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Research Article

Using the Cloud-Bayesian Network in Environmental Assessment of Offshore Wind-Farm Siting

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Offshore wind energy has become the fastest growing form of renewable energy for the last few years. And the development of offshore wind farms (OWFs) is now characterized by a boom. OWF siting is crucial in the success of wind energy projects. Therefore, this paper aims to introduce intelligent algorithms to improve the siting assessment under conditions of multisource and uncertain information. An optimization macrositing model based on Cloud-Bayesian Network (Cloud-BN) is put forward. We introduce the cloud model and adaptive Gaussian cloud transformation (A-GCT) algorithm to grade indicators and apply BN to achieve nonlinear integration and inference of multi-indicators. Combined with the fuzzy representation of the cloud model and probabilistic reasoning of BN, the proposed model can investigate the most efficient siting areas of OWFs in the North Sea of Europe. The experimental results indicate that the siting accuracy is up to 86.67% with reference to the actual OWF location.

1. Introduction

With the growing energy and environmental problems, wind energy, a clean renewable energy, is preferred by the public due to its great advantages and exploitation potential. At the same time, wind power is developing rapidly, becoming an industry with strong vitality. Because of the unparalleled advantages compared with onshore wind power, offshore wind power has become the developing direction of global wind power [1]. It is no doubt that the site selection for offshore wind farms (OWFs) is vital to the development of offshore wind energy. However, OWF siting can be considered in an early stage at present and a systematic management strategy for OWFs has not yet been established [2].

The site selection for wind farms is a process of finding locations with rich wind energy resources and great economic benefit through evaluation of all kinds of conditions, such as meteorology, geography, society, and economy. According to the different scale of siting areas, it is divided into macrosite selection (the regional scale) and microsite selection (the scale of the farm) [3]. What we study is macrositing in this paper.

At present, scholars have conducted some researches about wind-farm siting problems. Initially, most studies are limited to onshore wind farms. Some scholars summarized all kinds of indicators for wind-farm site selection including wind energy resource conditions, natural geographical conditions and social conditions [4–9], and graded these indicators with equal-interval rating method, k-means clustering method and grey clustering method, which can achieve superficial siting assessment based on statistical analysis of the actual data [10–12].

However, these studies just graded assessment factors and did not use any method or model for multi-indicator fusion and comprehensive evaluation. The later studies aimed at providing a more precise preassessment approach to evaluate the suitability of potential sites. And the classical Analytic Hierarchy Process (AHP) method and multicriteria decision-making (MCDM) method were widely applied based on geographic information system (GIS) [13–16]. Even though these studies could integrate a variety of factors to identify the suitable sites, the entire siting evaluation was carried out subjectively based on opinions of experts, with little objective and quantitative data.

With in-depth research of siting assessment, scholars have gradually applied intelligent algorithms to location problems, in order to discover the suitable site rapidly and accurately. Na R H et al. [17] used a fuzzy comprehensive evaluation method to optimize the wind-farm siting. In this study, the fuzzy mathematics was introduced to deal with the uncertain fuzziness of factors. Liu F et al. [18] used a genetic algorithm (GA) to optimize the wind-farm layout. The authors established multiobjective decision-making equation based on siting factors and power generation benefits. Then, searched for the optimal solution to satisfy the constraints through nondominated ranking GA based on fast classification (NSGA-II), selecting the most suitable sites. Tao et al. [19] adopted the grey correlation and improved AHP to select the appropriate wind-farm macrositing objectively. Harren et al. [20] proposed a comprehensive evaluation framework for the optimal wind-farm site based on ESRI-ArcGIS software.

In addition to onshore wind farms, the site selection for offshore wind farms is a new hot spot in recent years. As sea environment is more complex, siting factors have obvious difference. The studies aiming at assessment of siting suitability or the optimization of sites for OWFs is still scarce: Dan W et al. [21] analyzed the relationship between the marine environment and OWFs' location. For several OWFs with different offshore distance, Bishop I D et al. [22] analyzed and compared different weather conditions. Taking Fujian Province as an example, Liu B J et al. [23] discussed the factors influencing OWF location. Sun X J et al. [24] provide a brief overview of the current development states of offshore wind power in different countries. These studies just sorted out the OWF siting indicators, but siting evaluation was rarely conducted to find the suitable potential location.

Later, Esteban M.D. et al. [25] summarized some key issues in offshore wind foundation design. And he applied an integral management model considering not only technical and financial feasibility of the OWF project, but also respect for the environment. Besides, he also combed the different factors with impact on an OWF project, including natural extrinsic factors, socioeconomic factors and intrinsic factors. Vagiona D G et al. [26] proposed a systematic methodology in order to investigate the most efficient areas of OWF siting, integrating MCDM method and GIS tools. Annette et al. [27] presented an overview of the development of the integrated macro-and micrositing tools, combined with principal component analysis and GA.

In summary, the main weakness of the above studies about wind-farm site selection refers to (1) Subjectivity. Indicators are graded based on expert experience; thus it is mainly the unsubstantiated and mostly subjective assignment of indicator weights without objective quantitative data. (2) Nonfuzziness and Nonrandomness. The siting assessment is a rigid and absolute process, taking no account of the ambiguity and probability of the information. But the data needed for siting assessment usually includes quantitative data and qualitative information, which is uncertain caused by data acquisition and expert consultation (3) Linearity. Different indicators are integrated through the liner weighted sum method, but the impact of indicators on the siting assessment is nonlinear and uncertain.

So how to evaluate OWF siting objectively and scientifically? As we all know, OWF macrositing is a multifactor problem. In essence, OWF macrosite assessment is the nonlinear fusion of natural, economic, social and other multisource information. Specially, the information includes both quantitative data and qualitative reviews, with randomness, ambiguity and other uncertain characteristics. Therefore, how to express, integrate and infer the uncertain information accurately and effectively is the key to the OWF macrositing.

Aiming at the above problem, we introduce these two intelligent algorithms: The cloud model [28] proposed by Academician Li is an effective way to deal with the uncertainty, which has been applied in data mining, intelligent decision-making and threat assessment [29–31]. The cloud model forms a mapping between the quantitative data and qualitative concepts, and it is a two-way expression model of uncertain knowledge. The model can be explained with the classical theory of probability and fuzzy mathematics, considering both the ambiguity and randomness, which can be applied to indicator grading effectively. Bayesian Network (BN) is a graphical description of the probabilistic relationship between variables, which is the ideal model for the knowledge representation and reasoning, having an important application in the intelligent system to process uncertain information [32–34].

The cloud model is superior to BN in knowledge expression, while BN is superior to the cloud model in knowledge fusion and reasoning. We apply the cloud model to automatically convert the data distribution into multiple concepts, achieving indicators grading and data preprocessing. Then, with BN structure learning, parameter learning and probabilistic reasoning, a comprehensive assessment model based on Cloud-BN is constructed. The assessment model is used for OWF macrositing and decision-making considering the uncertainty for the first time.

The purpose of our work is to provide a new approach to OWF siting on a large scale, as a preliminary screening tool. After the introduction, the basic theory of cloud model and BN are introduced in Section 2. The assessment model based on Cloud-BN is presented, and the technical framework is detailed in Section 3. A practical model application is carried out by using the proposed model in Section 4. Finally, the discussion and conclusion are presented in Section 5.

2. Theory and Concept

2.1. Gaussian Cloud Model. The cloud model is defined as follows: suppose U is a quantitative domain with exact values, and C is the qualitative concept on U. If the quantitative value $x \in U$, and x is a stochastic realization of the qualitative concept C, the certainty of x for C:$\mu(x) \in [0,1]$ is a random number with stable tendency.

$$\mu : U \longrightarrow [0,1], \quad \forall x \in U, \ x \longrightarrow \mu(x) \tag{1}$$

Then, the distribution of x on the domain U is called the cloud $drop(x, \mu(x))$.

The cloud can represent a concept with expectation Ex, Entropy En and Super entropy He, as $C(Ex, En, He)$. Ex is

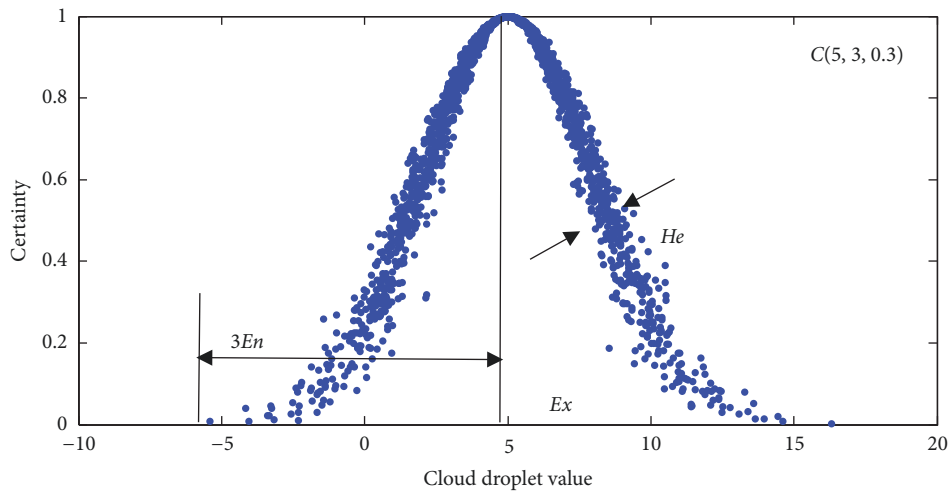


FIGURE 1: Gaussian cloud model diagram.

the mathematical expectation of the cloud and the certain measure of the qualitative concept. *En* is the size of the range of values that can be accepted by the qualitative concept in the domain space, which is the uncertain measurement of the qualitative concept, reflecting the degree of discretization of the cloud. *He* is the uncertain measure of entropy, which can reflect the degree of convergence of a qualitative concept, together with the entropy [35].

Cloud models are achieved in a variety of ways. Different clouds can be generated based on different probability distributions such as Uniform cloud, Gaussian cloud, Power Law cloud, etc. The Gaussian cloud model based on the second-order Gaussian distribution is one of the most important and widely used cloud models, universal in the conceptual representation. Figure 1 shows a Gaussian cloud model with $Ex = 5, En = 3, He = 0.3$, and number of cloud droplets is 2000. This paper adopts the Gaussian cloud model.

In cloud models, the conversion between numerical features of the qualitative concept and quantitative data is achieved by the forward and reverse cloud generator. In this paper, we use the forward Gaussian cloud generator shown in Figure 2 to realize the mapping from qualitative concept to quantitative value.

The Gaussian mixture model (GMM) is an important method in probability statistics; the core is to convert any frequency distribution of actual problems into a stack of multiple Gaussian distributions [36]. The Gaussian cloud transformation (GCT), combining the Gaussian cloud and the Gaussian mixture model, provides a method to discretize continuous variables. The adaptive Gaussian cloud transformation (A-GCT) is an improvement over GCT. Without specifying the number of concepts in advance, the A-GCT starts from the actual data, generates multiple concepts and adjusts these concepts with the degree of inclusion. Thus, the data distribution is automatically divided into different concepts. A-GCT considers the clustering principle of "strong interclass relations and weak intraclass relations" and provides a soft-grading method from quantitative data into multiple qualitative concepts.

2.2. Bayesian Network. Bayesian Network (BN), also known as the Bayesian reliability network, is a combination of graph theory and probability theory [37]. It is not only a graphical description of the probabilistic relationship among variables, but also a probabilistic reasoning technique. BN is expressed intuitively as a complex and causal diagram, and one BN can be represented by a binary $B =< G, \theta >$:

(i) $G = (V, E)$ represents a directed acyclic graph. V is a set of nodes where a node represents the variable in the problem domain. E is a set of arcs, and a directed arc represents the probability dependence between variables.

(ii) θ is the network parameter, that is, the conditional probability table (CPT) of the nodes. θ expresses the degree of mutual influence between nodes and reflects quantitative characteristics in the knowledge domain.

Assume a set of variables $V = (V_1, \cdots, V_n)$. The mathematical basis of BN is the Bayesian formula (as shown in (2)). The reasoning calculation can be realized under the assumption of conditional independence (as shown in Eq. (3)).

$$P\left(V_i \mid V_j\right) = \frac{P\left(V_i, V_j\right)}{P\left(V_j\right)} = \frac{P\left(V_i\right) \cdot P\left(V_j \mid V_i\right)}{P\left(V_j\right)} \tag{2}$$

where $P(V_i)$ is prior probability and $P(V_i \mid V_j)$ is posterior probability. Based on a priori probability, the Bayesian formula can derive the posterior probability based on the relevant conditions.

$$P\left(V_1, V_2, \cdots V_n\right) = \prod_{i=1}^{n} P\left(V_i \mid \mathrm{Pa}\left(V_j\right)\right) \tag{3}$$

where $P(V_1, V_2, \cdots, V_n)$ represents the joint probability distribution of variables. $\mathrm{Pa}(V_i)$ represents the parent of V_i. If the prior probability distribution of root nodes and the conditional probability distribution of nonroot nodes are

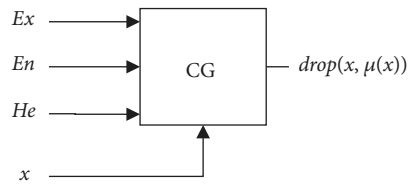


Figure 2: Forward Gaussian cloud generator.

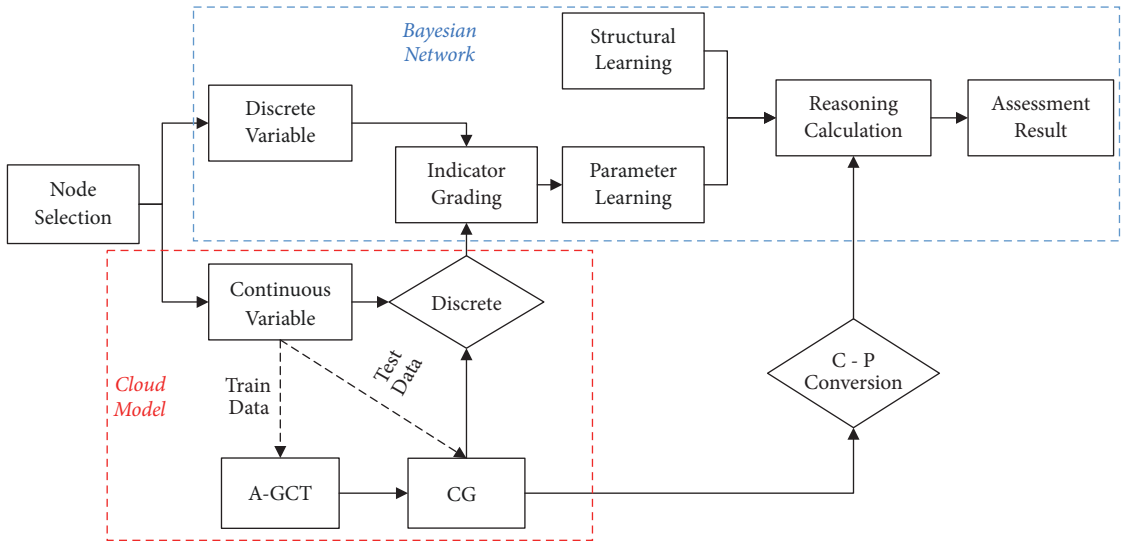


Figure 3: Model technical framework.

given, the joint probability distribution containing all nodes can be obtained by reasoning.

BN modeling process includes variable definition, node selection, data processing, structure learning, parameter learning and probability reasoning. Among these, structure learning and parameter learning are the most important links, that is, to determine the network topology and CPT.

2.3. Cloud-BN Model. The cloud model and BN combine qualitative analysis and quantitative calculation effectively, which are good tools to describe and address multisource uncertain information [38]. In this paper, we combine them to construct the new Cloud-BN model. The A-GCT algorithm is used to preprocess the raw data and grade indicators and BN is used to fuse and infer multisource information, considering the uncertainty fully. By integrating the knowledge expression ability of cloud model for fuzziness and randomness and the probabilistic reasoning ability of BN, the assessment and decision-making of OWF macrositing with complex indicators are carried out based on the Cloud-BN model.

3. Assessment Model Based on Cloud-BN

The macrositing assessment for OWFs is essentially a nonlinear integration of multi-indicators. According to siting characteristics, the assessment should focus on two aspects ignored in previous studies: first, how to grade indicators objectively considering fuzziness and randomness; second, how to effectively achieve integration of qualitative information and quantitative data considering the uncertainty. Aiming at the above problems, we will discuss the siting assessment model based on Cloud-BN and its application.

3.1. Model Framework. The Cloud-BN based assessment model is a new information fusion and reasoning model taking into account of fuzziness and randomness [39]. The detailed technical framework is shown in Figure 3.

The siting assessment model includes two modules: cloud grading module and BN evaluation module. The first is to grade indicators through the cloud conversion model; thus continuous quantitative data is transformed into discrete levels. Data discretization is realized through indicator grading so as to train the BN. The other is to evaluate sites by structure determination, CPTs learning and probabilistic reasoning. The model could combine the subjective and objective knowledge effectively and achieve siting assessment considering the uncertainty.

3.2. Model Construction

3.2.1. Indicators Grading. The indicator grading has a significant impact on the assessment result. Rough grading causes difficulties in comparing and analyzing assessment results, while detailed grading leads to tedious calculations. We use the A-GCT algorithm to form multiple levels automatically.

Input: Data sample set X, confusion degree of concepts α
Output: Number of Gaussian clouds according to concept m
Step1: Calculate the number of peaks M of the frequency distribution p of X, as the initial value of the concept
Step2: Adopt heuristic Gaussian cloud transform (H-GCT) to cluster X into M Gaussian clouds
Step3: Compare confusion degree of Gaussian cloud according to α, adjust the number of concepts
Step4: Loop Step2 ~ 3 to generate m Gaussian clouds with confusion degree less than α

Algorithm 1

Then, we design the cloud generator based on numerical features of level clouds to convert quantitative data into levels and grade indicators. The implementation steps of the A-GCT algorithm are as shown in Algorithm 1 [36]:

3.2.2. Structure Learning. BN structure learning includes selecting nodes and determining the causal dependencies between nodes. The former is to determine the siting assessment indicators; the latter is to connect arcs among indicators. As OWF siting is a complex process that requires a comprehensive analysis of the effects of natural, economic, and social factors, the structure is constructed manually in this paper.

3.2.3. Parameter Learning. We use the EM algorithm to learn the CPTs, that is, to find the maximum likelihood estimate of each parameter. First, initialize the probability distribution for each node. Then, modify the initial CPTs according to the reasoning mechanism and training data to obtain the probability distribution that is most consistent with the objective training data. The EM algorithm has two steps [40]:

(i) E step: infer the distribution $P(Z \mid X, \theta^t)$ of hidden variables Z from the current θ^t and observed variables X, and calculate the expectation of logarithm likelihood $LL(\theta^t \mid Z, X)$ about Z.

$$Q\left(\theta \mid \theta^t\right) = E_{Z|X,\theta^t}\left[LL\left(\theta \mid X, Z\right)\right] \tag{4}$$

(ii) M step: find the maximized expectation of parameters.

$$\theta^{t+1} = \operatorname{argmax}\left[Q\left(\theta \mid \theta^t\right)\right] \tag{5}$$

3.2.4. Inference and Calculation. The network reasoning is to input information to update the initial state of the network nodes with the causal relationship between nodes, and finally deduce the probability distribution of the target node [41]. In this paper, we adopt a joint tree reasoning mechanism to reasoning. For the evidence input into the network: for the continuous nodes, convert the degree of certainty into probability through the cloud model, as a soft evidence input network. For discrete nodes, input the value as hard evidence into the network.

4. Model Application

4.1. Study Area. Nowadays, Europe has the most developed offshore wind power. By the end of 2016, Europe has a total of 84 OWFs in 11 countries [42]. In terms of space distribution, 69.4% of the total installed capacity of offshore wind power is located in the North Sea, reaching 7656.4MW; 17.6% is in the Irish Sea with 1943.2MW; and 1420.5MW is in the Baltic Sea, accounting for 12.9%. We select the North Sea as the research area [0° ~ 58°N, 2°W ~ 10°E]. In Figure 4, *Area I* [50°N ~ 58°N, 2°W ~ 6°E] is the model-train region and *Area II* [50°N ~ 58°N, 6°E ~ 10°E] is the model-test region. Based on the assessment model with Cloud-BN, macrositing conditions of an OWF are evaluated under the *matlab2012a* environment. The corresponding library function required for the experiment comes from the BNT toolbox written by K. P. Murphy.

The North Sea is the marginal sea of the Atlantic Ocean, which is 965.4km long from north to south and 643.6km wide from east to west, with an area of 575000km^2 and an average depth of only 96m. It has the temperate maritime climate and steady west wind is dominant in the region most time. The flow near the surface is regular and weak. However, the cyclones there occur frequently, especially in winter (from November to March), forming wave height up to several meters or even more than 10m. So what position in the sea is suitable for an OWF site? We will use the proposed model to fuse the multisource information and make siting assessments.

4.2. Assessment Indicators

4.2.1. Indicator Analysis. As we all know, macrositing selection of wind farms is a complex project involving many aspects, such as natural geography, social politics, environmental protection, and so on. It is the process of determining the construction site, development value and strategy in a large scale, through the analysis and comparison of wind energy resources and other construction conditions at a number of candidate sites.

Natural and socioeconomic factors have possible influence on an OWF siting. Natural extrinsic factors are the geographical properties of contact area between the atmosphere and ocean, mainly dynamic properties, such as wind, wave, current, storm surge, etc. Besides, they also include territory, terrain, planetary dynamics and external geodynamics. The extrinsic socioeconomic factors are the legislative and financial framework, as well as infrastructure of the different human activities in the surroundings. These are mainly to do with sailing, military, fishing and urban settlements.

According to reference [10], key factors for finding optimal OWF sites in the North Sea are defined based on

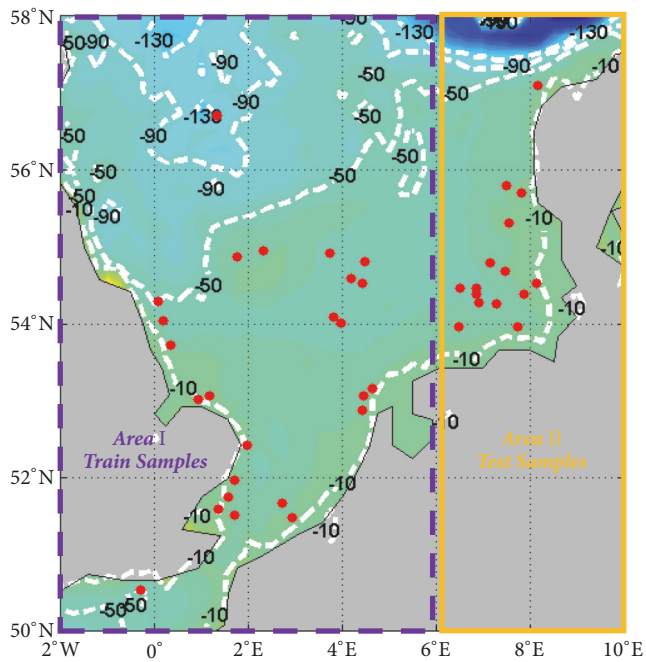


Figure 4: Study area (the white dotted line is the water depth contour; the red dot is the actual OWF position).

Table 1: Assessment indicators.

Natural factors	Wind energy potential	Wind speed (*Ws*)
		Wind power density (*Dwp*)
		Wind speed coefficient of variation (*Cv*)
	Terrain	Offshore distance (*Od*)
		Water depth (*Wd*)
	Littoral	Wave height (*Wh*)
		Flow speed (*Fs*)
Socioeconomic factors		Distance from road network (*Dr*)
		Distance from electricity grid (*De*)
		Distance from natural environment (*Dn*)

the natural features, social environment and wind-farm site selection specifications. The ten factors used for OWF siting assessment are listed in Table 1. These factors are briefly described in Table 1.

For natural factors, wind energy potential, including *Ws*, *Dwp* and *Cv*, are considered to be the most important indicators in almost every study [1–5]. Terrain and littoral factors, including *Od*, *Wd*, *Wh*, and *Fs*, are also crucial to the engineering construction of OWFs [25]. For example,*Wh* has a strong effect on the pile foundation structure of the OWF and may cause damage to the structure when *Wh* reaches a certain limit. For socioeconomic factors, *Dr* considers the transportation in OWF siting. To reduce construction costs, OWFs should be located as closely as possible to the existing road network. *De* considers the cost of wind power transmission. OWFs should be set as close as possible to the substations or power grids with corresponding voltage levels, to reduce the loss of lines and investment in their construction. *Dn* considers the ecological protection in OWF engineering. The natural environment serves the protection of nature and wildlife and is therefore away from OWF construction.

4.2.2. Indicator Process. After indicators selection and analysis, we will grade the indicators to get discrete data, which can be used for BN modeling. We first introduce the raw data, then grade the assessment factors.

(1) Data Preparation. Natural data are mainly obtained from ERA-Interim reanalysis dataset (spatial resolution is $1/4^\circ \times 1/4^\circ$), ETOP elevation dataset (spatial resolution is $1/12^\circ \times 1/12^\circ$), and SODA dataset (spatial resolution is $1/2^\circ \times 1/2^\circ$). We load and read the grid data of natural factors from 1996 to 2015 (a total of 20 years) and calculate the 20-year annual average. As the spatial resolution differs from data sources, for ease of calculation, drawing, and comparison of different assessment results, we interpolate the natural data to the regular latitude-longitude grid with a spatial resolution of

Table 2: Grid data in *Area I*.

Grid Number	1	2	3	4	⋯	282	⋯	1089
Ws (m/s)	7.62	7.53	7.12	4.61	⋯	7.26	⋯	7.93
Dwp (W/m^2)	471.23	455.51	390.36	121.84	⋯	393.35	⋯	546.39
Cv	0.48	0.48	0.48	0.53	⋯	0.47	⋯	0.48
Od (km)	16.11	17.52	12.36	0.12	⋯	94.54	⋯	0.09
Wd (m)	-68.25	-54.36	-30.18	4	⋯	-45.61	⋯	2
Wh (m)	1.79	1.81	1.85	1.90	⋯	1.21	⋯	0.86
Fs (cm/s)	11.41	11.56	11.82	12.14	⋯	8.15	⋯	7.61

$1/4^\circ \times 1/4^\circ$; thus there are 1089 grid points (33×33) in *Area I* and 561 grid points (33×17) in *Area II*. The grid data after preprocessing is shown in Table 2, taking *Area I* as an example.

For socioeconomic factors, by referring to statistics from Eurostat and the European Wind Power Association and consulting experts, we first identify several typical road centers, electricity grid centers and nature reserves along the North Sea coast. Then calculate the distance between each grid point and these centers one by one to get socioeconomic data. Both natural factors and socioeconomic factors, the acquisition, and preprocess of initial data will cause the uncertainty of data.

(2) Indicator Grading. We use the A-GCT algorithm to discrete and grade natural indicators. While for socioeconomic factors, we adopt the classical interval division method based on expert knowledge. Because socioeconomic factors are too complicated to be described in mathematical language, it is more reasonable to grade them subjectively with experts' experience.

The grade division with cloud transformation is shown in Figure 5. Figure 5 shows that *Wh* and *Cv* are divided into two levels (states), *Fs* and *Wd* are divided into three levels, *Dwp* and *Ws* are divided into four levels, and *Od* is divided into five levels. The corresponding standard level cloud is shown in Figure 6. Table 3 shows the complete discrete expression of grade. We can see the cloud expression of natural indicators grade can reflect the ambiguity and randomness. Compared with the grade method of traditional hard segmentation, the grade division is more reasonable.

4.3. Assessment Network

4.3.1. Network Structure. According to Section 3.2.2, we construct network structure with indicators listed in Table 1, as shown in Figure 7. All parent nodes are assessment indicators, and the state taken by the node is the indicator grade. The child node "*OWF*" is also a discrete node whose states include "Yes" and "No", respectively representing the site is appropriate and inappropriate.

4.3.2. Conditional Probability Table

(1) Data Preparation. For natural nodes, according to the mathematic features of the cloud model in Table 3, we designed the corresponding cloud generator and input the grid data of *Area I* in Table 2 to discrete the data. For socioeconomic factors, we discrete the data directly in *Area I* according to the level shown in Table 3.

Besides, each OWF position (latitude and longitude) is also interpolated and stored in the above grid with spatial resolution of $0.25^\circ \times 0.25^\circ$. The value state of the grid point where the OWF exists is quantized to "2", and the nonexistent is quantized to "1", resulting in 1089 training samples for *Area I*, as listed in Table 4. Test samples for *Area II* can be obtained in the same way.

(2) Parameter Learning. According to Section 3.2.3, we input the training samples in Table 4 and use the EM algorithm to calculate the probability distribution of each node. The CPTs of the network can be obtained as shown in Table 5.

4.3.3. Inference and Calculation

(1) Prior Information. For natural nodes, we input test data generated in Section 4.2.2 (a total of 561 grid points in *Area II*) to the cloud generator, and the certainty is converted to probability according to the certainty-probability conversion formula:

$$P_i = \frac{{\mu_i}^{1/\alpha}}{\sum_{i=1}^{\max[\text{Level}i]} {\mu_i}^{1/\alpha}} \tag{6}$$

where $0 < \alpha \leq 1$, constant. The larger α is, the greater the degree of consistency between certainty and probability is. This paper takes $\alpha = 1$. Therefore, the natural nodes of each grid will get a set of soft evidence. While for socioeconomic nodes, we input the their level for each grid in *Area II* as hard evidence, as shown in Table 6.

(2) Siting Assessment

(i) Single point reasoning: *Netica* developed by *Norsys* in Canada is a BN implementation software. We put the above network structure, CPTs in Table 5 and the evidence of parent nodes in Table 6 into the platform, thereby obtaining the probability distribution of OWF macrositing in each grid in *Area II*. Figure 8(a) shows the BN assessment result for grid *No. 1*.

(ii) Sea zoning: calculate under the *matlab* environment, and divide *Area II* into different siting zones.

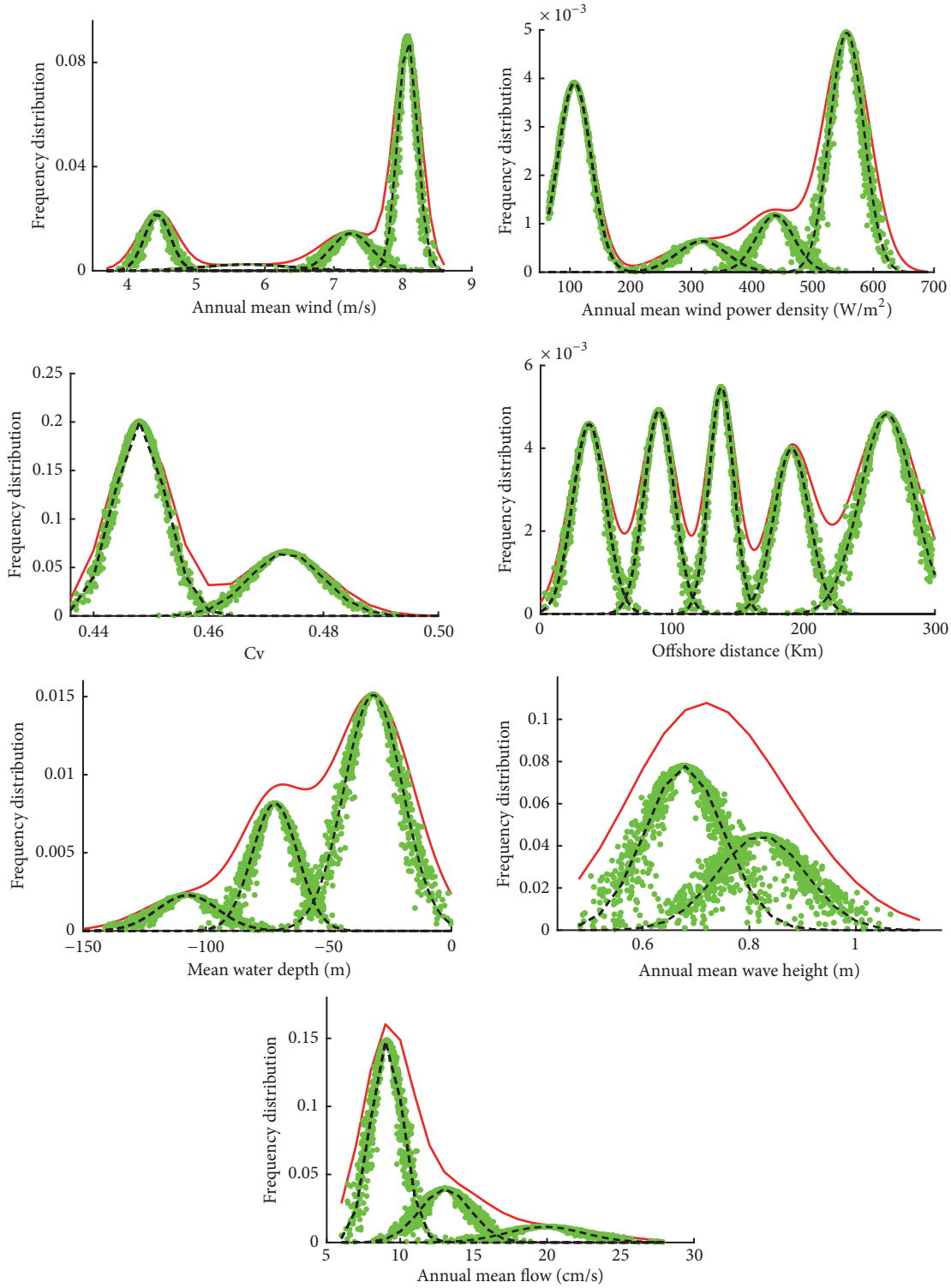


FIGURE 5: A-GCT division graph (the green cloud droplet represents the concept of the Gaussian cloud. The black dotted line is the expectation curve of the Gaussian cloud. The red solid line is the fitting curve of the A-GCT).

Figure 8(b) shows the "*Yes*" probability zoning of the OWF location in *Area II*, where the white dot is the actual location of the OWF, the white solid line is the probability zonation line.

Figure 8(a) shows the result of OWF siting for the single point based on *Netica*. The probability that the position is suitable for OWF is 0.265. The result [0.265, 0.735] reflects the uncertainty of siting assessment. Besides, the

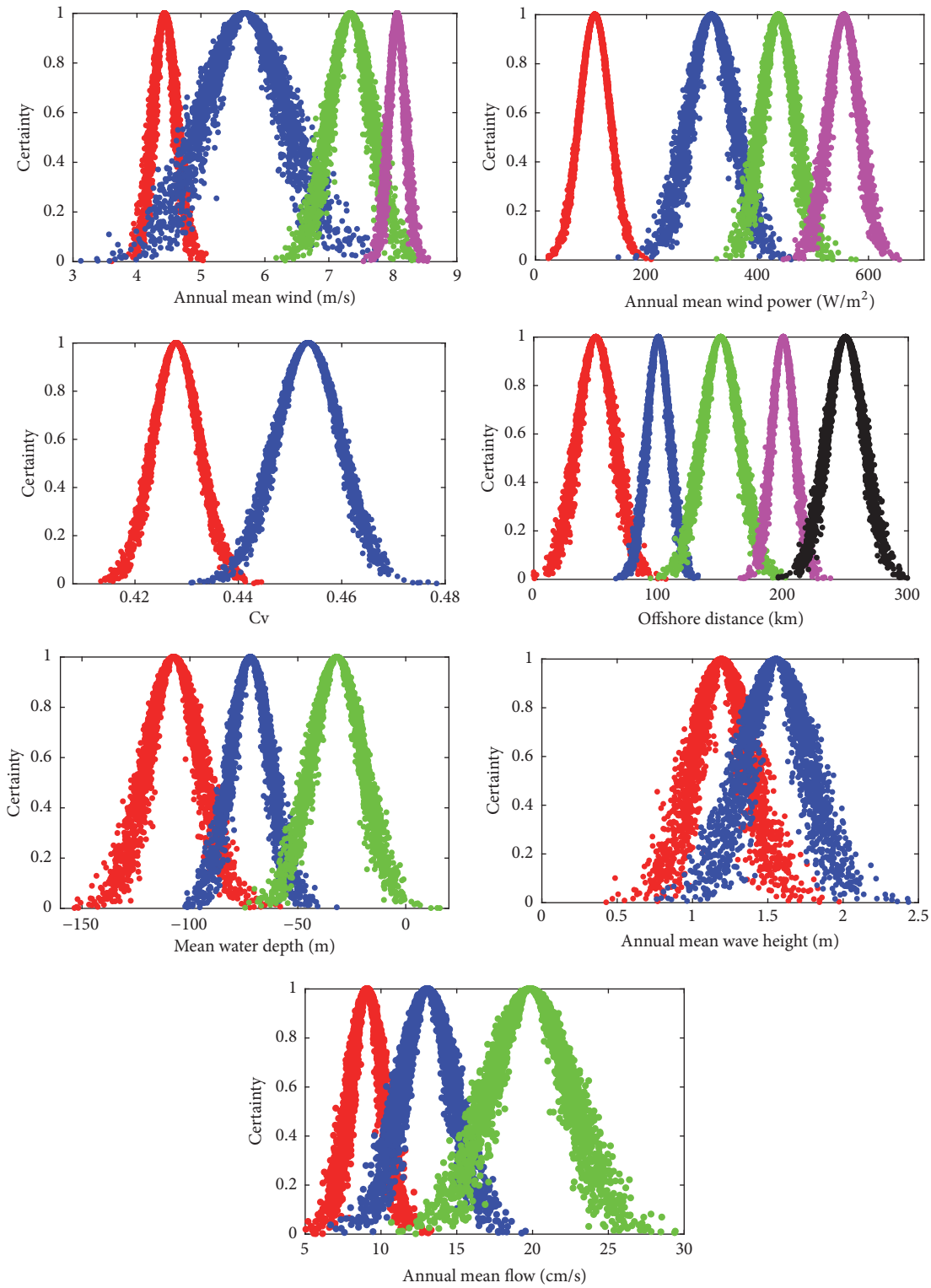


Figure 6: Grade cloud graph (different colour represents different concept (state)).

quantitative comparison of different positions can be made according to assessment results. Figure 8(b) is the "*Yes*" probability zoning of the OWF siting in the *Area II*. From the figure, the region that shows the suitable probability for the location more than 0.5 covers nearly all the actual OWFs; the accuracy exceeds 86.67%. The dense area of the actual OWFs also coincides with the large value area of suitable siting probability [> 0.7], which verifies the scientific nature of the model. However, there are the following questions:

Table 3: Grade division of indicators.

Indicator	Grade	Cloud	Discrete Value
Annual mean wind (m/s)	Level 1	C_1(4.438,0.181,0.003)	1
	Level 2	C_2(5.692,0.651,0.108)	2
	Level 3	C_3(7.342,0.329,0.051)	3
	Level 4	C_4(8.071,0.129,0.02)	4
Annual mean wind power density (W/m^2)	Level 1	C_1(107.451,27.614,1.166)	1
	Level 2	C_2(317.637,41.031,6.083)	2
	Level 3	C_3(437.955,31.202,4.626)	3
	Level 4	C_4(556.165,27.936,3.315)	4
Cv	Level 1	C_1(0.534,1.583,0.113)	1
	Level 2	C_2(0.471,1.123,0.079)	2
Offshore distance (km)	Level 1	C_1(36.988,12.473,1.062)	1
	Level 2	C_2(90.198,11.345,0.966)	2
	Level 3	C_3(137.586,9.310,0.746)	3
	Level 4	C_4(191.023,13.396,1.270)	4
	Level 5	C_5(263.354,20.287,1.922)	5
Mean water depth (m)	Level 1	C_1(-107.375,12.317,1.852)	1
	Level 2	C_2(-71.867,9.245,1.391)	2
	Level 3	C_3(-31.779,11.927,1.519)	3
Wave height (m)	Level 1	C_1(1.557,2.058,0.474)	1
	Level 2	C_2(1.195,1.842,0.424)	2
Flow speed (cm/s)	Level 1	C_1(19.857,2.616,0.423)	1
	Level 2	C_2(13.069,1.725,0.305)	2
	Level 3	C_3(9.093,1.102,0.195)	3
Distance of road network (km)	Level 1	>30	1
	Level 2	15~30	2
	Level 3	5~15	3
	Level 4	1~5	4
Distance of electricity grid (km)	Level 1	>50	1
	Level 2	25~50	2
	Level 3	10~25	3
	Level 4	5~10	4
Distance of natural environment (km)	Level 1	>15	1
	Level 2	10~15	2
	Level 3	5~10	3
	Level 4	0~5	4

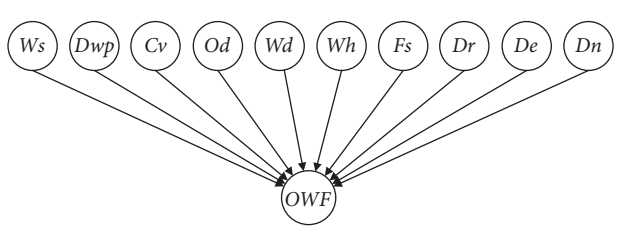


Figure 7: OWF siting assessment structure.

Table 4: Discrete training samples in *Area I*.

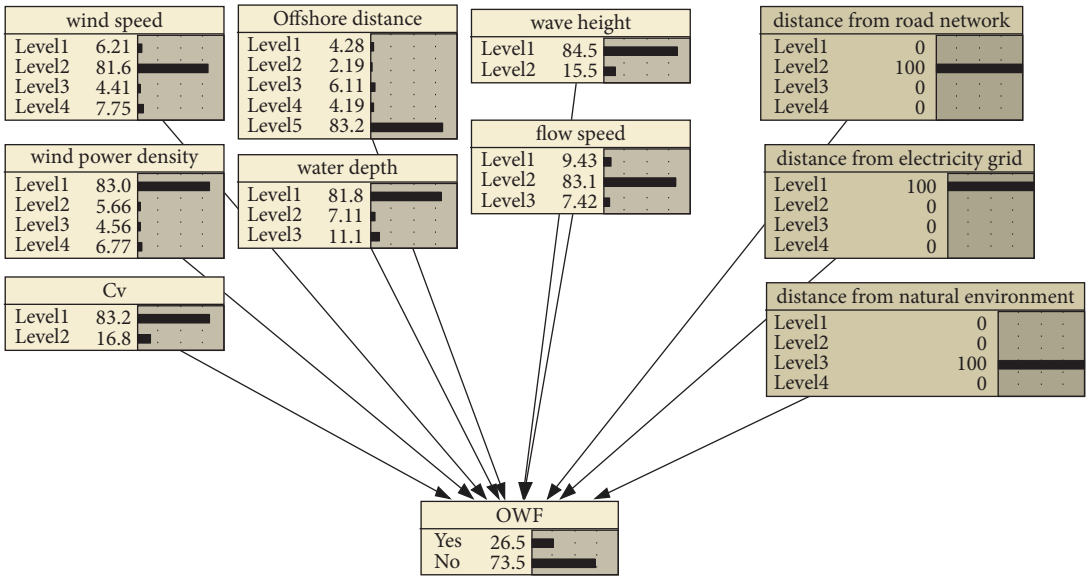
Sample number		1	2	3	4	⋯	282	⋯	1089
Parent nodes	*Ws*	3	3	3	1	⋯	3	⋯	3
	Dwp	3	3	3	1	⋯	3	⋯	3
	Cv	2	2	2	1	⋯	2	⋯	2
	Od	5	5	5	5	⋯	3	⋯	5
	Wd	2	2	3	3	⋯	3	⋯	3
	Wh	1	1	1	1	⋯	2	⋯	2
	Fs	2	2	2	2	⋯	3	⋯	3
	Dr	2	2	2	2	⋯	3	⋯	4
	De	1	1	1	1	⋯	3	⋯	3
	Dn	3	3	3	3	⋯	2	⋯	2
Child node	*OWF*	1	1	1	1	⋯	2	⋯	1

Table 5: The CPTs of child nodes.

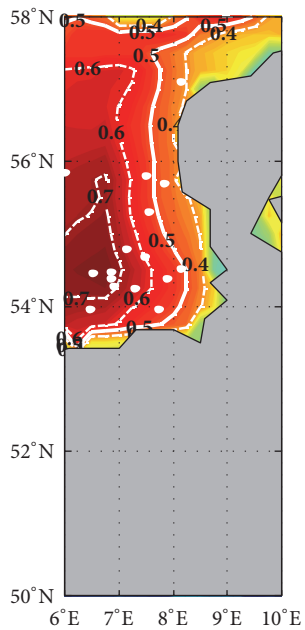
Child nodes										*OWF*	
Ws	*Dwp*	*Cv*	*Od*	*Wd*	*Wh*	*Fs*	*Dr*	*De*	*Dn*	1	2
1	1	1	1	1	1	1	1	1	1	*1*	*0*
2	1	1	1	1	1	1	1	1	1	*1*	*0*
3	1	1	1	1	1	1	1	1	1	*1*	*0*
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
3	3	2	2	3	2	2	3	3	3	*0.1218*	*0.8782*
4	4	2	2	3	2	2	3	3	3	*0.0896*	*0.9104*
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
3	3	2	5	3	2	3	4	4	4	*0.0437*	*0.9563*
4	4	2	5	3	2	3	4	4	4	*0*	*1*

Table 6: Evidence (prior probabilities) of the *Area II*.

Grid number	Child nodes		Discrete value of the grade				
			1	2	3	4	5
No.1	*Natural factor*	*Ws*	0.0621	0.8163	0.0441	0.0775	\
		Dwp	0.8301	0.0566	0.0456	0.0677	\
		Cv	0.8321	0.1679	\	\	\
		Od	0.0428	0.0219	0.0611	0.0419	0.8323
		Wd	0.8176	0.0711	0.1113	\	\
		Wh	0.8452	0.1548	\	\	\
		Fs	0.0943	0.8315	0.0742	\	\
	Socioeconomic factor	*Dr*	0	1	0	0	\
		De	1	0	0	0	\
		Dn	0	0	1	0	\
No.2	*Natural factor*	*Ws*	0.0606	0.8183	0.0501	0.0711	\
		Dwp	0.8142	0.0619	0.0504	0.0724	\
		Cv	0.8786	0.1214	\	\	\
		Od	0.0143	0.0449	0.0272	0.0432	0.8272
		Wd	0.8201	0.079	0.1009	\	\
		Wh	0.8269	0.1731	\	\	\
		Fs	0.0633	0.8421	0.0946	\	\
	Socioeconomic factor	*Dr*	0	1	0	0	\
		De	1	0	0	0	\
		Dn	0	0	1	0	\
⋮		⋮	⋮	⋮	⋮	⋮	⋮



(a) BN assessment result of *Grid No. 1*



(b) Probability zonation of OWF

Figure 8: BN assessment result of OWF location.

(1) There are also several actual OWFs located in the small value area of probability [0.4 ~ 0.5].

(2) In the area [56°N ~ 57.5°N, 6°E ~ 7°E], the suitable probability for the OWF location is above 0.6, but there is no actual OWF.

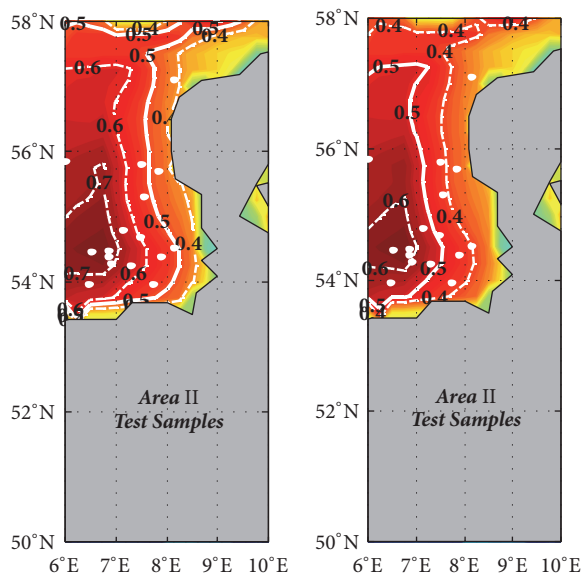
Reason analysis: in this paper, OWF siting assessment and probability zoning is only based on finite indicators. We just select ten prominent indicators, seven natural factors and three social factors, without considering more economic and other human factors, resulting in zoning error.

5. Discussion and Conclusion

5.1. Model Analysis

5.1.1. Comparison with Traditional Indicator Grading Method. The traditional grading method for continuous indicators is the equal-interval division method, which ignores the fuzziness of grade. We also use BN with traditional grading method for assessment and zoning of OWF siting in the *Area II*, and the results are shown in Figure 9.

We compare the results of the two siting assessment. The distribution is roughly consistent, but the accuracy of the



(a) Assessment and zonation of Cloud-BN

(b) Assessment and zonation of traditional BN

Figure 9: Comparison of different BN assessments.

location is quite different: The accuracy of the traditional grading method is only 53.33%, while our model is 86.67%, according to the number of actual OWFs covered by the area with probability suitable for OWF more than 0.5. Besides, probability isoline is sparse and zoning distinction is small, which makes difficulty in site selection. Thus it can be seen that the indicator grading has a noticeable impact on assessments and grading method considering fuzziness can produce more accurate results.

5.1.2. Comparison with Traditional Linear Weighting Fusion Method. Site selection for OWFs is a multi-indicator assessment problem, so the fusion method of different indicators has a significant impact on results. Linear weighting fusion is the most widely used method in previous studies. So we also use this method to evaluate site selection for OWFs and compare it with our proposed model.

We can see that the spatial distribution and spacing of probability isoline in Figure 10 are generally consistent. However, the accuracy has a big difference. The proposed model is more accurate than linear weighting fusion (86.67% vs. 46.67%). With linear weighting fusion method, there are appreciable quantities of OWFs siting outside suitable area.

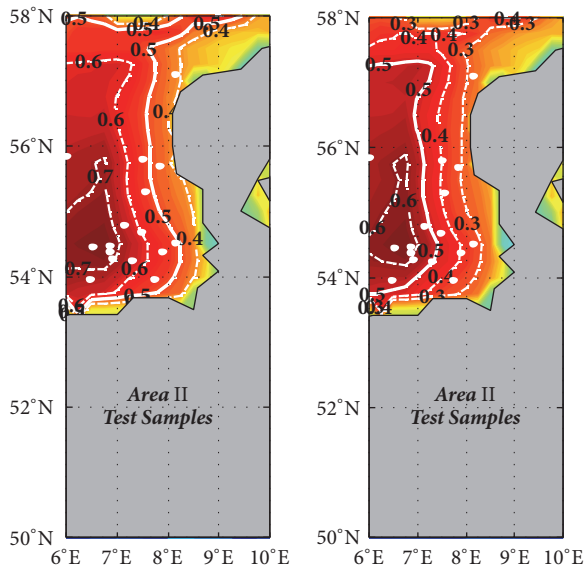
5.1.3. Comparison with FAHP and FCA. The fuzzy analytic hierarchy process (FAHP) and fuzzy comprehensive appraisal (FCA) are currently the most wide-used methods in the wind-farm siting assessment and decision-making [43, 44]. Although these methods introduce the fuzzy mathematics to consider the ambiguous factors and reduce the divergence caused by subjective judgment, the assessment results are fundamentally derived from expert knowledge and subjective experience. These two methods do not fully exploit the objective relationships among the data, and the results have a great randomness and subjectivity. In addition, they can only be used to evaluate and compare for a limited number of candidate sites.

In contrast, the biggest advantage of our model is that the uncertainty is fully taken into account in the whole assessment process, which comes from both the objective data and expert knowledge. In the application, not only can the single point be evaluated and analyzed but also sea zoning for the large area can be analyzed.

5.2. Conclusion. Through the analysis of this paper, there are many uncertainties in the siting assessment. But few studies consider the randomness and fuzziness. We combine the complementary advantages of the cloud model and BN to propose an OWF siting assessment model considering the uncertainty. Through the indicator grading, network structure constructing, node parameter learning and probabilistic reasoning, we achieve the probability assessment and zoning of OWF macrositing in the European North Sea.

(i) In the indicator grading, the A-GCT algorithm is introduced to discrete the level of indicators, fully considering the fuzziness and randomness of knowledge expression. The siting precision is obviously improved. In the BN reasoning process, with the cloud generator to convert data, the priori information is put into the network in the form of soft evidence, considering the uncertainty of the information, thus improving the accuracy of network reasoning.

(ii) The Cloud-BN model makes full use of the advantages of the cloud model in uncertain knowledge expression and the advantages of BN in knowledge fusion



(a) Assessment and zonation of Cloud-BN

(b) Assessment and zonation of linear weighting fusion

Figure 10: Contrastive analysis of different BN assessments.

and reasoning. We take full account of the uncertainty and effectively address it in OWF macrositing, achieving siting assessment, and zoning for a single point of the sea and a large area.

Under the realistic conditions, macrositing of OWF should take into account factors such as wind energy, transportation and construction, geography, and landform. However, in this paper, siting assessment is only for seven natural conditions and three social conditions. In the next research, we will fully consider economic, social, and other human factors, to achieve a comprehensive assessment. In addition, the anomaly test of the Cloud-BN assessment model is also the focus of the later work.

Data Availability

The dataset used to support the findings of this study is included within the article. In Section 4.2.2 Indicator process, we have explained the source of the data. To further state the data availability, we add the detailed data source links as follows: ERA-Interim data (European Centre for Medium-Range Weather Forecasts, ECMWF): http://apps.ecmwf.int/datasets/; ETOP data (from National Oceanic and Atmospheric Administration): http://maps.ngdc.noaa.gov/viewers/wcs-client/; SODA data (simple ocean data assimilation): http://iridl.ldeo.columbia.edu/SOURCES/.CARTON-GIESE/SODA/.v2p0p2-4/).

Conflicts of Interest

The authors declare no conflicts of interest.

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