall performance (“Bad” as 0.35)	Ranking	Overall performance (proposed method)	Ranking
WTG-1	(0.30,0.26,0.32,0.11)	0.630	6	0.547	6
WTG-2	(0.30,0.28,0.31,0.11)	0.633	5	0.549	5
WTG-3	(0.31,0.24,0.34,0.11)	0.640	4	0.554	4
WTG-4	(0.19,0.29,0.30,0.22)	0.701	3	0.619	3
WTG-5	(0.15,0.23,0.33,0.29)	0.750	2	**0.667**	1
WTG-6	(0.12,0.22,0.47,0.19)	**0.753**	1	0.659	2

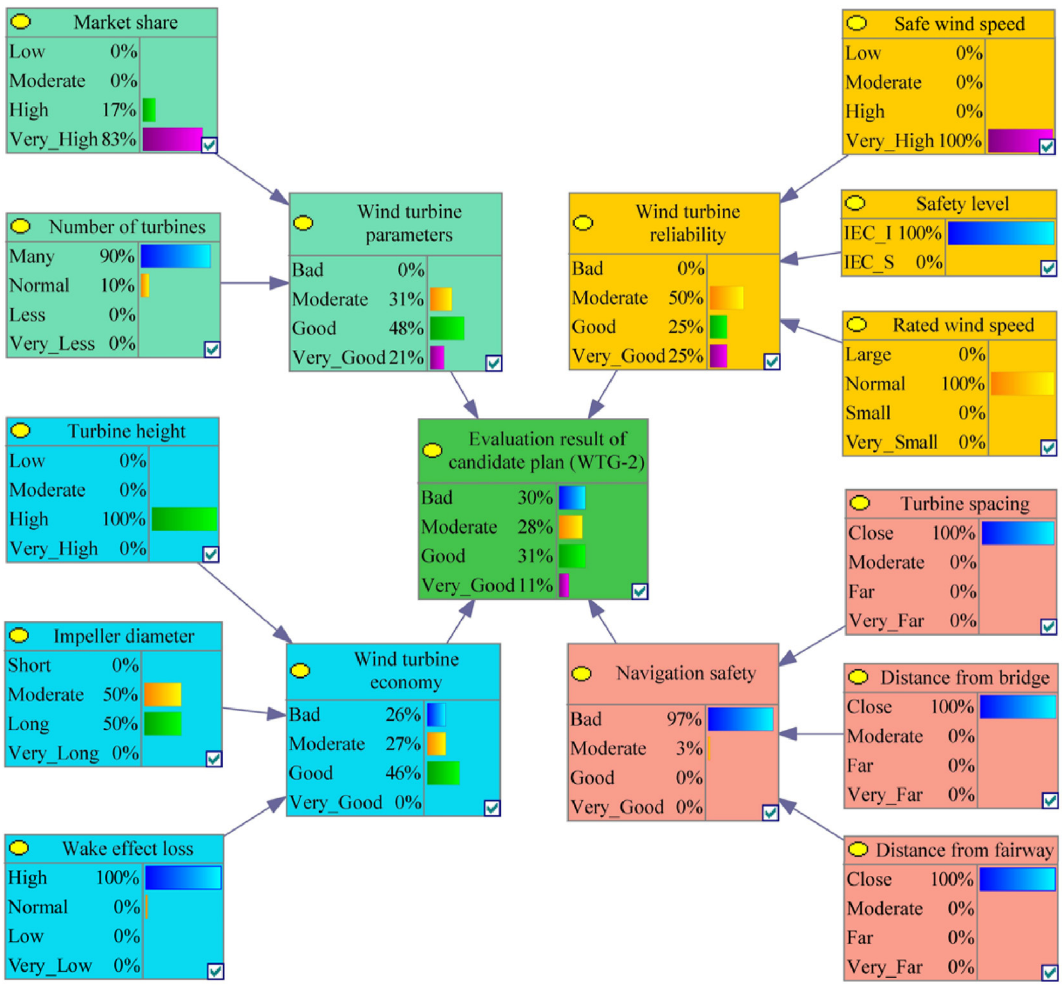

Fig. 10. Evaluation results of candidate plan WTG-2.

probabilities for various linguistic terms is one, and the differences of the actual sum results of Table 9 are due to the number is rounded to two significant figures.

Fig. 10 shows the evaluation process for candidate plan WTG-2. Obviously, the fuzzification results of input variables of market share, number of turbines, turbine spacing, distance from bridge, distance from fairway, are the same as the results of plan WTG-1 (Table 8). Thus, the Bayesian network reasoning results for the decision attribute values of wind turbine parameters and navigation safety are the same as WTG-1. However, though the fuzzification results of turbine height and safe wind speed is the with plan WTG-1, the fuzzification results of impeller diameter (Moderate, 0.50; Long, 0.50), wake effect loss (High, 1.00), safety level (Moderate,1.00) (moderate for IEC I, and good for IEC S, as shown in Tables 3 and 8), and rated wind speed difference (Normal,1.00) are different from plan WTG-1. Therefore, the BN reasoning results for the wind turbine economy (Bad, 0.26; Moderate, 0.27; Good, 0.46) and wind turbine reliability (Moderate, 0.50; Good, 0.25; Very Good, 0.25) are changed. Accordingly, the final evaluation result of plan WTG-2 becomes to (Bad, 0.30; Moderate, 0.28; Good, 0.31; Very Good, 0.11).

As shown in Fig. 11, compared with the fuzzification results of various input variables of candidate plan WTG-1, since only the safe wind speed, safety level, turbine spacing, and distance from fairway are not changed. Thereby, the Bayesian network reasoning results for the four decision attribute values of wind turbine parameters (Bad, 0.24; Moderate, 0.41; Good, 0.28; Very Good, 0.80), wind turbine economy (Bad, 0.10; Moderate, 0.45; Good, 0.45), wind turbine reliability (Good, 0.64; Very Good, 0.36), and navigation safety (Bad, 0.91; Moderate, 0.09) are all changed, which also led to

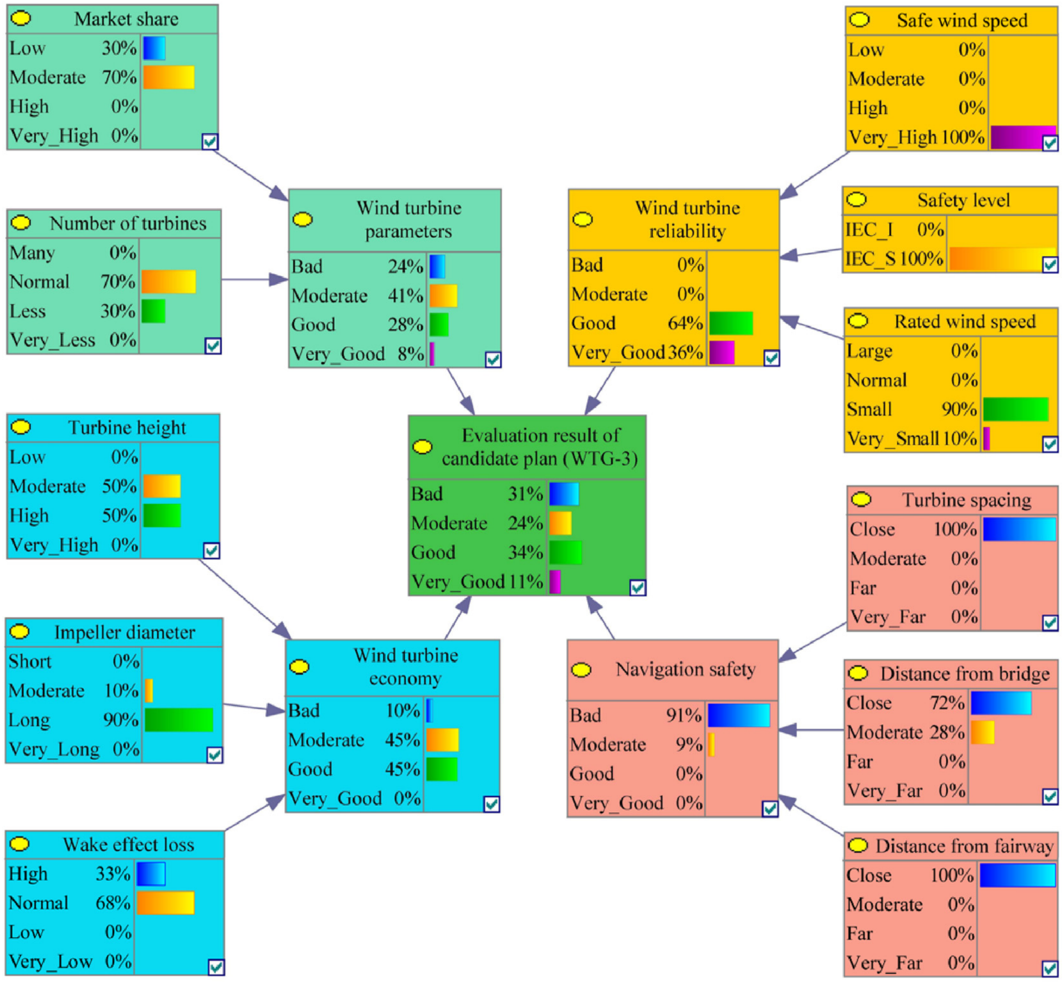

Fig. 11. Evaluation results of candidate plan WTG-3.

the different output for the final evaluation result of plan WTG-3 (Bad, 0.31; Moderate, 0.24; Good, 0.34; Very Good, 0.11).

Fig. 12 illustrates the evaluation results of candidate plan WTG-4. Similarly, there are only four input variables of turbine height, safe wind speed, safety level, and distance from fairway are the same with WTG-1, and the other seven fuzzification results of input variables are all different. Therefore, the wind turbine parameters (Bad, 0.19; Moderate, 0.39; Good, 0.33; Very Good, 0.09), wind turbine economy(Bad, 0.02; Moderate, 0.33; Good, 0.53; Very Good, 0.13), wind turbine reliability (Good, 0.35; Very Good, 0.65), and navigation safety (Bad, 0.57; Moderate, 0.43) are all changed, Accordingly, the final evaluation result of plan WTG-4 becomes to (Bad, 0.19; Moderate, 0.29; Good, 0.30; Very Good, 0.22).

From Fig. 13, we can see that, compared with candidate plan WTG-1, the two input variables of safe wind speed and safety level are the same as plan WTG-1, and the other nine fuzzification results of input variables are all different: market share (Low, 1.00), number of turbines (Less, 0.70; Very Less, 0.30), turbine height (Very High, 1.00), impeller diameter (Very Long, 1.00), wake effect loss (Normal, 0.15; Low, 0.85), rated wind speed difference (Normal, 0.50; Small, 0.50), turbine spacing (Moderate, 0.50; Far, 0.50), distance from bridge (Close, 0.64; Moderate, 0.36), and distance from fairway (Close, 0.76; Moderate, 0.24) are all different with plan WTG-1 (Table 8), resulting in the Bayesian network reasoning results for the four decision attribute values of wind turbine parameters (Bad, 0.17; Moderate, 0.31; Good, 0.36; Very Good, 0.16), wind turbine economy (Moderate, 0.03; Good, 0.31; Very Good, 0.66), wind turbine reliability (Moderate, 0.17; Good, 0.51; Very Good, 0.33), and navigation safety (Bad, 0.44; Moderate, 0.43; Good, 0.13) are all changed. Therefore, the final output of the evaluation result of plan WTG-5 is (Bad, 0.15; Moderate, 0.23; Good, 0.33; Very Good, 0.29).

Fig. 14 presents the fuzzification results of various input variables of candidate plan WTG-6. Since only the safety level is the same as the plan WTG-1, which leads to the Bayesian network reasoning results for the four decision attribute values of wind turbine parameters (Bad, 0.14; Moderate, 0.22; Good, 0.42; Very Good, 0.22), wind turbine economy (Good, 0.50; Very Good, 0.50), wind turbine reliability (Moderate, 0.28; Good, 0.71), and navigation safety (Bad, 0.34; Moderate, 0.38; Good, 0.25; Very Good, 0.04) are all changed. Thus, the output is also different for the final evaluation result of plan WTG-6 (Bad, 0.12; Moderate, 0.22; Good, 0.47; Very Good, 0.19).

Therefore, by employing the BN model, the values of the decision attributes can be obtained (shown in Table 9). It can be seen from Table 9 that among the six wind turbine candidates, WTG-6 has the best wind turbine parameters, WTG-5 has the best wind turbine economy, WTG-4 has the best wind turbine reliability, and WTG-6 has the best navigation safety.

To select the optimal wind turbine selection solution, this paper defines the utility value "Bad" as 0.35 , "Moderate" as 0.55 , "Good" as 0.85 , "Very Good" as 1.00 from previous studies

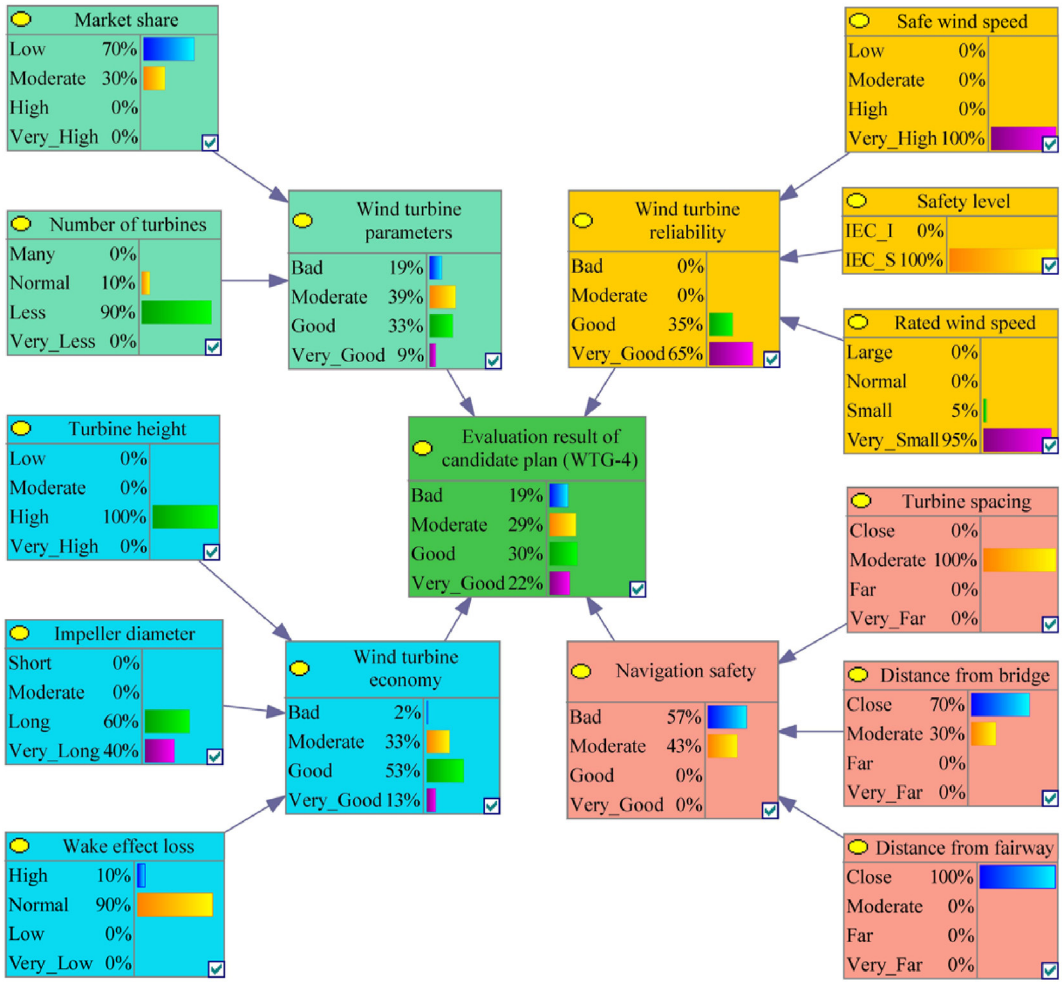

Fig. 12. Evaluation results of candidate plan WTG-4.

[57], we can get the overall performance by utilizing the utility value calculation Eq. (13), then the ranking results can be obtained. For further comparative analysis, we utilized the method proposed in Section 2.6; the crisp number of different linguistic terms based on the domain experts' knowledge is employed. For instance, the overall performance value based on the utility value from previous studies is $0.30*0.35 + 0.26*0.55 + 0.32*0.85 + 0.11*1.00 = 0.630$, and the overall performance value utilizing the proposed method is $0.30*0.29 + 0.26*0.48 + 0.32*0.72 + 0.11*0.95 = 0.547$. The overall performance and ranking results for each candidate turbine are shown in Table 10 and Fig. 15.

As can be seen from Table 10 and Fig. 15, the ranking results for the proposed wind turbine selection model are slightly different from those calculated by the utility values commonly used in various traditional engineering fields. The main differences are concentrated in the two kinds of wind turbine candidates: WTG-5 and WTG-6. This is also consistent with the actual situation. From Table 8, we can see that the wind turbine candidate WTG-6 has advantages in six aspects, while the WTG-5 has advantages in only four aspects, and the two candidates both have their advantages and disadvantages. Therefore, the specific situation needs to be further analyzed in detail.

From a practical point of view, due to the relatively small power of the wind turbine candidates of WTG-1, WTG-2, and WTG-3, the number of turbines required is relatively large, the distance between the turbines is relatively small, and the wake effect loss is relatively large, although there are certain advantages in terms of market share, but inferior in terms of wind turbine economy and navigation safety. Therefore, these three wind turbine candidates are not the best solution for this wind farm construction. The candidate WTG-4 is similar to the first three candidates and is the best in terms of the rated wind speed difference, but on the whole, it still has certain disadvantages compared to the candidate WTG-5. The candidate WTG-6 has advantages in many aspects, but the safe wind speed is lower than the other five wind turbine candidates. Considering the influence of tropical cyclones in the East China Sea, the reliability of the turbine needs to be fully considered. In addition, the candidate WTG-5 is more economical. Therefore, on the whole, the candidate WTG-5 is taken as the final optimal wind turbine selection scheme.

Based on the results calculated by the model proposed in this paper, after a comprehensive evaluation, the utility value for the candidate WTG-6 is still lower than that of WTG-5. Thus, this paper chooses the candidate WTG-5 as the best OWT selection scheme. This result is consistent with the actual evaluation workshop for OWT selection in the wind farm project of CGN, which shows that the proposed OWT selection model can obtain a reasonable result. This also illustrates the importance of various influencing factors when conducting OWT selection.

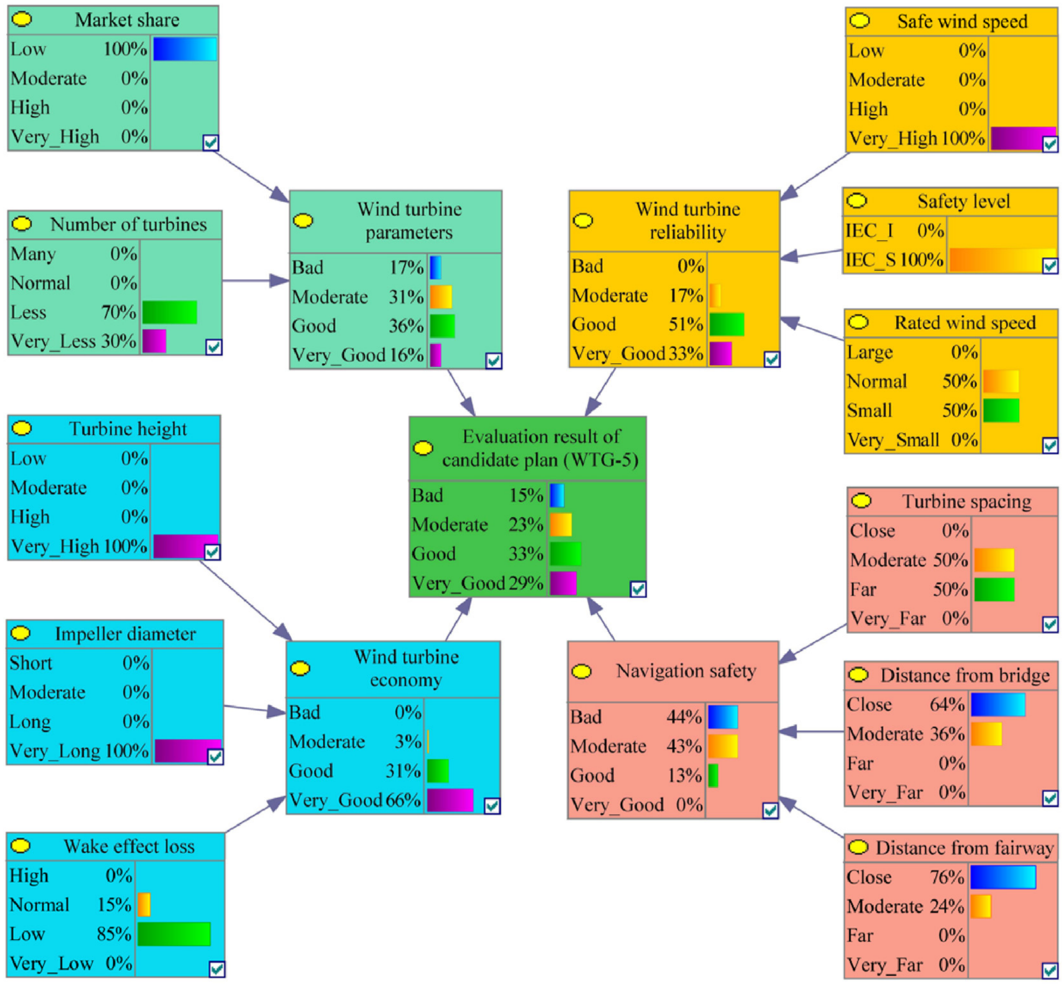

Fig. 13. Evaluation results of candidate plan WTG-5.

5. Conclusions

This paper proposes a novel offshore wind turbine (OWT) selection model based on fuzzy Bayesian networks and expert domain knowledge. In addition, a three-layer decision-making framework for OWT selection, including the influencing factor layer, the decision-making criterion layer, and the target layer for OWT selection, is established, and principal component analysis (PCA) is employed to reduce the subjectivity of decision variables' selection and address the choice of the influencing factors for the attribute wind turbine economy. Moreover, each influencing factor's qualitative and quantitative characteristics and the fuzziness and uncertainty of the data are taken into consideration, and fuzzy logic is introduced to fuzzify the data. At the same time, considering that traditional fuzzy logic uses a 100% belief degree to describe output variables when performing rule inference, it is difficult to accurately describe the difference of various influencing factors, which may affect the final decision-making result. Therefore, this paper employs various belief degrees for different linguistic variables corresponding to the specific influencing factor into the fuzzy *IF-THEN* rule system, and finally transform the belief rule base into the Bayesian network as the CPTs. On the one hand, this method can solve the problem of difficulty in describing the output variables accurately. On the other hand, it can intuitively describe the relationship between various influencing factors. The application results show that the model has good accuracy and applicability.

Offshore wind turbine selection is a complicated process. It is necessary to comprehensively consider the influences of wind turbine parameters, wind turbine economy, wind turbine reliability, and navigation safety. If the stakeholders concluded an inappropriate selection, it may cause maritime accidents or make it challenging to utilize wind energy fully. This paper systematically sorts out the main influencing factors for OWT selection, which can provide a useful reference for the selection of OWT. At the same time, the use of the fuzzy Bayesian network can solve the uncertain problem of OWT selection caused by ambiguity. In addition, the conversion between fuzzy logic and Bayesian network can be realized by introducing the improved *IF-THEN* rule, thus to intuitively display the output results. The comparison analysis between the proposed model calculation results and the actual wind turbine selection scheme shows that this model can accurately realize the purpose of OWT selection.

Nevertheless, this study still has some limitations which need to be considered and adapted in a specific application scenario. First, the fuzzy criteria for various influencing factors are obtained from previous studies and existing experience of OWT selection. When applying it to other situations/scenarios, more data sources need to be explored and investigated to identify and determine the fuzzy criteria. Second, in practical applications, some expert judgment data are applied in our model, which requires experts to be familiar with wind turbine parameters, the coverage range of the candidate sites, output of wind-power characteristics, and the surrounding water environment, etc. So experts need to be carefully selected. Third, though the proposed three-layer decision-making

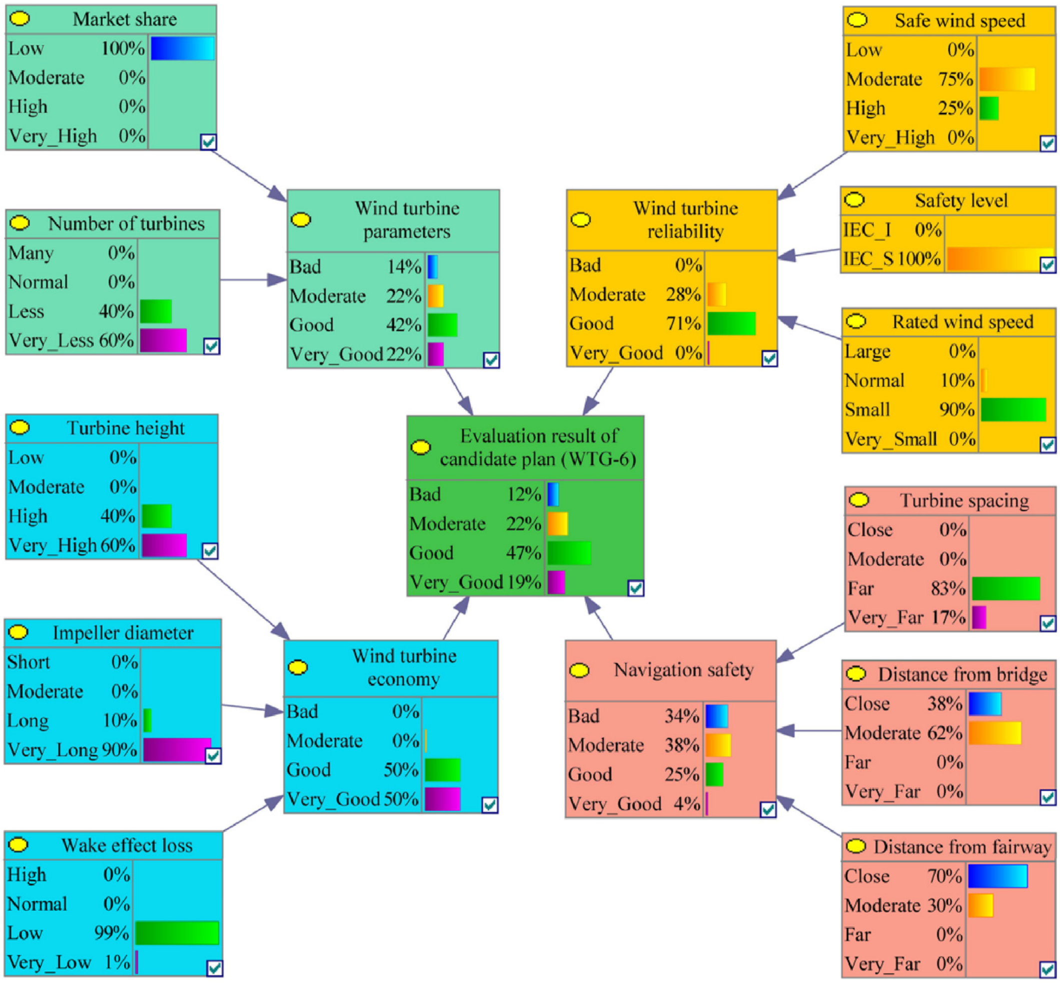

Fig. 14. Evaluation results of candidate plan WTG-6.

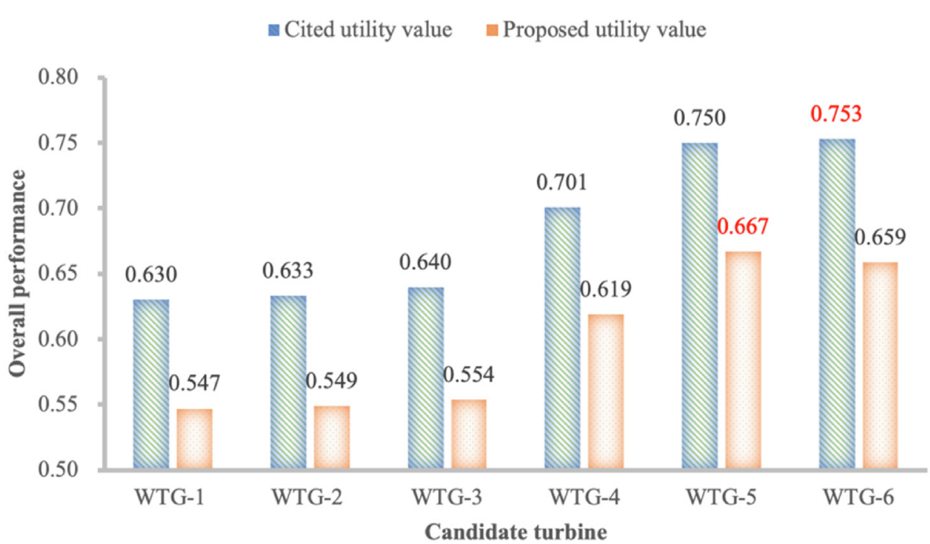

Fig. 15. Overall performance of the cited and proposed utility value for various offshore wind turbines.

framework and fuzzy Bayesian network-based MADM model for OWT selection are feasible and practical, some specific influencing factors corresponding to various decision criteria should be adjusted and updated according to the application scenario when applying the proposed method.

CRediT authorship contribution statement

Jie Xue: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Funding acquisition. **Tsz Leung Yip:** Formal analysis, Writing – review & editing. **Bing Wu:** Validation, Resources, Investigation, Writing – review & editing, Funding acquisition. **Chaozhong Wu:** Methodology, Writing – review & editing, Supervision, Funding acquisition. **P.H.A.J.M. van Gelder:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

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

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Appendix A

Table A1
The data of each influencing factor of wind turbine economy.

Plan	Turbine height (m)	Impeller diameter (m)	Wake effect loss (%)	Annual average wind speed (m/s)	Wind power density (W/m^2)	Annual energy production (*10^4 kWh)
WTG-1	100	146	15.90	8.03	507.80	136130.9
WTG-2	100	140	14.99	8.03	507.80	129900.0
WTG-3	95	148	13.65	7.97	495.65	126250.2
WTG-4	100	158	13.20	8.03	507.80	127738.5
WTG-5	110	172	11.30	8.11	522.60	130947.5
WTG-6	106	168	10.98	8.08	516.68	124129.4
Average	101.83	155.33	13.34	8.04	509.72	129182.75
Standard Deviation	5.31	12.82	1.96	0.05	9.20	4198.28

Table A2
Standardization results of each influencing factor of wind turbine economy.

Plan	Turbine height	Impeller diameter	Wake effect loss	Annual average wind speed	Wind power density	Annual energy production
WTG-1	−0.345	−0.345	−1.288	−0.345	1.539	0.785
WTG-2	−0.728	−1.196	−0.572	0.208	1.300	0.988
WTG-3	1.311	0.845	0.160	−0.070	−1.041	−1.205
WTG-4	−0.241	−0.241	−1.483	−0.241	1.414	0.793
WTG-5	−0.209	−0.209	−1.529	−0.209	1.400	0.756
WTG-6	1.655	0.171	−0.699	−0.344	0.420	−1.204

Table A3
Correlation coefficient matrix between the variables of wind turbine economy.

	Turbine height	Impeller diameter	Wake effect loss	Annual average wind speed	Wind power density	Annual energy production
Turbine height	1.000	0.821	−0.695	0.991	0.987	0.018
Impeller diameter	0.821	1.000	−0.923	0.777	0.760	−0.345
Wake effect	−0.695	−0.923	1.000	−0.634	−0.610	0.648
Annual average wind speed	0.991	0.777	−0.634	1.000	0.999	0.064
Wind power density	0.987	0.760	−0.610	0.999	1.000	0.087
Annual energy production	0.018	−0.345	0.648	0.064	0.087	1.000

Table A4
Contribution ratio and accumulative contribution ratio (ACR) of each component variance.

Component	Initial eigenvalues		
	Total	% of Variance (contribution ratio)	Cumulative variance (ACR), %
1	4.326	72.107	**72.107**
2	1.481	24.682	**96.789**
3	0.174	2.902	99.690
4	0.018	0.304	99.994
5	0.000	0.006	100.000
6	1.641E-16	2.735E-15	100.000

Table A5
Principal component loading matrix for various variables (influencing factors of the wind turbine economy attribute).

Name	Component loading matrix	
	Component 1	Component 2
Turbine height	0.463	0.204
Impeller diameter	0.447	−0.177
Wake effect	−0.410	0.419
Annual average wind speed	0.453	0.253
Wind power density	0.448	0.274
Annual energy production	−0.103	0.782

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