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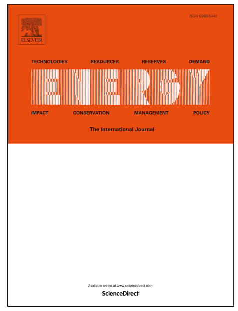

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A novel decision-making system for selecting offshore wind turbines with PCA and D numbers☆

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Abstract

Offshore wind turbine selection is a complex multi-attribute decision-making (MADM) problem with multiple variables and schemes. As a result of the intervention of expert judgment and linguistic assessment, various uncertainties arise in the process of wind turbine selection. This work presents a novel decision-making system for selecting offshore wind turbine by combining D numbers with principal component analysis (PCA). Firstly, we build five main attribute indexes involving technology, matching with wind resources, economy, historical performance of wind turbine and after-sales service of manufacturer through historical experience and expert advice. Then, to reduce the subjectivity of experts in selecting decision variables, PCA is employed to select twelve secondary indicators and determine the corresponding weights. Secondly, experts evaluate the performance of schemes according to the language set, and give the confidence of judgment. We propose to quantify the evaluation results in the form of D numbers, which can directly express the incomplete information of experts and realize the integration of expert opinions. Finally, the optimal scheme is obtained through the technique for order preference by similarity to ideal solution (TOPSIS). The selection results from an actual case show that the proposed model can effectively realize offshore wind turbine selection.

Keywords: `Offshore wind turbine, Decision-making system, D numbers, PCA, TOPSIS`

1. Introduction

Under the increasingly severe situation of climate change, vigorously developing renewable clean energy has been a major trend to promote the sustainable development of global energy. In recent years, more and more countries and regions have declared net-zero carbon commitment, driving a much broader consensus that offshore wind can play a key role in combating climate change. Offshore wind power is a fast-growing global energy industry. New installation for offshore wind has been primarily concentrated in Europe and China in the past decade as shown in Figure 1. Offshore wind capacity estimated will be increased by 235GW in the next decade, yielding 270GW of total volume by 2030 [1].

Wind turbine selection is a key technology in offshore wind development scenarios. An excellent decision-making model for wind turbine selection can contribute to the progress of offshore wind project, stimulated by the following reasons.

• Offshore wind turbine selection and offshore wind siting affect and restrict each other. Offshore wind power generation operates in extremely complex environments including tides, giant waves, and typhoons [2]. Hence, different types of wind turbines are needed to match offshore wind with different site features. Generally, the requirements for offshore turbine rating, rotor diameter and hub height are much higher than onshore counterparts.

• Cost reduction is the key factor for the large-scale development of offshore wind. Wind turbine spends 30%-45% of the project capital expenditures incurred prior to commercial operation date (COD) [1, 3], and also affects operational expenditures (OpEx) incurred from COD to decommissioning. Assuming the lifetime of an offshore wind project operation is raised from 20 years to 30 years, OpEx will increase by around 50%, which can be effectively reduced by upgrading wind turbine technology [1]. Offshore wind turbine technology advancement can unquestionably contribute to cost reduction due to business-driven and price competitiveness enhancement [4, 5].

• Offshore wind turbine manufacturing is flourishing with the emerging offshore wind market. Rotor size and turbine rating are mounting up with the continuous efforts of offshore wind turbine manufacturers from countries (See Figure 2). Over the past decade, the global average power rating experienced the increase from around 3MW to 6MW [6]. Meanwhile, larger size turbines were continuously launched: Vestas 164D-8.8MW represents the world's largest turbine installed in Scotland of Europe in 2018 [3]; DEC DF 185D-10MW turbine, the Asian largest one, was connected to the grid in China in 2020 [7]; GE 12MW turbine was tested in 2020; 222D-14MW, 236D-15MW, 242D-16MW turbine models released by Siemens Gamesa in 2020 [8], Vestas and MingYang in 2021 respectively, will be commercially available in the future three years [1]. Therefore, offshore wind turbine selection can gravely affect power generation efficiency after the project is put into operation.

Obviously, offshore wind turbine selection is related to multi-factors, so it is a multi-attribute decision-making (MADM)

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problem. Selecting an optimal wind turbine that makes the offshore wind achieve the maximum economic and social benefits is undoubtedly a significant but challenging task. Thus, many decision-making approaches to selecting offshore wind turbines have been presented.

Analytic hierarchy process (AHP) [9], weighted aggregates sum product assessment (WASPAS) [10], technique for order preference by similarity to ideal solution (TOPSIS) [11], analytic network process (ANP) and entropy-weight method (EWM) [12], as traditional and classic decision-making methods, were applied to wind turbine selection. Notably, AHP provides a paradigmatic foundation framework for wind turbine selection decision model. Based on AHP, Sagbansua and Balo [13] regarded wind turbine selection index as a complex multi-dimensional structure embodying four main standards: technology, economy, environment and customer attributes with various sub-standards. To rank alternative wind plants in accordance with cost related standards, Lee et al. [14] presented an AHP-based BOCR (benefit, opportunity, cost and risk) model. In addition, some optimization algorithms were also extended for wind turbine selection. In [15], a practical mathematical model chose the hub height, blade diameter and rated power of wind turbines as the optimization parameters, wherein an improved genetic algorithm was utilized to find the best wind turbine design.

During the actual wind turbine selection, experts need to evaluate all aspects of wind turbine via their own knowledge or experience, resulting in two problems: (1) The fuzziness of expert language produces uncertain information in selection process; (2) Decision-making program relies largely on the experts' subjective judgments. Therefore, how to express and handle these various uncertainties whilst eliminate the subjectivity has been an urgent issue to be settled for selecting the ideal offshore wind turbine. Presently, there are several theories against uncertainty, such as fuzzy set [16], probability theory [17], Dempster-Shafer (D-S) evidence theory [18] etc. Beskese et al. [19] developed a decision-making tool through combining hesitant fuzzy set and AHP against the fuzziness in standard priority, and sorting the alternatives with TOPSIS. This tool makes the evaluation process systematic with advantages in terms of handling fuzziness. For the problem of hardly describing output variables in selecting wind turbine, neutrosophic number is enforced to deduce the criterion weights [20]. This method, an extension of intuitionistic fuzzy set, can partly imitate thinking logic and reflect the value of uncertainty. In [21], the fuzzy Bayesian network was considered, where the triangular fuzzy number was introduced into the parameters of technology, economy, reliability and safety for offshore wind turbine in East China Sea.

Although fuzzy sets reflect the imprecision of language, they cannot reduce the sub-objectivity of expert evaluation [22]. D-S evidence theory, a generalization of Bayesian theory, can comprehensively handle uncertain multi-source information. Using trust function instead of probability as a measure brings the considerable advantage of directly expressing uncertainty. Specifically, the trust function is established by restricting the

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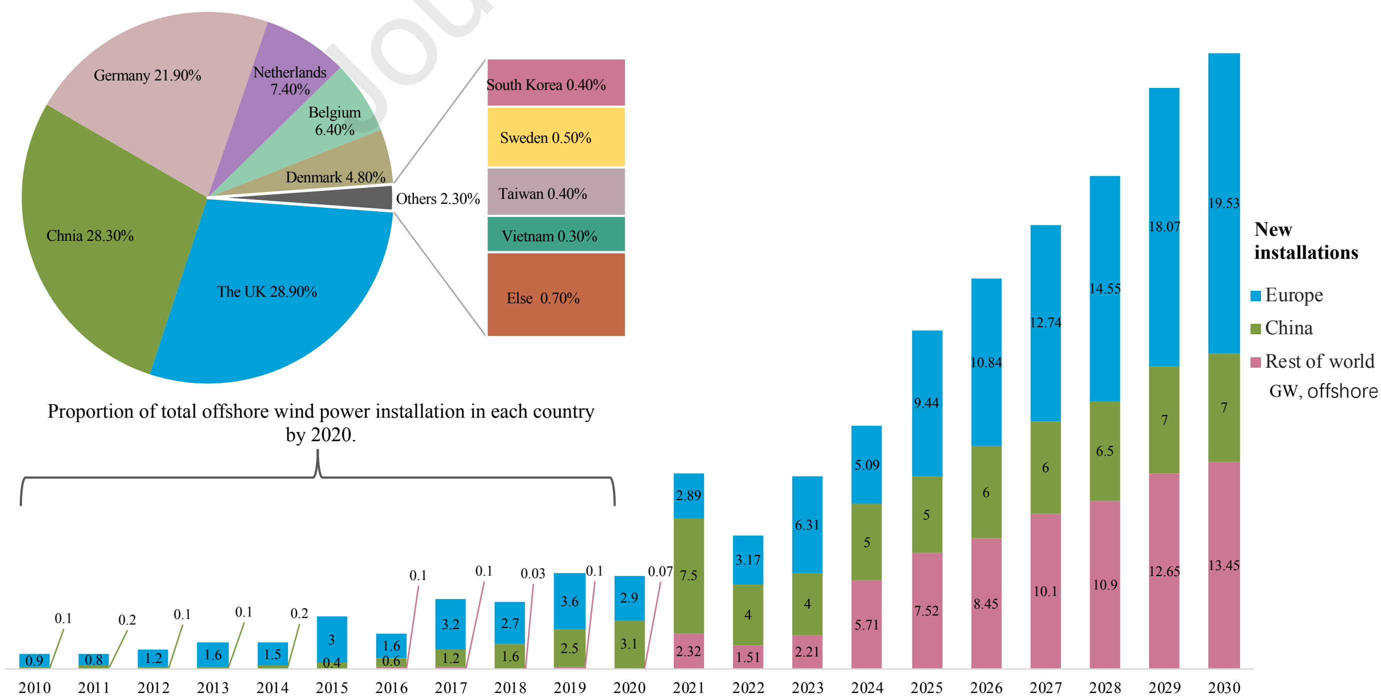

Figure 1: Annual new installation of global offshore wind over the past decade and market forecasts to 2030.

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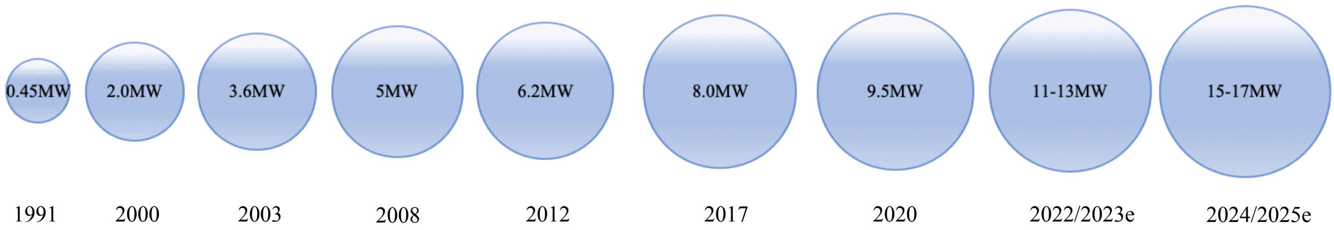

Figure 2: Offshore wind turbine rotor size and turbine rating roadmap.

Nomenclature

Symbols

A	Focal element
m	Mass function
R	coefficient matrix
U	Discernment frame

Greek symbols

Ω	Discernment frame

Abbreviations

ACR	Accumulative contribution rate
AHP	Analytic hierarchy process
ANP	Analytic network process
BPA	Basic probability assignment
COD	Commercial operation date
D-S	Dempster-Shafer
EWM	Entropy-weight method
MADM	Multi-attribute decision-making
OpEx	Operational expenditures
PCA	Principal component analysis
TOPSIS	Technique for order preference by similarity to ideal solution
WASPAS	Weighted aggregates sum product assessment

probability of some events without addressing the exact probability hardly gained. However, D-S evidence theory is based on strong mathematical assumptions, such as exclusivity and completeness constraints, which restricts its ability to express some information [23]. Thus, D-number theory, extension model of D-S evidence theory, was proposed [24]. D-number theory has the characteristics of allowing incomplete information, and allowing decision makers to evaluate less or even no, without considering the constraint that the evaluation information must be complete. Zhou et al. [25] expressed their assessment of emergency management factors with intuitionistic fuzzy numbers, converted them into D numbers and fused the group opinions. It solves the problems of fuzziness and subjectivity in language evaluation. For the imprecision of risk assessment in Failure mode and effects analysis, Bian et al. [26] proposed a risk priority model based on D numbers and TOPSIS method. The assessment provided by experts is expressed by D number which effectively expresses the uncertain information. TOPSIS was used to sort the failure modes of turbine rotor blades of an aircraft.

In the present work, we construct a new decision-making system for selecting offshore wind turbine selection. In particular, we develop D numbers to address the uncertainty caused by fuzziness in language evaluation and subjectivity in expert evaluation. Before this procedure, based on historical experience and expert advice, we consider five main attribute indexes including technology, matching with wind resources, economy, historical performance of wind turbine and after-sales service of manufacturer. Selection decision for offshore wind turbine is related to various secondary factors, whereas the proportion of each factor is different and there may be a correlation between factors. Thus, we apply PCA to reduce the index dimension and determine weights of the selected indexes so as to reduce the computational complexity and reduce the subjectivity of experts in selecting influencing factors [21]. Furthermore, TOPSIS, as a MADM method, is used to rank the preferences of wind turbine alternatives with respect to the evaluation indexes in final procedure.

The rest of this article is organized as follows. Section 2 presents preliminaries covering PCA and D numbers. Section 3 expounds decision-making system for selecting offshore wind turbine. Section 4 performs case verification. Section 5 summarizes the work.

2. Preliminaries

This paper proposes a new decision-making system for selecting offshore wind turbines based on PCA and D numbers. Actually, selection decision for offshore wind turbine is affected by various factors, and the influence proportion of each factor is different. Considering the possible correlation between factors, PCA is applied to dimension reduction of indicators so as to reduce the computational complexity whilst reduce the subjectivity of experts in selecting influencing factors. Meanwhile, PCA is also enforced to determine the weight of each index. On the other hand, experts give different evaluations on these principal factors, but the fuzziness of expert language is a central challenge in selection decision for offshore wind turbine. So, we develop D-number theory to solve the imprecision of expert language scale and the subjectivity of expert evaluation.

This section presents the basic principles of PCA and D numbers. Next section will give the specific decision system for selecting offshore wind turbines.

2.1. Principal component analysis

PCA [27] is often used in the data dimensionality reduction. Its purpose is to map high-dimensional data to low-dimensional space through some linear mapping, whilst retain the characteristics of more original data points with fewer data dimensions. In addition, PCA has also been proved to be a feasible method to identify influencing variables, and an effective way to determine the relationship between various variables [28].

Suppose there are n samples $\{X^1, X^2, \ldots, X^n\}$, each sample $X^i = \{x_{i1}, x_{i2}, \ldots, x_{ip}\}^T$ has p indicators, the sample dataset can be expressed as a matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}. \tag{1}$$

Note that the original variable indexes are $x_1, x_2, \ldots, x_p$, and the transformed new variable indexes are $z_1, z_2, \ldots, z_m (m \leqslant p)$. The new variables can usually be expressed as a linear combination of the original variables:

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_2 + \ldots + l_{1p}x_p, \\ z_2 = l_{21}x_1 + l_{22}x_2 + \ldots + l_{2p}x_p, \\ \cdots \\ z_m = l_{m1}x_1 + l_{m2}x_2 + \ldots + l_{mp}x_p. \end{cases} \tag{2}$$

Where the new variable index z_i is called the principal component_i of the original variable indexes $x_1, x_2, \ldots, x_p$, and l_{ij} is the coefficient of the original index variable x_j $(j = 1, 2, \ldots, p)$ on the principal component z_i $(i = 1, 2, \ldots, m)$.

The specific steps of PCA can be described as follows.

Step 1: Calculate correlation coefficient matrix $R = (r_{jk})_{p\times p}$:

$$r_{jk} = \frac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2}\sqrt{\sum_{i=1}^{n}(x_{ik} - \bar{x}_k)^2}}, \tag{3}$$

where $\bar{x}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}$ is the average value. r_{jk} is the correlation coefficient of the original variables x_j and x_k.

Step 2: Solve characteristic equation $|R - \lambda E| = 0$ (E is the identity matrix) to obtain initial eigenvalues, and arrange them in descending order of size as $\lambda_1 \geqslant \lambda_2 \geqslant \ldots \geqslant \lambda_p \geqslant 0$.

Step 3: Compute the eigenvectors $\vec{e^i}$ corresponding to the eigenvalues λ_i from the following equation:

$$R\vec{e^i} = \lambda\vec{e^i}, \tag{4}$$

where $\vec{e^i}$ should satisfy the condition $\vec{e^i}^T \vec{e^i} = 1$ $(i = 1, 2, \ldots, p)$.

PCA is an analysis method to select as few comprehensive indicators as possible to reflect as much information of the original data as possible. The selection of principal components is implemented according to the accumulative contribution rate (ACR):

$$ACR = (\frac{\sum_{j=1}^{m}\lambda_j}{\sum_{k=1}^{p}\lambda_k}) \times 100\%. \tag{5}$$

Generally, m $(m \leqslant p)$, corresponding to $ACR \geqslant 80\%$, is the recognized number of principal components [29].

2.2. D numbers

As a mathematical method to deal with uncertainty, D-S evidence theory [30] is based on a finite nonempty set $\Omega = \{H_1, H_2, \ldots, H_n\}$ also called discernment frame in which the n elements are mutually exhaustive and exclusive. The basic probability assignment (BPA) is defined by:

$$m : 2^\Omega \rightarrow [0, 1], \tag{6}$$

satisfying the following condition:

$$m(\emptyset) = 0, \quad \sum_{A\subseteq\Omega} m(A) = 1. \tag{7}$$

If $m(A) > 0$, A is referred to focal element. The mass $m(A)$ is interpreted as the degree to which the evidence supports proposition A.

As an extension of D-S evidence theory, D-number theory is a new tool for uncertain information processing. It absorbs the advantages of D-S evidence theory, and overcomes some limitations and shortcomings of D-S evidence theory, as well as provides a more flexible approach to expressing and processing information. D-number theory is introduced as follows [31].

A relation between a finite nonempty set U and a mapping D is defined as follows:

$$D : U \rightarrow [0, 1], \tag{8}$$

which satisfies

$$D(\emptyset) = 0, \quad \sum_{A\subseteq U} D(B) \leqslant 1, \tag{9}$$

where $\emptyset$ is an empty set and B is any subset of U.

Compared with D-S evidence theory, the elements in the set U of D numbers do not require mutual exclusivity and allow the existence of cross phenomena. For example, it is difficult to find a clear boundary between the elements when using the linguistic assessment set $U = \{very\,poor(VP), poor(P), average(A), good(G), very\,good(VG)\}$ to evaluate the wind turbine. For clarity, Figure 3 shows the frameworks of D-S evidence theory and D-number theory [32]. The identification framework of D numbers can be incomplete. When $\sum_{A\subseteq U} D(B) < 1$, the information is incomplete; When $\sum_{A\subseteq U} D(B) = 1$, the information is complete. It indicates that the D numbers are acceptable for incomplete information. Then, decision makers can flexibly express the corresponding evaluation information according to the actual situation without considering whether the information is complete or not.

If $U = \{b_1, b_2, \ldots, b_i, \ldots, b_n\}$, where $b_i \in R$ and $b_i \neq b_j$ for $i \neq j$, D numbers can be expressed as a special form

$$\begin{aligned} D(\{b_1\}) &= v_1 \\ D(\{b_2\}) &= v_2 \\ \vdots \quad & \quad \vdots \\ D(\{b_i\}) &= v_i \\ \vdots \quad & \quad \vdots \\ D(\{b_n\}) &= v_n \end{aligned} \tag{10}$$

and denoted by $D = \{(b_1, v_1), (b_2, v_2), \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}$, where $v_i > 0$ and $\sum_{i=1}^{n} v_i \leqslant 1$. Then, combination rule of D numbers is defined as follows.

Suppose D_1 and D_2 are two D numbers, indicated by

$$D_1 = \{(b_1^1, v_1^1), (b_2^1, v_2^1), \ldots, (b_i^1, v_i^1), \ldots, (b_n^1, v_n^1)\},$$

$$D_2 = \{(b_1^2, v_1^2), (b_2^2, v_2^2), \ldots, (b_i^2, v_i^2), \ldots, (b_m^2, v_m^2)\}.$$

Then combination of D_1 and D_2 denoted by $D = D_1 \oplus D_2$ is defined as

$$D(b) = v, \tag{11}$$

with

$$b = \frac{b_i^1 + b_j^2}{2}, \tag{12}$$

$$v = \frac{v_i^1 + v_j^2}{2} / C. \tag{13}$$

$$C = \begin{cases} \sum_{j=1}^{m}\sum_{i=1}^{n}\left(\frac{v_i^1+v_j^2}{2}\right), & \sum_{i=1}^{n} v_i^1 = 1, \sum_{j=1}^{m} v_j^2 = 1; \\ \sum_{j=1}^{m}\sum_{i=1}^{n}\left(\frac{v_i^1+v_j^2}{2}\right) + \sum_{j=1}^{m}\left(\frac{v_c^1+v_j^2}{2}\right), & \sum_{i=1}^{n} v_i^1 < 1, \sum_{j=1}^{m} v_j^2 = 1; \\ \sum_{j=1}^{m}\sum_{i=1}^{n}\left(\frac{v_i^1+v_j^2}{2}\right) + \sum_{i=1}^{n}\left(\frac{v_i^1+v_c^2}{2}\right), & \sum_{i=1}^{n} v_i^1 = 1, \sum_{j=1}^{m} v_j^2 < 1; \\ \sum_{j=1}^{m}\sum_{i=1}^{n}\left(\frac{v_i^1+v_j^2}{2}\right) + \sum_{j=1}^{m}\left(\frac{v_c^1+v_j^2}{2}\right) + \sum_{i=1}^{n}\left(\frac{v_i^1+v_c^2}{2}\right) + \frac{v_c^1+v_c^2}{2}, & \\ \sum_{i=1}^{n} v_i^1 < 1, \sum_{j=1}^{m} v_j^2 < 1. & \end{cases} \tag{14}$$

where $v_c^1 = 1 - \sum_{i=1}^{n} v_i^1$ and $v_c^2 = 1 - \sum_{j=1}^{m} v_j^2$.

Meanwhile, the overall evaluation of D numbers is defined as:

$$I(D) = \sum_{i=1}^{n} b_i v_i. \tag{15}$$

3. Proposed decision model

The new decision-making system for selecting offshore wind turbines consists of four stages: decision-making modeling, expert assessment, fusion of expert advice, selection result ranking. The specific steps are as shown in Figure 4.

3.1. Establishment of decision-making model

The comprehensive evaluation of offshore wind turbine selection will inevitably involve many aspects of evaluation indicators. Based on the historical experience and expert advice, we determine five main indicators, namely, technology, matching with the wind resources, economy, historical performance of wind turbine and after-sales service of manufacturer. Meanwhile, there are many secondary indicators under each main indicator through further subdividing the influencing factors. Considering the possible correlation between secondary factors, we apply PCA to dimension reduction of indicators, yielding the final twelve secondary indicators that can evaluate wind turbine. Table 1 describes and analyzes the five major indicators and the twelve secondary indicators.

After determining the influencing factors of wind turbine selection, each evaluation index should be given a certain weight embodying its affecting extent. Figure 5 shows the hierarchical decision model. In the model, the relative weights of all indicators were determined by PCA to avoid the influence of subjective opinions of specialists. Meanwhile, we adopt range method to standardize the data first to avoid negative values in

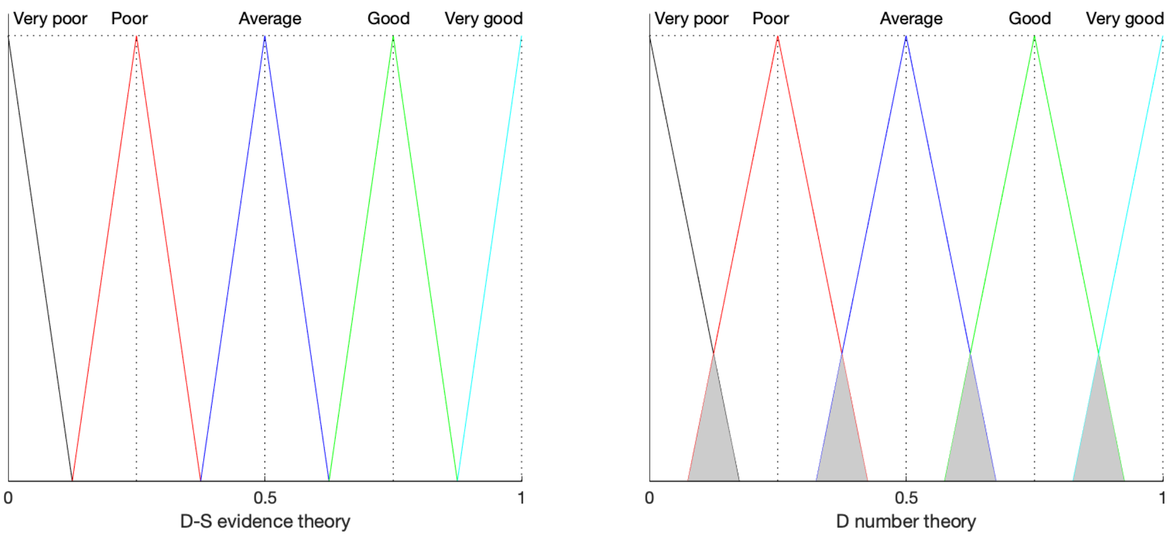

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Figure 3: The framework of D-S evidence theory and D-number theory.

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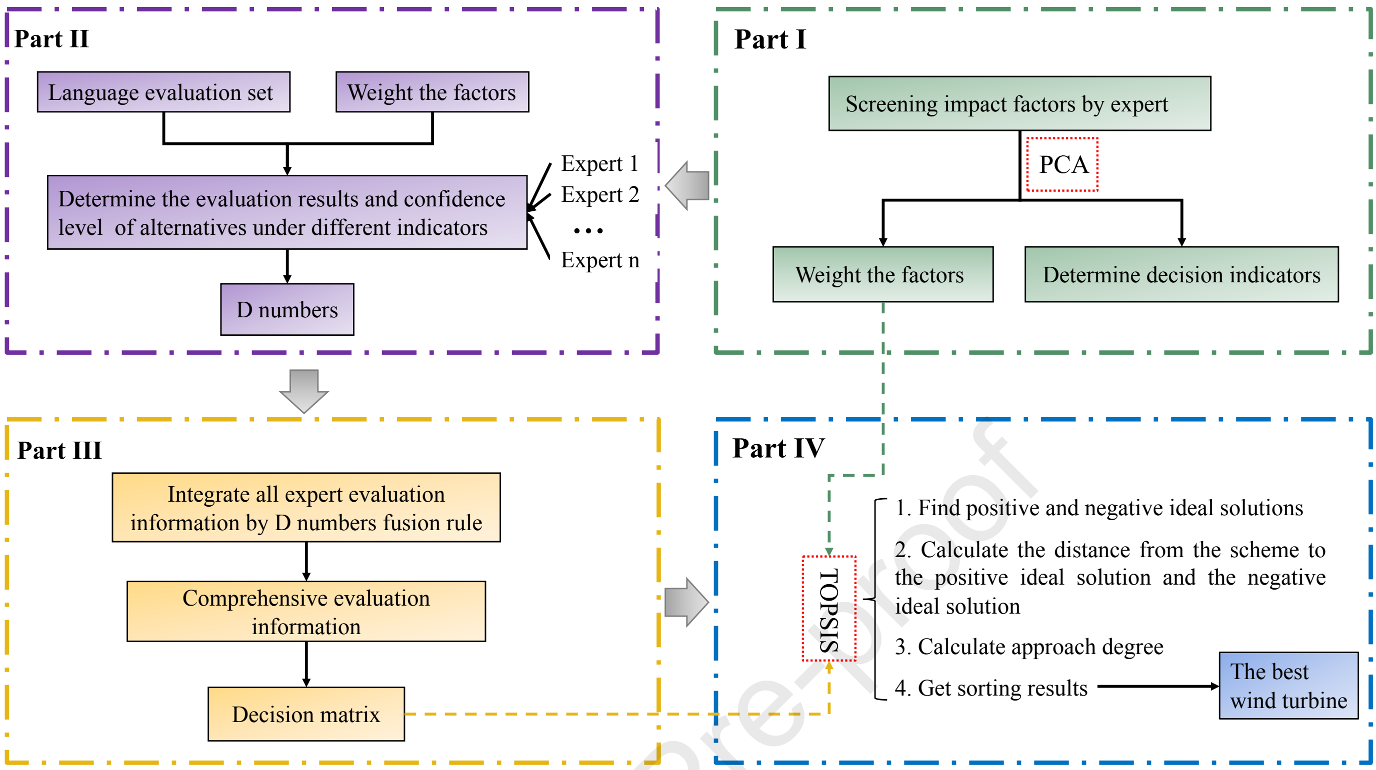

Figure 4: Flow chart of the proposed method.

Table 1: Detailed description of offshore wind turbine indicators.

Sub-criteria	Explanation
Gearbox and generator [12]	The main function of the gearbox is to increase the low speed of the impeller to the high speed of the generator. The main function of generator is to convert the mechanical energy of the impeller into electrical energy.
Professional safety design of wind turbine [33]	Offshore wind turbines face the challenges of harsh natural environment such as lightning, typhoon and salt spray. Professional safety design is very important for the efficient operation of power system.
Swept area [13]	The larger the sweeping area is, the stronger the wind capturing ability is.
Rated wind speed [12]	Under the same wind resource conditions, the lower the rated wind speed, the more wind energy absorbed by offshore wind turbines, and the higher the utilization rate of wind resources.
Wind class (IEC) [34]	It is necessary to select the wind turbine in combination with specific wind resources, with the key veto, that is, the selected wind turbine must meet the minimum requirements of IEC level.
Annual power generation [35]	The annual on grid power of wind turbine is a direct factor to evaluate the overall performance of wind turbine, and it also directly affects the benefit of the whole offshore wind farm.
Kilowatt cost [12]	The cost per kilowatt, an important index to measure the economic performance of wind turbines, can reflect the cost of purchasing wind turbines, which will directly impact the investment cost of wind farm projects.
KWh investment [36]	KWh investment that measures the investment and output ratio of wind farm is one of the most important factors used to evaluate the economic benefits of the whole offshore wind power project.
Sales performance [13]	It refers to the historical sales performance of operators.
Operating performance [12]	It refers to the historical performance of operators.
aintainability [13]	Reasonable evaluation for the maintainability of different wind turbine manufacturers contributes to more reasonable selection of wind turbines and avoids investment risk of offshore wind farms.
Warranty [12]	Under warranty, manufacturer shall provide corresponding technical services and guarantee items.

the final settlement results. Suppose that the standardized matrix Z is obtained by the following formula:

$$Z_{ij} = \begin{cases} \frac{x_j^i - min(x_j^i)}{max(x_j^i) - min(x_j^i)}, & j \in I; \\ \frac{max(x_j^i) - x_j^i}{max(x_j^i) - min(x_j^i)}, & j \in J. \end{cases} \tag{16}$$

I and J are associated with benefit and cost criteria, respectively.

Calculate the eigenvalues λ and eigenvectors $\vec{e}$ of the standardized matrix Z by using the PCA mentioned in section 2.1, the steps to calculate the weight are as follows:

Step 1: Determine the coefficients of original indexes in the linear combination of different components:

$$l_{ij} = \frac{e_{ij}}{\sqrt{\lambda_i}} \quad (i = 1, 2, \ldots, m; j = 1, 2, \ldots, p), \tag{17}$$

where e_{ij} is the load of principal component_i on the original index variable x_j.

Step 2: Calculate the contribution rate of each principal component:

$$u_i = \frac{\lambda_i}{\sum_{k=1}^{m} \lambda_k}. \tag{18}$$

Step 3: Obtain the coefficients of original indexes by the comprehensive model:

$$d_j = \sum_{i=1}^{m} u_i l_{ij}. \tag{19}$$

Step 4: Normalize the index weights:

$$w_j = \frac{d_j}{\sum_{k=1}^{p} d_k}. \tag{20}$$

3.2. Expert assessment

Often, due to the complexity and uncertainty of objective things and the fuzziness of human thinking, decision-making information could not be expressed by accurate numerical values, but is more suitable to be described by more convenient and intuitive language variables. In practice, experts may adopt a seven-point system [37] or five grades [38] to evaluate each influencing factor of the alternative. In order to more accurately express the uncertainty and fuzziness of decision information, we adopt the fuzzy language set $U = \{very\, poor(VP), poor(P), average(A), good(G), very\, good(VG)\}$ to evaluate each indicator of wind turbine selection, and convert the evaluation level into numerical values. Table 2 is the evaluation form of language quantitative information. Using the language quantitative evaluation criteria of wind turbine selection established in Table 2, the performance of different wind turbine alternatives is fuzzed. For example, "VG" indicating that experts believe that an indicator of the alternative performs well, is mapped to 1. "VP" representing that the alternative performs badly in some aspect, has the mapping relation with 0. The five elements in the linguistic terms can be regarded as the recognition framework in D numbers [18, 30].

However, the fuzziness and incompleteness induced by evaluation are inevitable. For quantifying the uncertain information, we use the value in [0,1] to express the confidence level of expert evaluation [39]. Table 3 shows the evaluation results and confidence levels related to alternatives provided by experts according to different standards. Then, we can express the evaluation of experts in the form of D numbers, where the evaluation

Table 2: Language quantitative information evaluation form.

Assessment grade	Description	Index
Very poor (VP)	Almost no recognition to the performance	0
Poor (P)	Low evaluation to the performance	0.25
Average (A)	The level of the performance is medium	0.5
Good (G)	Good evaluation to the performance	0.75
Very good (VG)	Almost fully recognized the performance	1

result of experts is equivalent to a focus element, and the confidence level is the corresponding belief. For instance, experts give a "G" assessment for the performance of one aspect of the alternative and are full of confidence in their own judgment. Then, the D numbers should be $\{(G, 1)\}$. Whereas, if an expert gives an assessment like "V", and he has only some confidence in his own judgment, then D numbers is expressed as $\{(V, 0.4)\}$, reflecting the uncertainty of information.

Table 3: Scale of the confidence level.

Judge confidence level	Scale
Fully confidence	1
Almost confidence	0.8
Properly confidence	0.6
Some confidence	0.4
Almost not confidence	0.2
Completely not confidence	0
Intermediate values between two adjacent levels	0.9,0.7,0.5,0.3,0.1

3.3. Fusion of expert advice

Expert E_k evaluates the alternative A_i under the indicator C_j, resulting in the result $D_{ij}^k = \{(b_{ij}^k, v_{ij}^k)\}$. Then, evaluation information matrix from all experts for A_i can be written as:

$$W_i = \begin{array}{c} \\ E_1 \\ E_2 \\ \vdots \\ E_p \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} (b_{i1}^1, v_{i1}^1) & (b_{i2}^1, v_{i2}^1) & \cdots & (b_{in}^1, v_{in}^1) \\ (b_{i1}^2, v_{i1}^2) & (b_{i2}^2, v_{i2}^2) & \cdots & (b_{in}^2, v_{in}2) \\ \vdots & \vdots & \ddots & \vdots \\ (b_{i1}^k, v_{i1}^k) & (b_{i2}^k, v_{i2}^k) & \cdots & (b_{in}^k, v_{in}^k) \end{bmatrix} \end{array}. \tag{21}$$

The information of all experts is fused based on the combination rule of D number in the formula (15). $D_{ij} = D_{ij}^1 \oplus D_{ij}^2 \oplus \ldots \oplus D_{ij}^p$ denotes the evaluation information after fusing the advice of all experts for the alternative A_i under the indicator C_j. In order to make decision, we need the comprehensive assessment of D numbers, namely, $I(D_{ij})$. The assessment information of A_i after integrating expert opinions can be expressed by:

$$p_i = [I(D_{ij})_{j=1,2,\ldots,n}. \tag{22}$$

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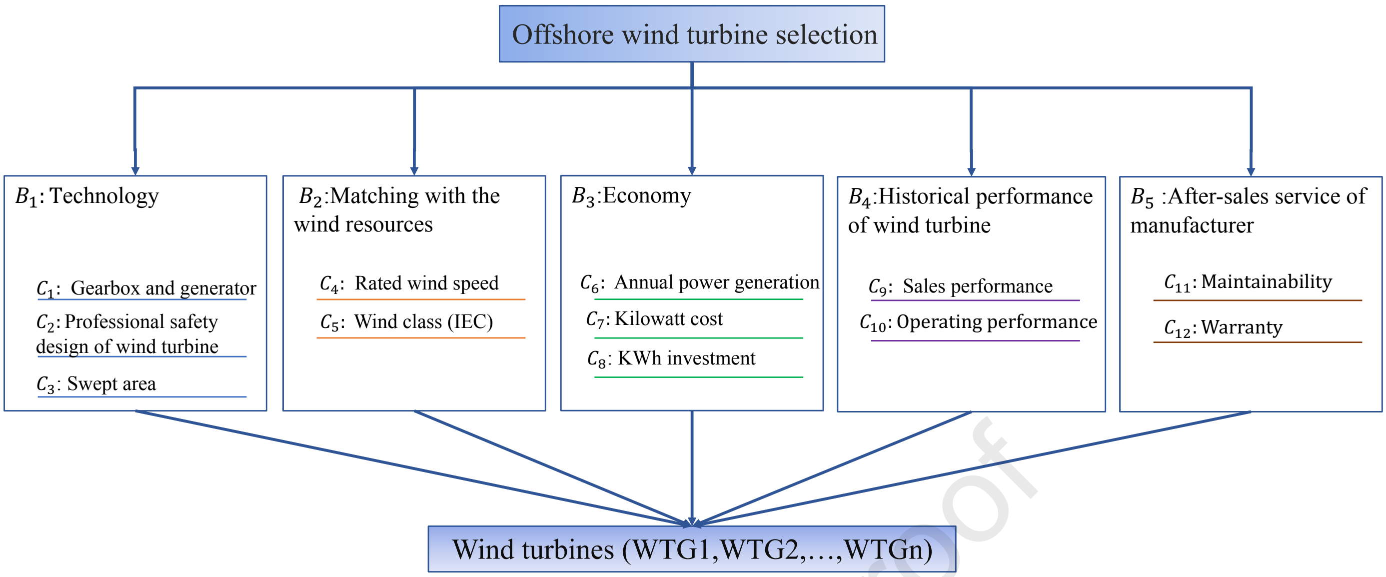

Figure 5: The hierarchical decision model for offshore wind turbine selection.

3.4. Selection result ranking

Given the alternatives A_i $(i = 1, 2, \ldots, m)$, the corresponding evaluation results can be regarded as a decision matrix $P = (p_1, p_2, \ldots, p_n)^T$:

$$P = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} I(D_{11}) & I(D_{12}) & \cdots & I(D_{1n}) \\ I(D_{21}) & I(D_{22}) & \cdots & I(D_{2n})) \\ \vdots & \vdots & \ddots & \vdots \\ I(D_{m1}) & I(D_{m2}) & \cdots & I(D_{mn}) \end{bmatrix} \end{array}. \tag{23}$$

The final ranking result of the scheme can be obtained through applying TOPSIS method. The principle is that the smaller the distance between each scheme and the ideal scheme, the farther the distance to the negative ideal scheme, and the better the alternative scheme. The specific steps are as follows [40].

Firstly, normalize all data. This work adopts vector normalization method:

$$V_{ij} = \frac{p_{ij}}{\sqrt{\sum_{j=1}^{n}(p_{ij})^2}}. \tag{24}$$

Secondly, construct positive and negative ideal solutions. $V^+ = (V_1^+, V_2^+, \ldots, V_m^+)$ denotes positive ideal points, and $V^- = (V_1^-, V_2^-, \ldots, V_m^-)$ denotes negative ideal points, where V_i^+ is the optimal one among all the alternatives for the attribute value_i, and V_i^- is the worst one, which can be expressed by

$$V_i^+ = max_j(V_{ij}), V_i^- = min_j(V_{ij}), \quad i \in I. \tag{25}$$

$$V_i^+ = min_j(V_{ij}), V_i^- = max_j(V_{ij}), \quad i \in J. \tag{26}$$

I and J are associated with benefit and cost criteria, respectively.

Based on the weights $W = (w_1, w_2, \ldots, w_n)^T$ obtained by PCA method, the positive and negative distances between decision scheme and ideal solution are given as follows:

$$D_i^{\pm} = \sqrt{\sum_{j=1}^{m}(\varphi_j(V_j^{\pm}V_{ij}))^2}. \tag{27}$$

Closeness is calculated by:

$$D_i = \frac{D_i^-}{D_i^+ + D_i^-}. \tag{28}$$

The closer D is to 1, the closer the decision object_i is to the optimal level. At last, the optimal wind turbine alternative can be attained by sorting the closeness values in descending order.

4. Case study

4.1. Case description

The offshore wind farm project is located in the East China Sea. The planned total installed capacity is 200MW, including two stages: planned installed capacity of 100MW at the northern and southern sites, respectively. This paper takes the phase I demonstration project of offshore wind power as the object to analyze the selection of wind turbines. According to the data measured by the 70m high wind tower and above, the annual average wind speed and power density are more than 7.4m/s and 400 W/m^2, and the comprehensive wind shear index is about 0.09 with small turbulence intensity. It can be seen from Figures 6 and 7 that the annual main wind direction of the site is stable, mainly concentrated in NE~ENE, with a frequency of about 24.8%, followed by S~SSW, with a frequency of about 20.2%. According to the calculation of the maximum wind speed and maximum wind speed once in 50 years based

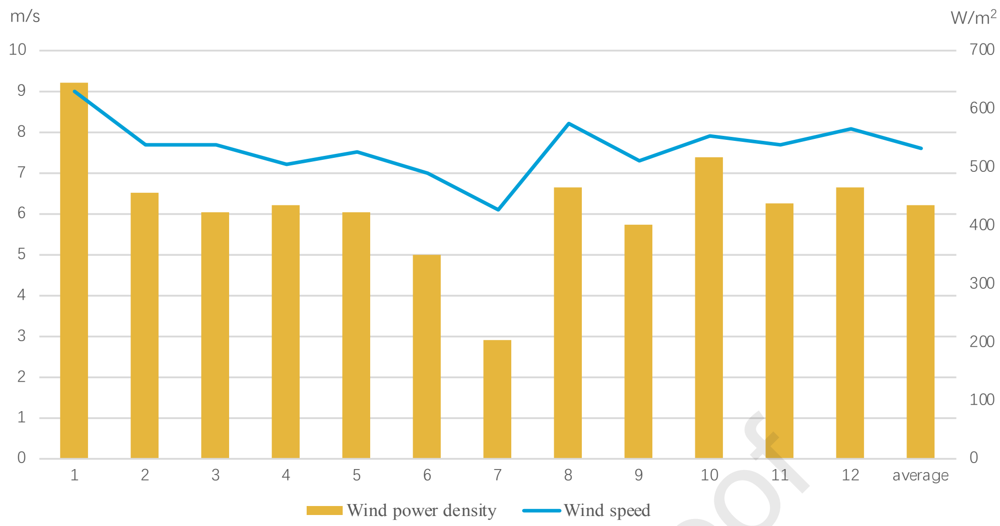

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Figure 6: Average wind speed and average wind power density at 100m.

on gumbel type I distribution function, it is recommended to select wind turbines of IEC IIC~ IC class and above with hub height greater than 80 *m*.

4.2. Preliminary selection

In order to meet the requirements of wind farm development enterprises and reduce the complexity of type selection calculation, this section determines the more suitable offshore wind turbine through preliminary screening. Preliminary screening of offshore wind turbines shall be implemented according to the following conditions:

(1) Rated power of offshore wind turbine shall not be less than 3MW.
(2) Offshore wind turbine must conform to safety level of IEC IIC~IC and above.
(3) Offshore wind turbine possesses mature technology and good operating performance.
(4) All wind turbine manufacturers should be consulted about the possibility of participating in the project.
(5) Manufacturer of wind turbine possesses comprehensive strength involving enterprise scale, market share, supply capacity and plant location etc.

After comprehensively considering the above preliminary selection conditions and the wind resources of the offshore wind farm, we determine nine offshore wind turbines for further detailed selection, marked as WTG1~WTG9 respectively.

4.3. Detailed selection

4.3.1. Determining indicators and weights

PCA is employed to reduce the secondary indexes in the two main categories of technology and economy which involve more indicators. Firstly, four economic indicators including annual power generation, capacity coefficient, kilowatt cost, KWh investment from nine alternatives are standardized by range method, as shown in Table 4. Then, Table 5 shows their correlation coefficient matrix. We can observe that there is a high positive correlation between annual power generation and capacity coefficient. The results of PCA are given in Table 6. The eigenvalues of two principal components are greater than 1, and their cumulative contribution rate is 98.73%, which indicates that these two principal components can basically reflect the main influencing factors of wind turbine in economy. Table 7 shows the composition matrix of the first two principal components, in which the component load represents the correlation between the principal component and the original variable, and the greater the absolute value of the load, the stronger the correlation. Therefore, the first principal component is composed of annual power generation, capacity coefficient and KWh investment. The main feature of the second principal component is kilowatt cost. Considering the high correlation between annual power generation and capacity coefficient, one of them can be selected as the influencing factor. Hence, in our case, the annual power generation with the maximum load is determined as the most important variable. Since the contribution rate of kilowatt cost in the first principal component is low, but its contribution rate is the highest in the second principal component. Thus, the annual power generation, KWh investment and kilowatt cost are determined as the main influencing factors of economy.

Similarly, PCA is employed to extract the principal features and reduce the dimension of five secondary indexes in the technology. Generator and gearbox, Professional safety design of wind turbine belong to qualitative evaluation indicators. The scores graded by experts on a scale of one to nine constitute the sample data. The results of PCA are shown in the appendix. There is a highly positive correlation among rated power, swept area and rotor diameter, which indicates their influence characteristics are similar. Meanwhile, the first principal component explains 79.72% of the total variation. The sweep area is the most important indicator, and the rated power and rotor diam-

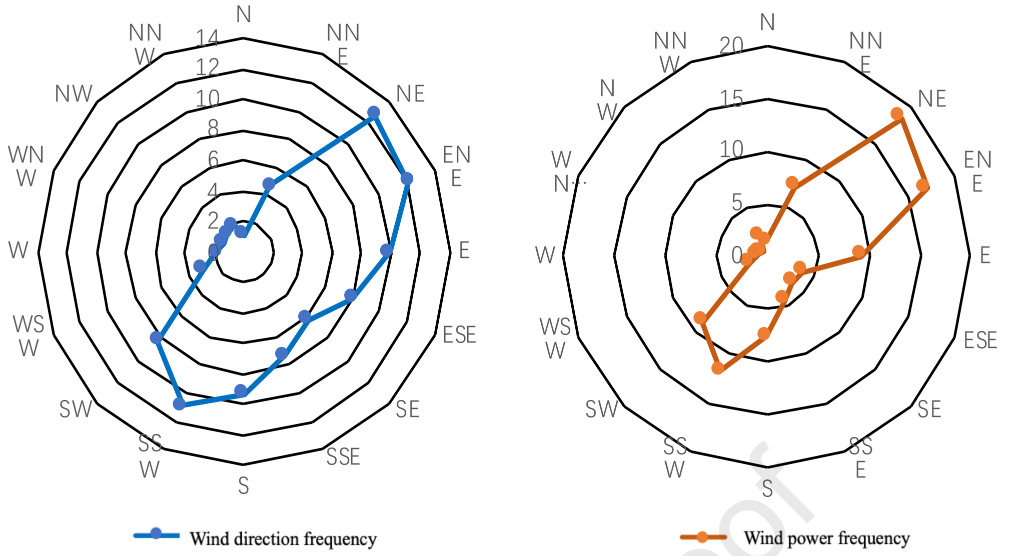

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Figure 7: Rose chart of wind direction and wind power at 100m.

Table 4: The data and standardization results of each influencing factor of wind turbine economy.

	Annual power generation		Capacity coefficient		Kilowatt cost		KWh investment	
	Original	Normalized	Original	Normalized	Original	Normalized	Original	Normalized
WTG1	22298	0.1475	0.25	0.1563	4380	1	6.38	0.6231
WTG2	22908	0.2185	0.256	0.2188	4560	0.9313	6.33	0.6482
WTG3	21031	0.01	0.235	0.01	5800	0.458	7.18	0.2211
WTG4	25302	0.4973	0.287	0.5417	4800	0.8397	5.86	0.8844
WTG5	24500	0.4039	0.28	0.4688	5400	0.6107	5.99	0.8191
WTG6	21445	0.0482	0.245	0.1042	6500	0.1908	7.62	0.01
WTG7	23168	0.2488	0.264	0.3021	7000	0.01	7.27	0.1759
WTG8	29620	1	0.331	1	5298	0.6496	5.63	1
WTG9	27043	0.7	0.306	0.7396	6500	0.1908	6.06	0.7839

Table 5: Correlation coefficient matrix between the variables of wind turbine economy.

	Annual power generation	Capacity coefficient	Kilowatt cost	KWh investment
Annual power generation	1	0.997	0.042	0.788
Capacity coefficient	0.997	1	-0.001	0.773
Kilowatt cost	0.042	-0.001	1	0.574
KWh investment	0.788	0.773	0.574	1

Table 6: Eigenvalue and cumulative contribution rate of each component variance on wind turbine economy.

Component	Initial eigenvalues	Contribution rate (%)	Cumulative contribution rate (%)
1	2.776	69.399	69.399
2	1.173	29.331	98.729
3	0.049	1.223	99.952
4	0.002	0.048	100

Table 7: Load of the first two principal components on the original index.

Component	Annual power generation	Capacity coefficient	Kilowatt cost	KWh investment
1	0.952	0.942	0.325	0.937
2	-0.293	-0.332	0.941	0.305

Table 8: Index weight in comprehensive model.

Primary indicators	Secondary indicators	Coefficient	Index weight	Ranking	Weight
Technology	Gearbox and generator	0.277	0.1147	2	0.2956
	Professional safety design of wind turbine	0.2534	0.1049	3	
	Swept area	0.1833	0.0759	9	
Matching with the wind resources	Rated wind speed	0.1512	0.0626	10	0.0934
	Wind class (IEC)	0.0744	0.0308	11	
Economy	Annual power generation	0.2257	0.0935	7	0.1915
	Kilowatt cost	0.0204	0.0084	12	
	KWh investment	0.2163	0.0896	8	
Historical performance of wind turbine	Sales performance	0.2459	0.1018	5	0.1969
	Operating performance	0.2297	0.0951	6	
After-sales service of manufacturer	Maintainability	0.284	0.1176	1	0.2226
	Warranty	0.2534	0.1049	4	

eter are not considered. Therefore, swept area, generator and gearbox, intelligent monitoring technology and anti-harsh environment technology are identified as the main factors affecting the advanced technology of offshore wind turbine.

In summary, based on PCA, we reduced the four economic indicators to three indicators, and the five technology indicators to three indicators. Dimension reduction is not required for other three categories due to their few secondary indicators. So far, five main indicators and 12 secondary indicators have been determined as the basis for offshore wind turbine selection. After normalizing the secondary indicators with formula (16), we calculate the corresponding weights and then rank these indicators based on the methodology in Section 2.1, which results are given in Table 8. We can see that the top five indicators with the largest influencing factors are maintainability, generator and gearbox, professional safety design of wind turbine, warranty and sales performance.

4.3.2. *Constructing D numbers*

Experts in the field evaluate the performance of alternatives through the language set defined in Table 2. The confidence of expert judgment is expressed by the confidence score in Table 3. Experts could determine the evaluation results and confidence level of each alternative according to its performance under different standards. Taking alternative WTG1 as an example, Table 9 shows the evaluation results of three experts on WTG1, where $\{P, A\}$ indicates that the evaluation level is between "bad" and "average", and $\{G\} : \{VG\} = 4 : 1$ represents the probability of "good" is four times that of "very good".

In the previous step, we have obtained the evaluation level and judgment confidence of WTG1. Therefore, we can construct D numbers to express the uncertain information generated in the evaluation process. Considering that D-number theory cannot directly handle language information, we convert the evaluation level into numerical form. Here are two examples to describe the transformation process.

Example 1. For WTG1, the assessment of expert E_2 is $\{P, A\}$ under standard C_1, with confidence of 0.4, that is, $D(\{P, A\}) = 0.4$. We need to quantify the evaluation level $\{P, A\}$. According to the proportional distribution of the corresponding value of each element in the set, the evaluation level can be given by $12 \times 0.25 + 12 \times 0.5 = 0.375$, resulting in the quantized D

Table 9: Evaluation results and confidence of WTG1 from experts.

Criteria	Experts	Assessment grade	Confidence
C_1	E_1	$\{A\}$	0.5
	E_2	$\{P, A\}^*$	0.4
	E_3	$\{A\}$	0.5
C_2	E_1	$\{G, VG\}$	0.2
	E_2	$\{G\}$	0.4
	E_3	$\{G\} : \{VG\} = 4 : 1^*$	0.5
C_3	E_1	$\{P\}$	0.8
	E_2	$\{P, A\}$	0.4
	E_3	$\{A\}$	0.5
C_4	E_1	$\{A\}$	0.4
	E_2	$\{A\}$	0.6
	E_3	$\{A, G\}$	0.4
C_5	E_1	$\{G\}$	0.4
	E_2	$\{G\}$	0.4
	E_3	$\{A, G\}$	0.5
C_6	E_1	$\{P\}$	0.6
	E_2	$\{P, A\}$	0.4
	E_3	$\{P\}$	0.5
C_7	E_1	$\{G\}$	0.4
	E_2	$\{G\} : \{VG\} = 4 : 1$	0.5
	E_3	$\{G, VG\}$	0.4
C_8	E_1	$\{G\}$	0.4
	E_2	$\{A, G\}$	0.5
	E_3	$\{A, G\}$	0.3
C_9	E_1	$\{A\}$	0.3
	E_2	$\{A\}$	0.5
	E_3	$\{G\}$	0.2
C_{10}	E_1	$\{A\}$	0.4
	E_2	$\{P, A\}$	0.5
	E_3	$\{P, A\}$	0.6
C_{11}	E_1	$\{A\}$	0.3
	E_2	$\{A\}$	0.5
	E_3	$\{A\}$	0.5
C_{12}	E_1	$\{P\}$	0.4
	E_2	$\{P, A\}$	0.6
	E_3	$\{P, A\}$	0.4

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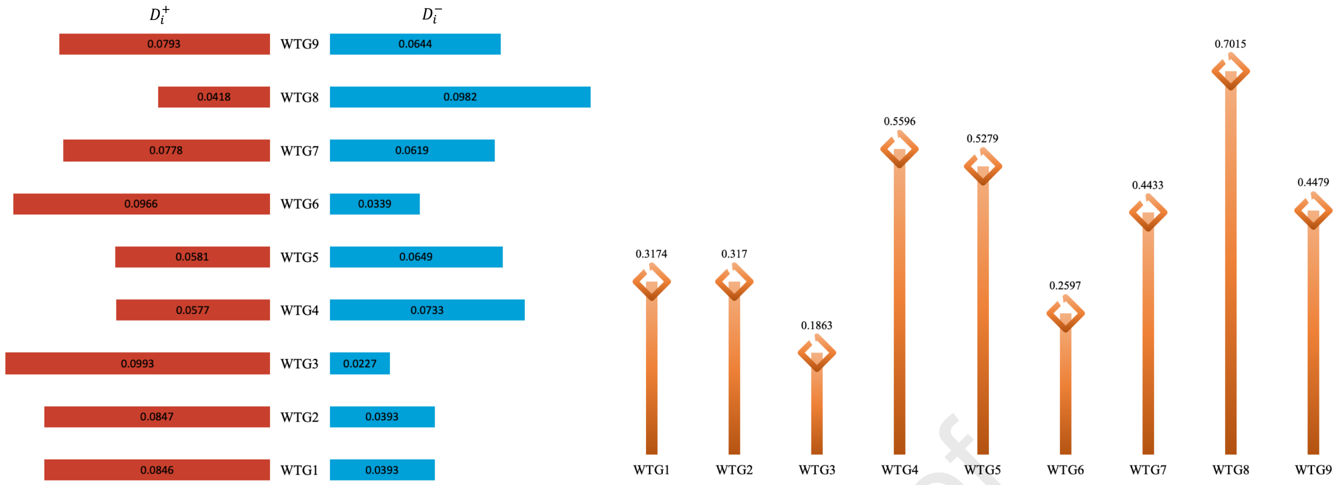

(a): The value of D_i^+ and D_i^-.

(b): Weights and ranking results of alternatives.

Figure 8: Results of the proposed method and alternatives ranking.

numbers $D = \{(0.375, 0.4)\}$.

Example 2. For WTG1, the assessment of expert E_3 is $\{G\} : \{VG\} = 4 : 1$ under standard C_2, with confidence of 0.5. By quantifying $\{P, A\}$ as $12 \times 0.25 + 12 \times 0.5 = 0.375$, the quantized D numbers is $D = \{(0.375, 0.4)\}$.

According to the above method, the evaluation information of all alternatives can be expressed in D numbers. and the results are shown in Table 10.

Finally, the evaluation results of different experts are fused based on D-number rule to reduce the subjectivity of expert evaluation. The final evaluation results can be achieved based on formula (22), as shown in Table 11.

4.3.3. Selection results

Based on the final evaluation results of nine alternative offshore wind turbines and the standard weights obtained by PCA, we utilize TOPSIS method to evaluate the performance of the alternatives whilst select the optimal one. Figure 8 illustrates the positive and negative distances between decision scheme and ideal solution, and the comprehensive scores for nine alternatives base on TOPSIS. It can be seen from Figure 8(a) that WTG8 has the characteristic of being closest to the positive ideal point and farthest from the negative ideal point. The comprehensive scores of the alternatives are shown in Figure 8 (b). The top three offshore wind turbines are WTG8, WTG4 and WTG5, where WTG8 achieves the highest evaluation score, ranking first in the alternatives. Therefore, WTG8 is identified as the best selection among the nine alternatives offshore wind turbines.

In practice, seventeen WTG8 with hub height of $110m$ and total installed capacity of $102MW$ won the bid during the first bidding of the project, which verifies the effectiveness of our proposed selection method.

5. Conclution

Wind turbine selection plays an important role in the planning stage of offshore wind farm project. During selecting offshore wind turbine, an appropriate index evaluation system should be established, where the indexes and their weights should be determined. It is necessary to solve the evaluation information of multiple experts on the offshore wind turbine, which tends to be different, fuzzy and uncertain. This work presents a novel decision-making model for selection offshore wind turbine involving D numbers and PCA to tackle the above problems.

The selection process is divided into preliminary selection and detailed selection. In the preliminary selection, the factors such as rated power and safety level are mainly considered as the screening conditions, and nine alternatives are identified for further selection. In the detailed selection, in view of the limitations and shortcomings of AHP in weight distribution. PCA is employed to reduce the dimension of indicators and execute weighting, so as to reduce the subjectivity of decision variable selection. Furthermore, we build language set for experts to evaluate alternatives. Then we apply D numbers to quantify the evaluation results including assessment level and probability, conforming to human expression for uncertainty information. On the one hand, the use of D numbers can make the decision-maker make corresponding evaluation more realistic. On the other hand, the relevant characteristics of D numbers are conducive to the rapid fusion of information and simplify the decision-making process. Finally, the comprehensive evaluation information of the alternatives is sorted by TOPSIS method, which can ensure the effective and reasonable sequencing of wind turbines.

In summary, this decision-making model fully utilizes the advantages of MADM and D numbers, hierarchizes and organizes complex problems, and has flexibility in information expression. Notably, this model also overcomes the shortcomings of

Table 10: D numbers of nine alternatives under twelve standards.

		WTG1	WTG2	WTG3	WTG4	WTG5	WTG6	WTG7	WTG8	WTG9
B_1	E_1	{(0.5, 0.5)}	{(0.5, 0.8)}	{(0.5, 0.5)}	{(0.625, 0.2)}	{(0.75, 0.6)}	{(0.625, 0.3)}	{(0.75, 0.5)}	{(0.875, 0.6)}	{(0.625, 0.2)}
	E_2	{(0.375, 0.4)}	{(0.5, 0.5)}	{(0.375, 0.4)}	{(0.55, 0.5)}	{(0.7, 0.5)}	{(0.55, 0.5)}	{(0.7, 0.3)}	{(0.75, 0.4)}	{(0.55, 0.3)}
	E_3	{(0.5, 0.5)}	{(0.5, 0.7)}	{(0.5, 0.5)}	{(0.5, 0.2)}	{(0.75, 0.6)}	{(0.5, 0.2)}	{(0.75, 0.4)}	{(1, 0.5)}	{(0.5, 0.2)}
B_2	E_1	{(0.875, 0.2)}	{(0.5, 0.4)}	{(0.5, 0.4)}	{(0.875, 0.2)}	{(0.875, 0.3)}	{(0.5, 0.4)}	{(0.875, 0.3)}	{(0.875, 0.3)}	{(0.75, 0.1)}
	E_2	{(0.75, 0.4)}	{(0.6, 0.7)}	{(0.6, 0.7)}	{(0.75, 0.4)}	{(0.75, 0.3)}	{(0.375, 0.6)}	{(0.75, 0.4)}	{(0.75, 0.5)}	{(0.625, 0.4)}
	E_3	{(0.8, 0.5)}	{(0.375, 0.7)}	{(0.375, 0.7)}	{(0.8, 0.5)}	{(0.8, 0.4)}	{(0.5, 0.4)}	{(0.8, 0.5)}	{(0.8, 0.5)}	{(0.5, 0.5)}
B_3	E_1	{(0.25, 0.8)}	{(0.25, 0.8)}	{(0.25, 0.8)}	{(0.375, 0.6)}	{(0.625, 0.7)}	{(0.625, 0.7)}	{(0.625, 0.5)}	{(0.75, 0.6)}	{(0.375, 0.3)}
	E_2	{(0.375, 0.4)}	{(0.375, 0.4)}	{(0.375, 0.4)}	{(0.5, 0.8)}	{(0.625, 0.7)}	{(0.625, 0.7)}	{(0.625, 0.5)}	{(1, 0.5)}	{(0.25, 0.7)}
	E_3	{(0.5, 0.5)}	{(0.5, 0.5)}	{(0.5, 0.5)}	{(0.5, 0.7)}	{(0.75, 0.5)}	{(0.75, 0.5)}	{(0.75, 0.5)}	{(1, 0.6)}	{(0.5, 0.3)}
B_4	E_1	{(0.5, 0.4)}	{(0.5, 0.4)}	{(0.5, 0.2)}	{(0.75, 0.4)}	{(0.75, 0.4)}	{(0.75, 0.4)}	{(0.5, 0.4)}	{(0.75, 0.5)}	{(0.75, 0.4)}
	E_2	{(0.5, 0.6)}	{(0.5, 0.6)}	{(0.5, 0.2)}	{(0.65, 0.3)}	{(0.5, 0.6)}	{(0.65, 0.3)}	{(0.5, 0.2)}	{(0.65, 0.4)}	{(0.5, 0.6)}
	E_3	{(0.625, 0.4)}	{(0.625, 0.4)}	{(0.375, 0.4)}	{(0.625, 0.5)}	{(0.625, 0.4)}	{(0.625, 0.5)}	{(0.625, 0.4)}	{(0.625, 0.5)}	{(0.625, 0.4)}
B_5	E_1	{(0.75, 0.4)}	{(0.5, 0.4)}	{(0.75, 0.7)}	{(0.5, 0.4)}	{(0.75, 0.4)}	{(0.75, 0.4)}	{(0.75, 0.5)}	{(0.5, 0.4)}	{(0.75, 0.4)}
	E_2	{(0.75, 0.4)}	{(0.5, 0.4)}	{(0.8, 0.5)}	{(0.5, 0.4)}	{(0.75, 0.4)}	{(0.75, 0.4)}	{(0.8, 0.5)}	{(0.5, 0.4)}	{(0.75, 0.4)}
	E_3	{(0.625, 0.5)}	{(0.375, 0.5)}	{(0.875, 0.4)}	{(0.625, 0.2)}	{(0.625, 0.5)}	{(0.75, 0.5)}	{(0.875, 0.4)}	{(0.375, 0.5)}	{(0.625, 0.5)}
B_6	E_1	{(0.25, 0.6)}	{(0.25, 0.6)}	{(0.25, 0.6)}	{(0.5, 0.4)}	{(0.5, 0.4)}	{(0.25, 0.6)}	{(0.25, 0.4)}	{(0.75, 0.4)}	{(0.5, 0.4)}
	E_2	{(0.375, 0.4)}	{(0.375, 0.5)}	{(0.375, 0.4)}	{(0.5, 0.4)}	{(0.5, 0.4)}	{(0.375, 0.5)}	{(0.375, 0.5)}	{(0.75, 0.4)}	{(0.5, 0.7)}
	E_3	{(0.25, 0.5)}	{(0.25, 0.5)}	{(0.125, 0.5)}	{(0.625, 0.2)}	{(0.5, 0.5)}	{(0.125, 0.5)}	{(0.25, 0.5)}	{(0.625, 0.5)}	{(0.625, 0.4)}
B_7	E_1	{(0.75, 0.4)}	{(0.75, 0.4)}	{(0.5, 0.3)}	{(0.75, 0.3)}	{(0.5, 0.3)}	{(0.375, 0.3)}	{(0.3, 0.3)}	{(0.625, 0.3)}	{(0.375, 0.4)}
	E_2	{(0.8, 0.5)}	{(0.8, 0.4)}	{(0.5, 0.3)}	{(0.8, 0.3)}	{(0.625, 0.3)}	{(0.25, 0.7)}	{(0.25, 0.4)}	{(0.75, 0.3)}	{(0.25, 0.7)}
	E_3	{(0.875, 0.4)}	{(0.875, 0.4)}	{(0.5, 0.4)}	{(0.875, 0.4)}	{(0.625, 0.2)}	{(0.5, 0.3)}	{(0.25, 0.4)}	{(0.625, 0.4)}	{(0.5, 0.3)}
B_8	E_1	{(0.75, 0.4)}	{(0.75, 0.4)}	{(0.5, 0.5)}	{(0.875, 0.4)}	{(0.875, 0.4)}	{(0.25, 0.7)}	{(0.5, 0.5)}	{(0.875, 0.6)}	{(0.5, 0.5)}
	E_2	{(0.625, 0.5)}	{(0.625, 0.5)}	{(0.375, 0.6)}	{(0.875, 0.2)}	{(0.875, 0.2)}	{(0.125, 0.4)}	{(0.375, 0.4)}	{(0.75, 0.5)}	{(0.5, 0.4)}
	E_3	{(0.625, 0.3)}	{(0.625, 0.3)}	{(0.375, 0.3)}	{(0.875, 0.3)}	{(0.75, 0.3)}	{(0.125, 0.3)}	{(0.375, 0.3)}	{(0.8, 0.5)}	{(0.625, 0.4)}
B_9	E_1	{(0.5, 0.3)}	{(0.5, 0.3)}	{(0.25, 0.4)}	{(0.625, 0.5)}	{(0.625, 0.3)}	{(0.25, 0.4)}	{(0.25, 0.4)}	{(0.625, 0.5)}	{(0.375, 0.3)}
	E_2	{(0.5, 0.5)}	{(0.5, 0.5)}	{(0.375, 0.6)}	{(0.625, 0.6)}	{(0.625, 0.5)}	{(0.375, 0.6)}	{(0.5, 0.2)}	{(0.625, 0.4)}	{(0.25, 0.5)}
	E_3	{(0.75, 0.2)}	{(0.5, 0.5)}	{(0.375, 0.4)}	{(0.75, 0.5)}	{(0.75, 0.4)}	{(0.5, 0.5)}	{(0.5, 0.5)}	{(0.75, 0.5)}	{(0.5, 0.3)}
B_{10}	E_1	{(0.5, 0.4)}	{(0.5, 0.4)}	{(0.25, 0.6)}	{(0.75, 0.3)}	{(0.75, 0.3)}	{(0.25, 0.6)}	{(0.25, 0.6)}	{(0.75, 0.5)}	{(0.625, 0.3)}
	E_2	{(0.375, 0.5)}	{(0.375, 0.5)}	{(0.25, 0.4)}	{(0.8, 0.4)}	{(0.75, 0.5)}	{(0.25, 0.4)}	{(0.375, 0.4)}	{(0.8, 0.5)}	{(0.5, 0.5)}
	E_3	{(0.375, 0.6)}	{(0.375, 0.6)}	{(0.25, 0.5)}	{(0.75, 0.4)}	{(0.625, 0.5)}	{(0.25, 0.5)}	{(0.25, 0.5)}	{(0.875, 0.4)}	{(0.5, 0.6)}
B_{11}	E_1	{(0.5, 0.3)}	{(0.5, 0.3)}	{(0.25, 0.4)}	{(0.625, 0.7)}	{(0.625, 0.3)}	{(0.25, 0.4)}	{(0.25, 0.4)}	{(0.625, 0.5)}	{(0.375, 0.3)}
	E_2	{(0.5, 0.5)}	{(0.5, 0.5)}	{(0.375, 0.6)}	{(0.625, 0.7)}	{(0.5, 0.5)}	{(0.5, 0.5)}	{(0.375, 0.2)}	{(0.625, 0.6)}	{(0.25, 0.5)}
	E_3	{(0.5, 0.5)}	{(0.75, 0.2)}	{(0.375, 0.4)}	{(0.75, 0.5)}	{(0.75, 0.4)}	{(0.5, 0.5)}	{(0.5, 0.3)}	{(0.75, 0.5)}	{(0.5, 0.3)}
B_{12}	E_1	{(0.25, 0.4)}	{(0.25, 0.4)}	{(0.25, 0.4)}	{(0.625, 0.7)}	{(0.5, 0.4)}	{(0.5, 0.3)}	{(0.375, 0.3)}	{(0.625, 0.3)}	{(0.375, 0.3)}
	E_2	{(0.375, 0.6)}	{(0.375, 0.6)}	{(0.375, 0.6)}	{(0.625, 0.7)}	{(0.5, 0.4)}	{(0.625, 0.3)}	{(0.5, 0.4)}	{(0.75, 0.3)}	{(0.5, 0.4)}
	E_3	{(0.375, 0.4)}	{(0.375, 0.4)}	{(0.375, 0.4)}	{(0.75, 0.5)}	{(0.5, 0.5)}	{(0.625, 0.2)}	{(5, 0.2)}	{(0.625, 0.4)}	{(5, 0.2)}

Table 11: The final evaluation results for nine alternatives under twelve standards.

	WTG1	WTG2	WTG3	WTG4	WTG5	WTG6	WTG7	WTG8	WTG9
C_1	0.085	0.1281	0.085	0.051	0.1613	0.0544	0.1106	0.1699	0.0442
C_2	0.131	0.1127	0.1127	0.131	0.1109	0.0762	0.1361	0.1411	0.0928
C_3	0.0813	0.0813	0.0813	0.123	0.1461	0.1461	0.1289	0.2051	0.0559
C_4	0.0914	0.0914	0.0547	0.1118	0.1016	0.1118	0.0773	0.1201	0.1016
C_5	0.1203	0.0766	0.1444	0.0563	0.1203	0.1313	0.1341	0.0766	0.1203
C_6	0.0527	0.0545	0.041	0.0563	0.0875	0.0424	0.051	0.1203	0.0949
C_7	0.1289	0.1238	0.0688	0.1134	0.052	0.0559	0.0377	0.0902	0.0584
C_8	0.0861	0.0861	0.0584	0.0984	0.0914	0.0225	0.0533	0.1562	0.0879
C_9	0.0625	0.0875	0.0559	0.1332	0.1031	0.0762	0.0711	0.1246	0.0508
C_{10}	0.0838	0.0838	0.0469	0.1096	0.1203	0.0469	0.0527	0.1341	0.1063
C_{11}	0.0875	0.0625	0.0559	0.1461	0.0984	0.0793	0.0457	0.1332	0.0508
C_{12}	0.0559	0.0559	0.0559	0.1461	0.0875	0.052	0.2549	0.0902	0.2549

expert evaluation in traditional wind turbine selection methods. The practicability of the proposed method is verified by an actual bid winning project of offshore wind turbine. The proposed decision method can be extended to solve similar problems.

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Appendix A

This appendix contains Tables A1-A3.

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Table A1: Correlation coefficient matrix between the variables of wind turbine technology.

	Rated power	Gearbox and generator	Professional safety design of wind turbine	Swept area	Impeller
Rated power	1	0.358	0.417	0.891	0.893
Gearbox and generator	0.358	1	0.652	0.501	0.504
Professional safety design of wind turbine	0.417	0.652	1	0.704	0.691
Swept area	0.891	0.501	0.704	1	0.997
Impeller	0.893	0.504	0.691	0.997	1

Table A2: Eigenvalue and cumulative contribution rate of each component variance on wind turbine technology.

Component	Initial eigenvalues	Contribution rate (%)	Cumulative contribution rate (%)
1	3.698	73.950	73.950
2	0.880	17.603	91.553
3	0.360	7.201	98.754
4	0.059	1.185	99.939
5	0.003	0.061	100.000

Table A3: Load of the first one principal components on the original index.

Component	Rated power	Gearbox and generator	Professional safety design of wind turbine	Swept area	Impeller
1	0.855	0.668	0.796	0.973	0.971

Highlights

- A new decision-making system for selecting offshore wind turbine selection is established.
- The affecting factors and the corresponding weights are determined by PCA.
- D-number theory transforms fuzzy and linguistic assessment into reliable quantitative form.
- MADM fused with D numbers addresses the uncertainty cause by expert judgment.

Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: