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Assessment Method of Offshore Wind Resource Based on a Multi-dimensional Indexes System

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***Abstract*—Traditional assessment indexes could not fully describe offshore wind resource for the meteorological properties of offshore are more complex than onshore. And as a result, the uncertainty of offshore wind power projects would be increased and final economic benefits would be affected. Therefore, a study on offshore wind resource assessment is carried out, including three processes of "studying data sources, conducting multi-dimensional indexes system and proposing offshore wind resource assessment method based on Analytic Hierarchy Process (AHP)". Firstly, measured wind data and two kinds of reanalysis data are used to analyze the characteristics and reliability of data sources. Secondly, indexes such as effective wind speed occurrence, affluent level occurrence, coefficient of variation, neutral state occurrence have been proposed to depict availability, richness, and stability of offshore wind resource, respectively. And combined with the existing parameters (wind power density, dominant wind direction occurrence, water depth, distance to coast), a multi-dimensional indexes system has been built and based on the above indexes system, an offshore wind energy potential assessment method has been proposed. Furthermore, the proposed method is verified by the annual energy production of five offshore wind turbines and practical operating data of four offshore wind farms in China. This study also compares the ranking results of the AHP model to two multi-criteria decision making (MCDM) models including a Weighted Aggregated Sum Product Assessment (WASPAS) and Multi-Attribute Ideal Real Comparative Analysis (MAIRCA). The results show that the proposed method gains well in practical engineering applications, where the economic score values has been considered based on the offshore reasonable utilization hours of the whole life cycle in China.**

***Index Terms*—Offshore wind resource; Data sources; Wind power density; Annual energy production; Atmospheric stability**

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I. Introduction

OFFSHORE wind power is emerging as a booming renewable energy source for power generation, potentially mitigating climate change, increasing energy security, and stimulating the global economy [1]. Compared with onshore wind energy, offshore wind energy has clear advantages, such as more significant wind resource, lower visual and acoustic impacts, larger untapped areas [2]–[5], closer to the load center. As a result, offshore wind energy has overgrown in the last decade: from just over 2 GW in 2009, the global installed capacity of offshore wind energy has increased more than 17 times to over 35 GW in 2020 [6], representing an annual growth rate of nearly 30%, and it is still expected to rise in the coming years [7]. The fast-growing offshore wind energy sector brings both opportunities and challenges in offshore wind energy utilization.

Offshore wind resource assessment plays a significant role in developing and constructing offshore wind energy projects [8] since the power is the cube function of wind speed. A minor speed change can cause large deviations in the output power [9], [10]. There are two essential prerequisites to ensure the accuracy of offshore wind resource assessment. The first is the reliability and continuity of wind measurement data. Generally, satellite data, reanalysis data, and numerical simulation data have been widely used in evaluating offshore wind resource due to the complex meteorological properties, short development time, and lack long-term observation of offshore wind energy [11]. The distribution of offshore wind resource in the South China Sea has been analyzed using the JRA-55 developed by the Japan Meteorological Agency(JMA) [12]. The regularities of wind speed distribution over China's Bohai and Yellow Seas have been analyzed according to the 35-year ERA-5 (European Center for Medium-Range Weather Forecasts Reanalysis V5) data [13]. Besides, reanalysis data has been widely used to evaluate the offshore wind resource at various locations worldwide, such as in Oman [14], the Mediterranean Sea [15], south and southeastern Brazil [16], North America [17], the Black Sea [18], Morocco [19] and the Indian Sea [20].

Another critical prerequisite that ensures the accuracy of offshore wind resource assessment is the scientific and comprehensive assessment method [21]. Traditional wind resource assessment is mainly proposed from the perspective of the total reserves and availability of wind energy. Still, the large-scale development of offshore wind energy is related to the characteristics of offshore wind energy resource itself and other factors such as economy, environment, and human activities. In terms of influencing factors, the situation for offshore wind energy is more complex and variable than for the onshore case. The temperature difference between water and atmosphere will affect the offshore atmospheric boundary layer's stability and vertical mixing trend, thus eventually rising to change the distribution of wind resource [22]. Geographical factors such as water depth and distance to coast [23] will also restrict the development and utilization of offshore wind energy. Therefore, the development of offshore wind projects requires an overall assessment that quantifies the crucial constraints. Zheng et al. [24] analyzed the distribution of global offshore wind resource by considering wind power density, effective wind speed and other factors. [25] researched the site selection method of potential areas for offshore wind power development assessed with a multi-criteria decision making analysis. Zheng et al. [26] proposed a new classification standard for offshore wind resource comprehensively considering resource and environmental factors. Emeksiz et al. [27] evaluated the wind energy resource in 31 coastal regions of Turkey. Costoya et al. [28] used 12 regional climate models to simulate the 30-year historical data of offshore wind power, and proposed a new classification method of offshore wind resource comprehensively considering wind resource, environmental risks, and economic costs, and predicted the future variation of offshore wind resource in North America. Table I provides a brief comparison between the relevant indexes and approaches discussed in the literature.

In summary, researchers have carried out many studies on the offshore wind resource assessment because of its particularity, but the following limitations still urgently need to be settled:

(1) The simulation and assimilation data applied in the above studies usually deviated from the measured data, which would increase the uncertainty of the assessment of offshore wind resource.

(2) There are overlaps and omissions among the above offshore wind resource evaluation studies, which could not fully and accurately describe the distribution of offshore wind resource.

Therefore, the main contributions of this paper are as follows:

(1) The reliability of data source has been studied based on wind mast measured data and two separate sources of reanalysis data (MERRA-2, CFSv-2) to reduce the assessment error due to data uncertainty.

(2) An offshore wind resource assessment method based on AHP model has been proposed, which considered a variety of factors such as total reserves, availability, stability, and actual construction conditions, in order to ensure the accuracy and comprehensive of the evaluation.

(3) The applicability and effectiveness of this method has been rigorously verified by four offshore wind farms in China. The results proved the high consistency with the actual running data.

(4) The assessment results has also been compared with two multi-criteria decision making (MCDM) models including a Weighted Aggregated Sum Product Assessment (WASPAS) and Multi-Attribute Ideal Real Comparative Analysis (MAIRCA). The results show that the proposed method gains well in practical engineering applications.

The rest of this study is structured as follows: Section 2 introduces the proposed assessment indexes system. Section 3 presents multi-source data comparison and screening. The proposed method and validation using measured and operating data from four offshore wind farms have been shown in Section 4, followed by a brief conclusion in Section 5.

II. The multi-dimensional indexes system of offshore wind resource

The traditional onshore and offshore wind resource assessment mainly determines the wind resource grade by two parameters: annual mean wind speed and annual mean wind power density. This paper proposes a multi-dimensional indexes system based on reserves, stability, and actual construction condition. Moreover, an offshore wind resource assessment method based on the above

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TABLE I: Comparison between the different offshore wind siting studies

Location,Year	Data	Index	Method
Eygpt, 2018, [23]	MERRA reanalysis data	Wind intensity, Distance to grid, Water depth, Distance to coast	Pairwise comparison
Global, 2014, [24]	ERA-40 reanalysis data	Wind power density, Seasonal stability, Coefficient of variation, Storage of wind energy	Not defined
Thailand, 2015, [25]	NCAR/NCEP reanalysis data	Wind speed, Distance to grid, Water depth, Distance to coast	Not defined
Global, 2018, [26]	ERA-Interim reanalysis data	Wind power density, Monthly stability, Rich level occurrence, Effective wind, Water depth, Distance to coast	Delphi method
Turkey, 2019, [27]	RET-screen database	Pipelines, Military zones, Sea floor morphology, Water depth, Distance to coast	AHP
North America, 2020, [28]	CMIP5	Mean wind speed, Extreme wind speed, Monthly stability, Water depth, Distance to coast	Delphi method
This paper	MERRA-2 reanalysis data, CFSv-2 reanalysis data, Measured data	Wind power density, Effective wind speed, Affluent level, Coefficient of variation, Dominant wind direction, Atmospheric stability, Water depth, Distance to coast	AHP

indexes system has been put forward by the form of score values.

A. Offshore wind power reserves indexes

1) Wind power density (WPD)): The wind power density is the most critical parameter to evaluate wind power resources. wind power density at a certain height is calculated as follows:

$$WPD = \frac{1}{2n} \sum_{i=1}^{n} \rho v_i^3 \tag{1}$$

For a selected region, the higher the *WPD* at the same height, the better the wind resource in the area are. So the paper defines *WPD* as a positive index.

2) Effective wind speed occurrence (EWSO): In general, power can be generated at wind speeds between 3 m/s and 25 m/s, and *EWSO* is defined as the proportion of available wind energy hours of the annual hours:

$$EWSO = \frac{t_{3 \leq v_i \leq 25}}{8760} \tag{2}$$

Where, $t_{3 \leq v_i \leq 25}$ is the the hour of wind speed in range 3 m/s and 25 m/s . The higher the *EWSO* is, the greater the wind resource potential of the evaluated region is. Therefore, *EWSO* is a positive index.

3) Affluent level occurrence (ALO): In this paper, the probability of wind power density greater than $200\,\mathrm{W/m^2}$ is defined as *ALO*. Larger *ALO* values reflect a higher utilization rate of wind resource in a specific place. Therefore, *ALO* is also a positive index.

B. Offshore wind power stability indexes

1) Coefficient of variation (CV): The reserves, availability, and stability of wind resource should be considered in utilizing wind power. *CV* is constructed through

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the mean and standard deviation of *WPD*, which mainly measures the dispersion degree of *WPD* in time series. In general, *CV* reveals the stability of wind resource, and a more considerable value means the more significant difference of *WPD* among different times; thus, *CV* is defined as a negative index:

$$CV = \frac{\sigma_p}{\overline{P}} \tag{3}$$

Where, $\sigma_p$is the standard deviation of *WPD*, and $\overline{P}$ is the mean *WPD*.

2) Dominant wind direction occurrence(DWDO): An offshore wind farm with basically stable wind direction is conducive to the wind farm layout and wind turbine yaw control, which can minimize the interaction of flow fields between turbines and increase the overall power generation. In brief, the higher the frequency of the dominant wind direction is, the more stable the wind resource is. Therefore, *DWDO* is a positive index.

3) Neutral state occurrence(NSO): Atmospheric stability is the leading thermal factor causing vertical variation of wind speed. The kinematic and thermodynamic structure of atmospheric motion only depends on atmospheric turbulence under the situation of the stationary and horizontal ground layer without radiation and phase transformation. The dimensionless value Monin-Obukhov length (*L*) is usually used to represent atmospheric stability [29] :

$$L = -\frac{u_*^3 \overline{\theta_v}}{\kappa g \overline{\omega \theta_v}} \tag{4}$$

Where κ a is von Karman coefficient, g is gravitational acceleration, u_* is friction velocity, $\overline{\theta_v}$ is virtual potential temperature, $\overline{\omega \theta_v}$ is surface buoyancy flux: $\overline{\omega \theta_v} = \frac{H_0}{\rho c_p} + 0.61 T_a \frac{L_0}{\rho l_v}$, H_0 and L_0 are sensible heat flux and latent heat flux, respectively. The classification standard of atmospheric stability is shown in Table II [30], [31]. As an essential issue in the design stage of wind farms, atmospheric stability has been rarely considered [32]. The paper takes atmospheric stability as the primary consideration of offshore wind resource assessment. The proportion of neutral state is used to represent the influence of atmospheric stability on the distribution of wind resource.

TABLE II: Standard of atmospheric stability classification

Atmospheric Stability	L
unstable	$-600 \leq L < 0$
neutral	$L \geq 600, L < -600$
stable	$0 \leq L < 600$

C. Offshore wind power construction condition indexes

Distance to coast(*DC*) and water depth(*WD*) are two crucial factors affecting site selection and the cost of offshore wind power projects. Usually, further *DC* and deeper *WD* values are unfavorable to offshore projects in infrastructure construction, construction and installation, submarine cable laying, electricity interconnection, and operation and maintenance of wind turbines. Therefore, from the perspective of project design and site selection, *WD* and *DC* are defined as negative indexes. Fig.1 is the multi-dimensional assessment indexes system of offshore wind resource constructed in this paper, in which the indexes marked with * are the indexes proposed in this paper.

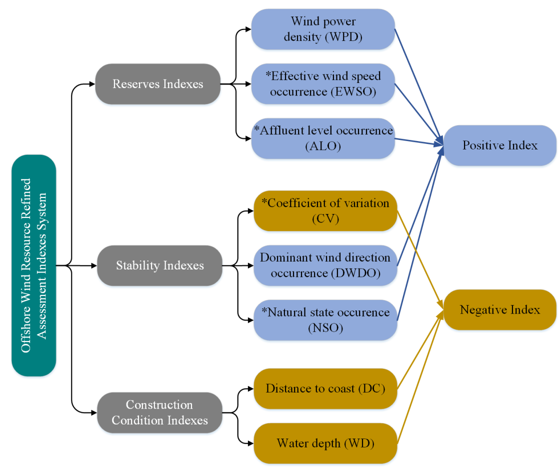

Fig. 1: The assessment indexes system of offshore wind resource

III. Multi-source data comparison

A. Data sources

The paper, based on different data sources (the measured data, operating data, MERRA-2 reanalysis data by National Aeronautics and Space Administration, and CFSv-2 reanalysis data by the National Center for Environmental Prediction) of four offshore wind farms (WF1, WF2, WF3, and WF4) in the areas of the Yellow Sea in China, has studied the offshore wind resource assessment method. The sampling period is 1h. The measured data includes wind speed, wind direction at 10m, 30m, 50m, 70m, and 100m, and best of all, the four wind farms are marked with no cutoffs during the data sampling period. CFSv-2 reanalysis data includes wind speed and wind direction at 10m, 100m, sensible heat flux, latent heat flux, air density, air pressure, temperature, and specific humidity. In comparison, MERRA-2 reanalysis data includes wind speed and wind direction data at 100m height. According to the Chinese national standard, GB/T18710 - 2002, and the industry-standard NB/T 31147-2018, the data integrity rate is above 90% after data interpolation. Table III shows the basic information of three data resources. Fig.2 shows the position of four offshore wind farms.

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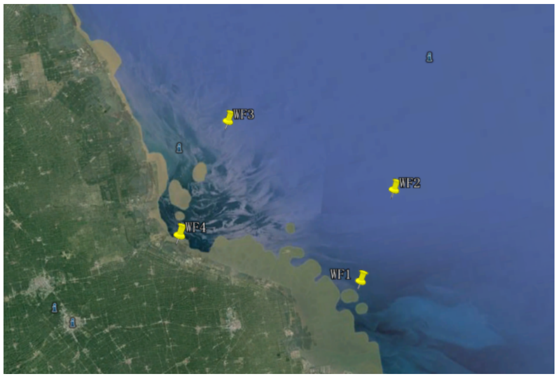

Fig. 2: Layout of four Offshore wind farms

TABLE III: The basic information of data resources

	Temporal/Spatial resolution	Data year
CFSv-2	1h, $0.2° \times 0.2°$	2017
MERRA-2	1h, $0.5° \times 0.625°$	2001-2020
Measured data	1h, –	2017

1) The essential characteristic of wind speed data: Describing and studying the basic variation rules would help improve the understanding of the characteristics of offshore wind resource and increase the accuracy of the assessment. Fig.3 shows the variation of the annual mean wind speed of the four wind farms in recent 20 years (data source: CFSv-2). The annual mean wind speed of WF4 is lower than that of other wind farms since it is an intertidal wind farm, and the annual mean wind speed of four wind farms has stayed in a relatively stable variation range in the past 20 years. Among the four wind farms, the maximum annual mean wind speed appeared in 2018, while the minimum appeared in 2020 and 2015. From a long time scale analysis, 2017 is not a "strong or light wind year", which would be more representative.

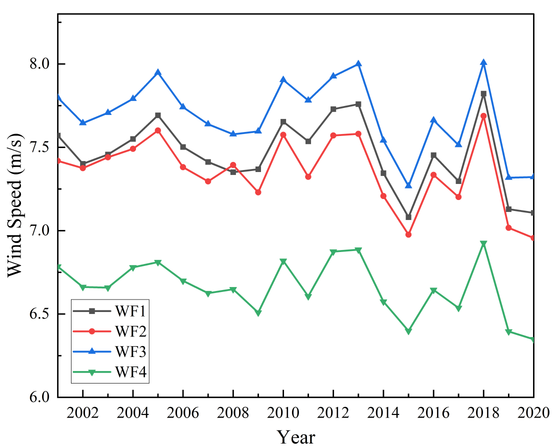

Fig. 3: Wind speed variation during 20 years at four offshore wind farms

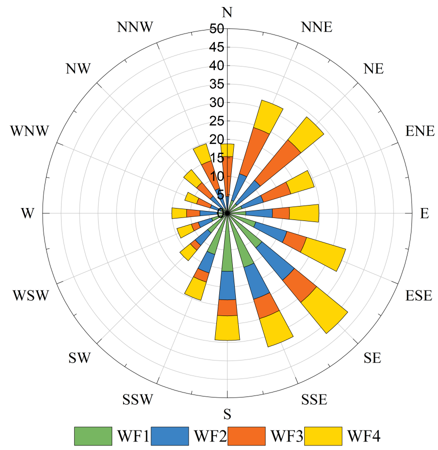

Fig. 4: Wind rose of four offshore wind farms

Table IV summarizes the basic information of measured wind speed at 100m height of four offshore wind farms, where k and c are shape and scale parameters of wind speed Weibull distribution, respectively, $\bar{v}$ is annual mean wind speed, $P(v_i > \bar{v})$ is probability of wind speed larger than $\bar{v}$. R^2 reflects the fitting quality of wind speed using Weibull distribution. As can be seen from Table IV, among the four offshore wind farms, WF3 has the maximum annual mean wind speed at 100m, and the wind speed distribution is closest to the Rayleigh distribution. WF4 has the minimum yearly mean wind speed of 100m. Besides, the probability of wind speed of four offshore wind farms greater than the mean value is basically between 0.44 and 0.46.

TABLE IV: The basic information of offshore wind resource

	WF1	WF2	WF3	WF4
$\bar{v}(m/s)$	6.553	7.117	7.854	5.943
k	3.000	2.225	2.148	2.402
c	7.333	8.039	8.887	6.697
$P(v_i > \bar{v})$	0.443	0.458	0.442	0.448
R^2	0.933	0.967	0.971	0.938

Fig.4 shows the wind direction distribution of four offshore wind farms in 2017. The dominant wind direction of WF1, WF3, and WF4 are relatively consistent, all in the order of E or ESE. The NE direction of WF2 has the highest proportion. The analysis of dominant wind direction has essential reference significance for the estimation of wind power generation under the influence of the wake effect.

2) Atmospheric stabilities based on CFSv-2 reanalysis data: Offshore wind power depends not only on meteorological factors such as wind speed and direction but also on complex sea-air interaction at a different time and spatial scales inside and outside of the wind farm. Under stable conditions, the phenomenon of air cooling from bottom to top (the ocean is cooler than

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the atmosphere) strengthens atmospheric stratification and inhibits vertical movement, resulting in higher wind shear. Conversely, under unstable conditions, the phenomenon of atmospheric heating from the bottom up (the ocean is hotter than the atmosphere) promotes convection and exchange of vertical momentum, resulting in lower wind shear [33]. Hence, the study on the spatial-temporal distribution of wind resource under the influence of atmospheric stability can improve the accuracy of offshore wind resource distribution assessment in selected regions [34].

TABLE V: *WPD* under different atmospheric stabilities

		WF1	WF2	WF3	WF4
Annual (W/m^2)	10m	126	245	238	59
	50m	178	298	387	149
	100m	241	382	536	212
Stable (W/m^2)	10m	65	99	188	60
	50m	76	196	342	155
	100m	97	247	490	245
Neutral (W/m^2)	10m	125	202	378	151
	50m	227	382	767	482
	100m	279	556	1170	785
Unstable (W/m^2)	10m	93	256	259	55
	50m	101	302	318	132
	100m	143	353	357	209
NSO		62.27%	2.62%	14.34%	1.14%

Like wind speed and wind shear, atmospheric stability is also a vital characteristic relevant to wind energy research, significantly impacting wind turbines' aerodynamic and power performance [35]. However, many current studies assume that the atmosphere always keeps neutral, which would limit the further increase in the accuracy of offshore wind resource assessment. The paper has quantitatively considered the influence of atmospheric stability on wind resource distribution in the process of offshore wind resource assessment.

Firstly, CFSv-2 reanalysis heat flux data was applied to calculate Monin-Obukhov length according to Eq.(4), and the atmospheric stability was classified based on classification criteria in Table II. Based on the above classification method, the moments with the same atmospheric stability were selected, and Eq.(1) was used to calculate the *WPD* to characterize the value of the certain atmospheric stability. Annual mean value represents the conventional annual *WPD*. Table V shows mean *WPD* under different atmospheric stabilities and annual mean values of four wind farms. As shown in Table V, when the *WPD* under different atmospheric conditions is separately calculated, the neutral state reflects the property with the highest value. The more significant the proportion of neutral state is, the more outstanding the contribution to *WPD* is. In both stable and unstable conditions, *WPD* at 100m of WF1 is below 150 W/m^2, but thanks to the large neutral proportion, the annual mean *WPD* is greater than that of WF4. Therefore, in the comprehensive offshore wind resource assessment, *NSO* has been taken as a parameter to consider atmospheric stability.

In addition, we suggest that at least two heights of temperature should be measured in the wind measurement process, for measured data would be more accurate in calculating atmospheric stability index to consider the effect of atmospheric stability in the wind resource assessment.

B. Diurnal variation of wind speed from different data sources

The diurnal variation of mean wind speed and mean WPD from various data sources (measured data at different heights, 100m MERRA-2 reanalysis data, and 100m CFSv-2 reanalysis data) have been shown in Fig.5 and Fig.6. Correlation coefficients between reanalysis data and measured data have been shown in Table VI, where M-M and C-M represents the correlation coefficient between MERRA-2 and CFSv-2 reanalysis data and measured data, respectively. This paper has calculated Kendall, Spearman and Pearson correlation coefficient. Compared with onshore wind resource, offshore wind resource have no evident diurnal variation trend of "wind is lighter at noon and stronger at night" according to diurnal variation of measured data, especially in WF1, WF2 and WF4. There appears to be little difference in mean wind speed at different heights at the same time, the same as the difference of mean wind speed at the same height at different times, which reflects the stable and low-shear characteristics of the offshore wind resource.

TABLE VI: Correlation coefficient between reanalysis data and measured data

	Kendall		Spearman		Pearson	
	M-M	C-M	M-M	C-M	M-M	C-M
WF1	0.327	0.335	0.464	0.477	0.473	0.495
WF2	0.394	0.470	0.559	0.650	0.586	0.666
WF3	0.643	0.320	0.824	0.378	0.827	0.410
WF4	0.506	0.342	0.677	0.493	0.703	0.515

According to the comparison results of data sources, the absolute error between measured data and MERRA-2 reanalysis data ranges from 0.16 m/s to 1.15 m/s in four wind farms, and MERRA-2 reanalysis data would overestimate the mean wind speed and mean WPD except for WF3. The absolute error between measured data and CFSv-2 reanalysis data ranges from 0.13m/s to 1.30m/s in four wind farms. The error range of MERRA-2 reanalysis data in the diurnal variation scale is minor than CFSv-2 reanalysis data. The minimum error occurred around noon when the intense atmospheric activity resulted in little wind speed difference of different heights. Therefore, data interpolation via the high correlation

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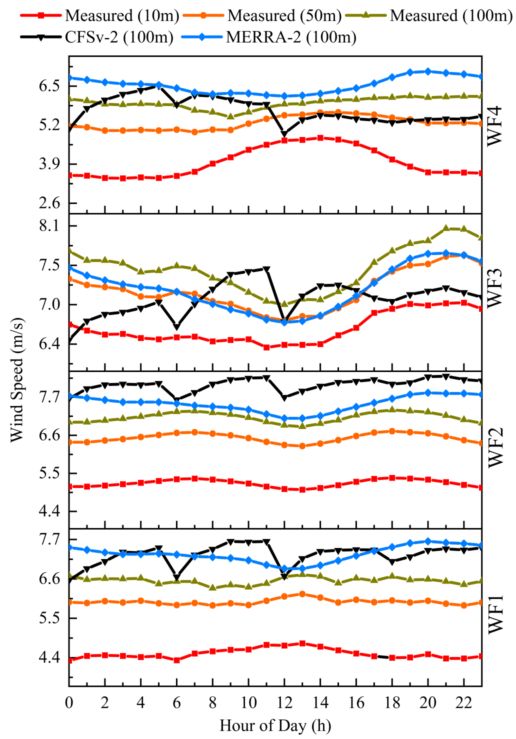

Fig. 5: Diurnal variation of wind speed of different data sources

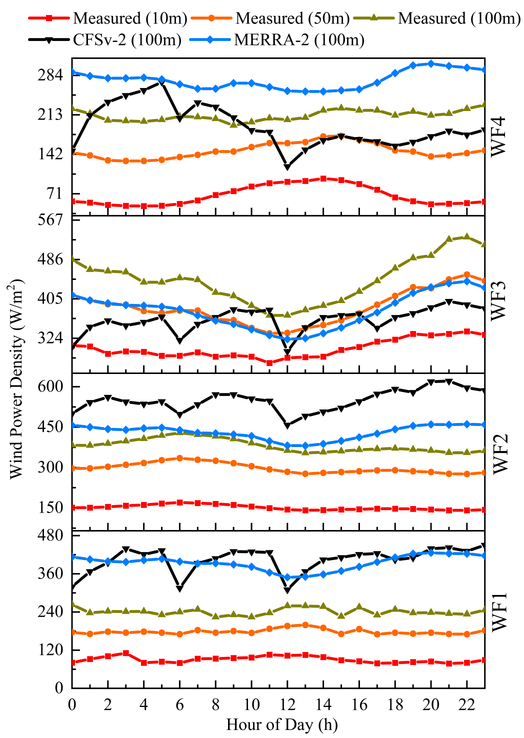

Fig. 6: Diurnal variation of wind power density of different data sources

reanalysis data of this period is feasible in the case of lack the measured data; The maximum error occurs at 21:00-23:00 and uses the reanalysis data of this period to interpolate the measured data may bring a significant error. Kendall correlation coefficient of M-M in WF1 and C-M in WF3 is only 0.327 and 0.320, respectively, which shows the low coefficient. Generally speaking, it is not advisable to rely too much on reanalysis data in practical application. Directly applying reanalysis data for wind resource assessment in some offshore wind farms lacking in measured data may lead to deviation of assessment results from the actual situation.

IV. The Proposed Offshore Wind Resource Assessment Method

A. Normalized important indexes

The proposed assessment method of offshore wind resource involves multi-dimensional evaluation indexes. The dimension and attribute of each index are not the same, making it difficult to compare and analyze directly. In this paper, the min-max normalization method shown in Eq.(5) and Eq.(6) is adopted to ze the indica-tors:

(1) In matrix $\boldsymbol{X}$, for a positive index:

$$y_{ij} = \frac{x_{ij} - \min\limits_{1\le i\le m} x_{ij}}{\max\limits_{1\le i\le m} x_{ij} - \min\limits_{1\le i\le m} x_{ij}}, (1 \le i \le m, 1 \le j \le n) \quad (5)$$

(2) In matrix $\boldsymbol{X}$, for a negative index:

$$y_{ij} = \frac{\max\limits_{1\le i\le m} x_{ij} - x_{ij}}{\max\limits_{1\le i\le m} x_{ij} - \min\limits_{1\le i\le m} x_{ij}}, (1 \le i \le m, 1 \le j \le n) \quad (6)$$

Where m and n denoted number of criteria $(j = 1, 2, \ldots, n)$ and alternatives $(i = 1, 2, \ldots, m)$. x_{ij} is the initial value, y_{ij} is the normalized value. The output target values are in the interval , and the negative indicators are processed positive after normalization.

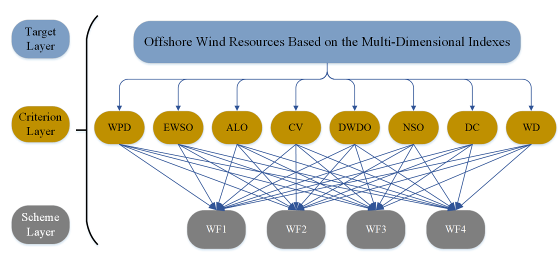

Fig. 7: The offshore wind resource assessment method.

B. AHP Method

Analytic Hierarchy Process (AHP) is a multi-objective decision analysis method combining qualitative and quantitative approaches to determine the weight of multiple indexes. It provides a rational framework for a

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needed decision by quantifying its criteria and alternative options, and for relating those elements to the overall goal. This paper has constructed an 8-order decision matrix based on eight evaluation indexes, i.e., *WPD*, *EWSO*, *ALO*, *CV*, *DWDO*, *NSO*, *DC*, and *WD*. The construction principle of the decision matrix is pairwise comparison, which can be expressed as:

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \ddots & a_{nn} \end{bmatrix} \tag{7}$$

Where $\boldsymbol{A}$ is a decision matrix, which is a standard reciprocal matrix.

In our AHP analysis, we used the Pairwise Comparison method to obtain decision matrix A. The intensity of importance has been indicated pairwise comparisons between evaluation indexes, which is range from 1 to 9. In this paper, Satty's [36] value criterion has been adopted in the pair comparison. The intensity of importance has been chosen by experts' judgement, and the process is accomplished by building the decision matrix, which has equal rows and columns. Finally, the decision matrix $\boldsymbol{A}$ is consistent with Mahdy's [23] result in trend of the same indexes. Table VIII shows the decision matrix $\boldsymbol{A}$ obtained in this paper.

The weight of each index can be calculated based on the decision matrix. In this paper, the root method is used to solve it, and it is expressed as:

$$\overline{w_j} = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \tag{8}$$

$$w_j = \frac{\overline{w_j}}{\sum_{j=1}^{n} \overline{w_j}} \tag{9}$$

Where w_j is weight of j^{th} criterion. However, the increase in the number of evaluation indexes would inevitably increase the complexity of the decision problem, so it is necessary to conduct a consistency test on the decision matrix to ensure the consistency of decision-making. The calculation principle of consistency indexes are as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{10}$$

$$CR = \frac{CI}{RI} \tag{11}$$

Where *CI* is consistency index, $\lambda_{\max}$ is a maximum eigenvalue, n is the order of decision matrix, *CR* is consistency ratio, *CI* is mean random consistency index and its value under different orders has been given in Table VII. The weight distribution of indexes obtained in this paper is shown in Table IX.

The final stage is to calculate *CR* to measure how consistent the judgements have been relative to large samples of purely random judgements. If *CR* is much in exceed of 0.1 the judgement are untrustworthy because they are too close for comfort to minimum number of judgements after which the rest can be calculated to enforce a perhaps unrealistically perfect consistency. [36], [37]. Finally, *CR* of decision matrix is 0.078, less than 0.1, indicating that the decision matrix meets the consistency test and the weight obtained by calculation is consistent.

Taking four offshore wind farms as examples, the proposed offshore wind resource assessment method is shown in Fig.7:

The proposed assessment method of offshore wind resource based on multi-dimensional indexes was finally expressed by score values (*SV*), which is shown as follows:

$$\begin{aligned} SV &= 0.241WPD + 0.152EWSO + 0.111ALO \\ &\quad + 0.121CV + 0.123DWDO + 0.079NSO \\ &\quad + 0.071DC + 0.103WD \end{aligned} \tag{12}$$

C. WASPAS Method

The WASPAS method was developed to solve MCDM problems in 2012 [38].The steps of the WASPAS method are listed as follows:

Step 1: The values of decision matrix are normalized by Eq.(5) and Eq.(6).

Step 2: The weighted sum (*WS*) (ϕ_i) and weighted product (*WP*) measures (ψ_i) for each offshore wind resource are expressed as follows:

$$\phi_i = \sum_{j=1}^{n} w_j y_{ij}, \tag{13}$$

and

$$\psi_i = \prod_{j=1}^{n} (y_{ij})^{w_j}. \tag{14}$$

where y_{ij} denotes the normalized value, w_j is weight of j^{th} criterion.

Step 3: The aggregated measure of *WS* and *WP* is obtained by:

$$\varpi_i = \gamma\phi_i + (1-\gamma)\psi_i, \tag{15}$$

where the parameter of the WASPAS method is defined as γ, which is the set of numbers between 0 and 1. If $\gamma = 1$, the WASPAS method is transformed into *WS*, whereas γ leads to *WP*.

Step 4: The alternatives are ranked in decreasing order using the values of ϖ_i.

D. MAIRCA Method

Multi-Attribute Ideal Real Comparative Analysis (MAIRCA) is one of the MCDM methods introduced by Pamucar et al. [39]. They presented that this method is stable compared to other popular MCDM methods such as TOPSIS or ELECTRE. It uses a simple mathematical algorithm and provides the possibility to combine it with other methods. It is also easy to develop [39].

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TABLE VII: Average random consistency index under different orders

Order	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

TABLE VIII: Decision matrix of proposed evaluation index system

Index	I1	I2	I3	I4	I5	I6	I7	I8
WPD(I1)	1	3	3	8	6	4	6	3
EWSO(I2)	1/3	1	1/2	2	4	1/3	1/3	2
ALO(I3)	1/3	2	1	2	2	2	1/3	2
CV(I4)	1/4	1/2	1/2	1	3	1/4	1/3	1/2
DWDO(I5)	1/6	1/4	1/2	1/3	1	1/3	1/3	1/2
NSO(I6)	1/4	3	1/2	2	3	1	1/3	1/2
DC(I7)	1/6	3	3	3	3	3	1	3
WD(I8)	1/3	1/2	1/2	2	2	2	1/3	1

TABLE IX: The weight distribution of indexes of the proposed assessment of offshore wind resources

Index	Eigenvector	Weight	$\lambda_{\max}$	*CI*
WPD(I1)	2.060	24.06%	8.765	0.109
EWSO(I2)	1.297	15.15%		
ALO(I3)	0.951	11.11%		
CV(I4)	1.037	12.11%		
DWDO(I5)	1.052	12.29%		
NSO(I6)	0.672	7.85%		
DC(I7)	0.607	7.10%		
WD(I8)	0.885	10.33%		

The steps of the MAIRCA method are as follows [40]:

Step 1. The first step in the MAIRCA method is the same as AHP and WASPAS methods.

Step 2. Determining the preferences according to the selection of alternatives Ω_{A_i}.

$$\Omega_{A_i} = \frac{1}{l}; \quad \sum_{i=1}^{m} \Omega_{A_i} = 1, \quad i = 1, 2, \ldots, l \tag{16}$$

where m represents the number of alternatives.

Step 3. Calculating the theoretical evaluation matrix elements $\boldsymbol{R_A}$. This matrix $\boldsymbol{R_A}$ is created in $l \times n$ matrix (l represents the number of alternatives, and n represents the number of criteria).

$$R_{A_{ij}} = \Omega_{A_i} w_j \tag{17}$$

Step 4. Calculating the real evaluation matrix $\boldsymbol{R_p}$.

$$R_{p_{ij}} = y_{ij} R_{A_{ij}} \tag{18}$$

where $\boldsymbol{y_{ij}}$ denotes the normalized decision matrix.

Step 5. Computing the total gap matrix $\boldsymbol{T}$.

$$T_{ij} = R_{p_{ij}} - R_{A_{ij}} \tag{19}$$

Step 6. Computing the final values of the alternatives (ω) in terms of criteria.

$$\omega_i = \sum_{i=1}^{m} T_i \tag{20}$$

Step 7. The alternatives are ranked with the help of ω_i. Among the alternatives, the minimum value of "ω_i" is chosen as the best alternative.

E. Case study

1) Results of the offshore wind resource assessment for four wind farms: The multi-dimensional evaluation indexes of the four offshore wind farms were calculated respectively and shown in Table X. The normalized values according to Eq.(5)and Eq.(6) of each wind farm were obtained according to the method proposed in this paper, as shown in Fig.8.

TABLE X: Offshore assessment indexes of 4 offshore wind farms

Index	WF1	WF2	WF3	WF4
WPD(W/m2)	241	431	536	212
EWSO(%)	97.13	91.52	91.82	90.84
ALO(%)	39.02	53.49	53.62	30.90
CV(-)	1.189	1.352	0.977	1.119
DWDO(%)	8.85	11.05	10.82	11.26
NSO(%)	62.27	2.63	14.33	1.14
DC(km)	25	20	36	0
WD(m)	15	18	11	0

The finally *SV* of the four wind farms obtained by the method in this paper are WF1: 0.383, WF2: 0.435, WF3: 0.654, WF4: 0.372, respectively. Considering the evaluation results of multi-dimensional indexes, WF3 has the highest *SV*, followed by WF2. The *SV* of WF1 and WF4 are very similar to each other, and WF1 is slightly higher. Judging from the mean wind speed and mean wind power density, WF2 and WF3 almost have the same offshore wind resource grade, according to the traditional wind resource evaluation method. In contrast, the difference of resource between the two wind farms

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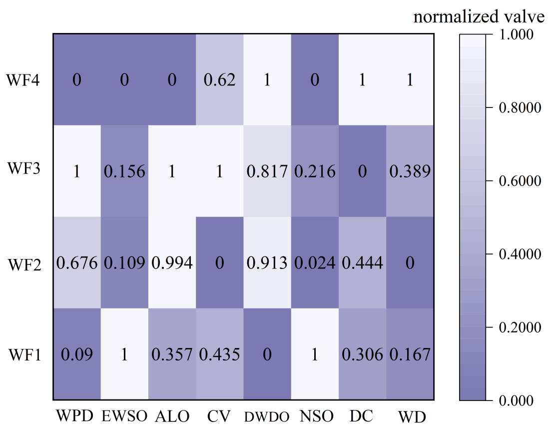

Fig. 8: Normalized assessment indexes of 4 offshore wind farms.

would appear when the multi-dimensional indexes are taken into account.

2) Verification of calculation results:

(1) Verification by annual energy production (*AEP*) of offshore wind turbines

Five different offshore wind turbines have been selected to evaluate the *AEP* in four offshore wind farms to test the practicability and reliability of the proposed method. Fig.9 shows the theoretical power curves of each offshore wind turbine.

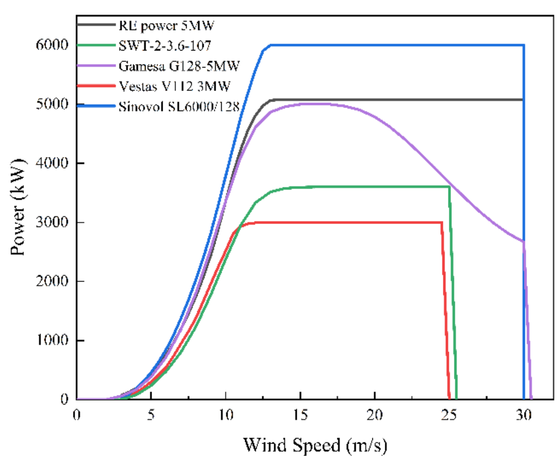

Fig. 9: Power curves of offshore wind turbines

Table XI shows the calculation results of *AEP* obtained by different wind turbines. Comparing the result, the maximum *AEP* appears in WF3, followed by WF2, and WF4 has the minimum value. In terms of output, the *AEP* of selected offshore wind turbines in WF3 is more than 1.5 times that of WF4, and there is not much difference between WF1 and WF4 wind farms. From the theoretical calculation perspective, the results are consistent with the ranking results of *SV* obtained in this paper.

TABLE XI: Annual energy production of different offshore wind turbines (GWh)

	WF1	WF2	WF3	WF4
RE power-5MW	8.343	10.394	12.322	6.954
SWT-3.6-107	5.264	7.030	8.380	4.360
Gamesa G128-5MW	7.717	10.079	11.979	6.381
Vestas V112-3MW	6.433	7.422	8.713	5.252
Sinovol SL6000/128	8.469	10.585	12.718	7.053
Rank	3	2	1	4

(2) Verification by practical *AEP* of four offshore wind farms

In addition to the theoretical calculation results, this paper uses the practical operating data of four wind farms to compare and verify the proposed assessment method based on multi-dimensional indexes. Table XII shows the practical *AEP* of four wind farms. As can be seen from Table XII, WF3 has the highest practical full power output hours and capacity coefficient, followed by WF2. WF4 has the lowest practical full power output hours 2084h, and only 108 hours less than WF1.

TABLE XII: Annual energy production of different offshore wind farms

	WF1	WF2	WF3	WF4
Installed capacity(MW)	150	300	200	100
Practical *AEP*(GWh)	328.77	888.22	711.78	208.45
Full power output hours(h)	2192	2960	3559	2084
Capacity coefficient	0.250	0.338	0.406	0.238
Rank	3	2	1	4

As the reasonable utilization hours of offshore wind power in the whole life cycle are 52000h and the life cycle is 25 years, the reasonable full power output hours are 2080h, which is very close to WF4. Therefore, the better economic benefits be obtained when the *SV* of the offshore wind resource is above 0.37. To sum up, the proposed assessment method with multi-dimensional indexes can comprehensively and effectively evaluate offshore wind resource. The technique can also be applied to micro-siting to reduce the uncertainty of wind resource assessment in offshore wind power projects' planning and designing stage.

F. Comparative Analysis

1) Method analysis: In order to test the rationality and effectiveness of the proposed approach, the ranking results are compared with WASPAS and MAIRCA methods. The comparative analysis is given in Table XIII and shown in Fig. 10. It can be seen that WF3 is the best alternative, while WF4 is the worst alternative, which indicates that the results of the three methods are consistent. However, the calculation process of the proposed method is more concise and easy to obtain.

The results showed that the ranking results of the AHP model is consistent. it uses pairwise comparison

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questions to reveal a judgment matrix of relative preference between each pair of alternatives in terms each criterion. AHP takes into account the relative priorities of alternatives in terms of criteria. Since the number of criteria and alternatives is low, the consistency rate is high and gives successful results.

TABLE XIII: Comparative analysis with other exisitng WASPAS and MAIRCA methods.

	Proposed Method		WASPAS		MAIRCA	
	SV	Rank	ϖ_i	Rank	ω_i	Rank
WF1	0.383	3	0.191	3	-0.346	3
WF2	0.435	2	0.218	2	-0.359	2
WF3	0.654	1	0.327	1	-0.413	1
WF4	0.372	4	0.186	4	-0.343	4

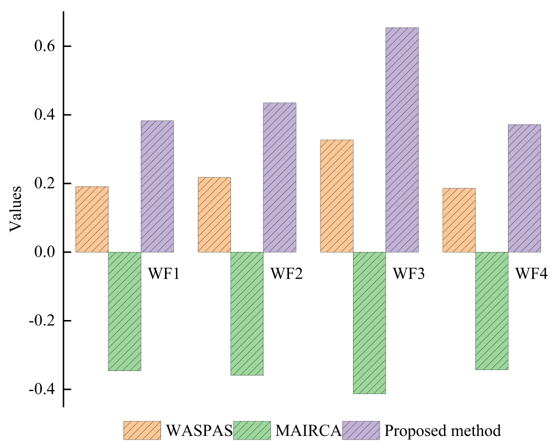

Fig. 10: The results of proposed models.

2) Evaluation index analysis: The paper has also compared the proposed indexes system with the existing indexes to test the superiority and practicality of the proposed method. when the existing evaluation indexes, including *WPD*, *DWDO*, *DC*, and *WD* have been considered in the process of offshore wind resource assessment, the expression of *SV* is as follows according to the AHP method: $SV = 0.516WPD + 0.062DWDO + 0.187DC + 0.235WD$. Table XIV shows the evaluation ranking result.

TABLE XIV: Comparative analysis with the existing evaluation indexes

	SV	Rank
WF1	0.143	4
WF2	0.489	2
WF3	0.658	1
WF4	0.484	3

As shown in Table XIV, the ranking result is different from the actual running result in Table XII. In the case study of this paper, the final assessment results of WF1 and WF4 are very close to each other. However, small differences are easily identified by the indexes system and method proposed in this paper while the conventional evaluation indexes would cause the evaluation errors, which further validates the effectiveness of the proposed method.

V. Conclusions

MW-level offshore wind farm development projects are highly interdisciplinary tasks such as technical, economic, social and political aspects to be considered as decision-making or decision-support process. Especially technical parameters such as wind speed, wind power and related parameters plays a primary role to make feasible investment decisions for large-scale offshore wind projects. High precision offshore wind resource assessment is the key to improve the core competitiveness of offshore wind power. Considering the offshore wind resource index scientifically and comprehensively is very important for the planning and designing of offshore wind power and the safe operation of the power grid. The paper mainly focuses on a practical and robust offshore wind resource assessment method. Specifically, the measured data, operating data, and different sources of reanalysis data have been utilized to analyze the influence of data sources on wind resource assessment. Then based on the multi-dimensional indexes reflecting resource reserves, stability, and construction conditions, the offshore resource assessment method has been proposed, verified in four offshore wind farms from different perspectives. Some conclusions and discussions have been obtained as follows:

1) The diurnal variation characteristics of offshore wind resource are not as evident as that onshore situation. In detail, mean wind speed variation at different moments is slight, and in addition, mean wind speed variation at different heights is also tiny. Offshore wind resource reveals a lower wind shear exponent and shows the relatively stable characteristic.

2) The accuracy of reanalysis data is limited. In this paper's cases, the maximum error between the measured and reanalysis data appears around noon, while the minimum usually occurs at night. The error range is 0.13m/s to 1.30m/s, reflecting that reanalysis data could not be directly applied to offshore wind resource assessment to avoid the significant valuation error caused by data sources itself and bringing poor wind farm economic performances eventually.

3) The spatial and temporal distribution of atmospheric stability would affect the allocation of offshore wind resource. Compared with the stable and unstable atmosphere, a neutral atmosphere reflects a higher mean wind power density. The paper has considered the influence of atmospheric stability by terms of neutral state occurrence to make up for the engineering application error caused by ignoring the influence of atmospheric stability.

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4) The proposed offshore wind resource assessment method based on multi-dimensional indexes, including wind power density, effective wind speed occurrence, affluent level occurrence, coefficient of variation, dominant wind direction occurrence, neutral state occurrence, distance to coast, and water depth, has been proposed in this paper. The score values of offshore wind farms above 0.37 is more likely to obtain acceptable economic benefits, providing a reference for the practical application of offshore wind resource assessment projects.

Since this study did not consider various economical, social, environmental and sociology-political criteria, the future related-work may be included as extension of the demonstrated framework.

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