Weight-Embedded Fuzzy FMEA Framework for Enhanced Risk Prioritization of Offshore Wind Turbines

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Abstract: With the rapid expansion of offshore wind power, wind turbines are increasingly exposed to complex environmental conditions and operational uncertainties. To ensure long-term operational reliability, this paper proposes an enhanced Failure Mode and Effect Analysis (FMEA) framework integrating Fuzzy Analytic Hierarchy Process (FAHP) with a Mamdani-based fuzzy inference system for risk assessment of offshore wind turbines. The proposed framework aims to simultaneously address the key shortcomings of conventional FMEA in risk assessment of offshore wind turbine, particularly the neglect of expert evaluation fuzziness, inefficient fuzzy rule generation, and inadequate risk classification. The main contributions of this method are as follows. First, FAHP-derived consensus weights for risk factors (Severity, Occurrence, Detection) are embedded into fuzzy rules. Second, risk level distribution matrices automate rule generation, ultimately improving efficiency by a factor of 40 compared to traditional multi-expert integration. Third, risk prioritization (risk value) and classification are conducted through defuzzification, enabling the implementation of differentiated operation and maintenance (O&M) strategies. The framework is validated using operational data from an 80-turbine offshore wind farm in China, where critical failure modes (e.g., generator overheating, r = 0.786) are successfully identified. A comparative analysis with Weighted FMEA confirmed the framework's effectiveness in preserving fuzzy information and enhancing risk ranking accuracy.

Keywords: Risk analysis; Failure mode and Effect Analysis; offshore wind turbine; Fuzzy inference system; Fuzzy Analytic Hierarchy Process

1. Introduction

Currently, the worldwide demand for power is rising, and wind energy, as a clean renewable resource, is considered as an effective way to meet this escalating demand.[Error! Reference source not found.]. Offshore wind power, characterized by its ample wind energy supplies and reduced land utilization, presents significant application potential compared to onshore wind power[Error! Reference source not found.].According to the 2024 Global Wind Power Express, the offshore wind sector added 10.8 GW of new capacity in 2023, bringing the global cumulative total to 75.2 GW[Error! Reference source not found.]. Nonetheless, offshore wind turbines are constantly exposed to harsh marine environments such as tides, storms, salt spray corrosion, and high temperatures, which can cause degradation or even failure of critical turbine components, potentially leading to power generation lossesError! Reference source not found.. Moreover, Offshore wind power operation and maintenance (O&M) is significantly constrained by various factors, including weather conditions, sea states, transportation availability, and personnel scheduling. In particular, under harsh marine environments, maintenance windows are short, operational time is limited, and O&M vessels often cannot arrive promptly. These restrictions lead to significantly higher O&M expenditures and longer fault response cycles. Consequently, conducting risk analysis on turbine components is essential to identify and assess potential failure modes, thereby providing decision support for the O&M measures and strategies of offshore wind farms and ensuring component reliability and operational safety.

Thus far, risk analysis of offshore turbines has been conducted using techniques such as Fault Tree Analysis (FTA), Failure Mode and Effects Analysis (FMEA), Failure Mode Effects and Criticality Analysis (FMECA), and Two-stage FMEA[5]Error! Reference source not found.[7]. Owing to its ease of construction and understanding, FMEA has emerged as predominant tools for conducting risk assessments on offshore wind turbine. As a widely recognized bottom-up, structured semi-quantitative risk assessment methodology, FMEA identifies potential failure modes of each component within a system and calculates the Risk Priority Number (RPN) to support risk-based ranking and prioritization of these failure modes[8][9]. The RPN is systematically determined through a rigorous evaluation process where experts assign scores to three risk factors: severity (S), occurrence (O), and detection (D). Each of these factors is typically evaluated and rated on a scale ranging from 1 to 10, with the RPN being the product of these scores[10]. Up to now, with regard to the application of FMEA in Offshore Wind Turbines, Arabian-Hoseynabadi et al.[11] pioneered the application of FMEA in the reliability analysis of offshore wind turbines, concluding that material failure is the most critical failure mode. Kang et al.[12] employed the FMEA to identify the failure modes with higher RPNs in floating offshore wind turbines. Sinha et al.[13] analyzed 36 failure modes of offshore wind turbine gearboxes using the FMEA method.

Despite advancements in applying FMEA for the risk assessment of offshore wind turbines, the current literature highlights several intrinsic limitations of conventional FMEA that must be acknowledged[14]. (1) The relative significance of risk factors is not taken into consideration. (2) The process of assigning accurate scores to risk factors may bring about the loss of experts' uncertain information. (3) The RPN is sensitive to variations in the scores, and different combinations of risk factor values may result in identical RPN, thereby posing a risk of misleading or inaccurate prioritization outcomes. To overcome the inherent limitations of the traditional FMEA method, Sharifi et al.[15] applied the FMEA to investigate the new product development process of a dairy company, integrating the Shannon Entropy method with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to assign weights and rank the associated risks. Başaran et al.[16] proposed an enhanced method that combines the Fuzzy Analytic Hierarchy Process (FAHP) with Grey Relational Analysis (GRA) to rank the risks associated with mobile learning platforms.

The aforementioned models have achieved notable improvements over the traditional FMEA approach, particularly in addressing limitations (1) and (3). However, limitation (2) has not been adequately considered. Experts frequently encounter uncertainty and ambiguity when evaluating risk factors, and when assessments rely on precise values, such fuzzy and uncertain evaluation information is disregarded. Consequently, the risk assessment may lack a sufficient foundation for informed decision-making. In response to the limitation, Li et al.[17] provided explicit definitions and probability ranges for each risk factor index (rated from 1 to 10), and proposed a relative-weight method to process the input scores in order to reduce the result uncertainty. However, such probability data are often difficult to obtain, and the computational complexity of this method increases exponentially with the number of failure modes. Yu et al.[18] employed a cloud model to handle the uncertainty in expert opinions as well as the fuzziness and randomness in the assessment data. However, the cloud model is inherently designed to describe the fuzziness and uncertainty of a single concept, making it difficult to capture the complex interactions among multiple input risk factors. In contrast, mature fuzzy linguistic and fuzzy mathematics methods, with their rule-based explicit relational modeling and interpretable reasoning mechanisms, outperform cloud models in terms of semantic interaction representation and dynamic decision support. Such methods are thus more suitable for multidimensional risk analysis scenarios such as FMEA. To date, Li et al.[19]have applied a fuzzy inference system in the safety risk assessment of water diversion infrastructure, enabling the fuzzification of risk factor scores and nonlinear risk computation. In this model, fuzzy rules are employed to characterize the causal relationships between varying combinations of risk factor levels and the corresponding risk levels of failure modes, serving as a crucial link between the system inputs and outputs. They have developed fuzzy rules based on the knowledge and experience of domain experts, and afterwards integrated the rules proposed by different experts to construct a fuzzy rule base that reflects multiple perspectives. However, when the number of experts is large and rule base itself contains numerous rules, the total number of collected rules can reach several hundreds or even thousands, culminating in low integration efficiency and time-consuming processing. Hu[20] proposed a rule simplification methodology; however, it relies on the unrealistic assumption of uniform importance across all risk factors, whereas in practice, different factors have varying degrees of impact on risk. Consequently, this simplification approach lacks practical applicability.

Overall, the motives for this paper's research on risk assessment methods for offshore wind turbines can be summarized as follows: Firstly, how to effectively preserve the fuzzy and uncertain information inherent in expert evaluations, which is often overlooked by conventional precise scoring. Secondly, improving the efficiency of fuzzy rule generation, particularly when dealing with large-scale rule bases, warrants further investigation. Thirdly, the development of rational O&M strategies that account for the limited accessibility and short maintenance windows of offshore wind farms—beyond risk-based prioritization—is essential for improving O&M efficiency.

In conclusion, this paper proposes an improved FMEA framework for the risk assessment of offshore wind turbines, providing a novel solution to current challenges.

Table 1 illustrates the comparison of existing literature with our paper, and the contributions of this study can be summarized as follows:

(1) The FAHP is employed to determine the consensus weights of risk factors, aiming to compress the experts' overall risk perception into three core parameters (the weights of S, O, and D) rather than hundreds of fuzzy rules.

(2) Based on the established consensus risk factor weights and risk factor level parameters, a risk index(*I*) is built and grading standards are developed. This process leads to the formulation of risk level distribution matrix that captures various combinations of risk factor levels. Ultimately, fuzzy rules integrating the perspectives of multiple experts are generated.

(3) A fuzzy inference system is applied to process expert evaluations, performing fuzzy inference based on predefined fuzzy rules. The defuzzified risk value (*r)* for each failure mode is then obtained to support risk prioritization. Next, the membership degrees for each failure mode are computed, facilitating the assignment of a discrete risk grade. This classification directly informs the selection of appropriate O&M strategies.

The remaining main content of this paper is as follows: In Section 2, we introduce the framework of this paper and the methods we have mentioned. In Section 3 we use the improved framework in the risk analysis of the offshore wind turbines. A discussion and a summary of the paper are presented in Sections 4 and 5, respectively.

Table 1 Literature comparison

Dimension \ Literature	[15]	[16]	[17]	[18]	[19]	Our paper
Limitation (1)	√	√	√	√		√
Limitation (2)			√	√ (Poor in revealing the interaction of risk factors)	√ (Revealing the interaction of risk factors but poor in generation of fuzzy rules)	√ (Revealing the interaction of risk factors and enhancing the efficiency of generating fuzzy rules)
Limitation (3)	√	√	√	√	√	√
Risk grade classification						√

2. Proposed approaches

2.1 A novel approach framework

To overcome the limitations of the present FMEA method in offshore wind turbine risk analysis, this paper proposes a fuzzy FMEA framework based on a risk level distribution matrix. The key steps in the framework are outlined as follows. Following the identification of failure modes in offshore wind turbine components and the assessment of associated risk factors, experts are initially engaged to evaluate the relative significance of risk factors through pairwise comparisons. The FAHP is then employed to represent the pairwise comparison results in the form of triangular fuzzy numbers, from which consensus weights for the risk factors are derived. Thereafter, a parameter I is defined, integrating both the risk factor level parameters and their corresponding weights. Based on I, create risk level distribution matrices with multiple combinations of risk factor levels to generate fuzzy rules. Finally, the risk factor scores are input into the fuzzy inference system, which processes them through fuzzification, fuzzy inference, and defuzzification to output r. Grounded in r, the precise risk level degree of membership is determined, enabling the final risk ranking and classification of failure modes. The proposed framework is illustrated in Fig. 1.

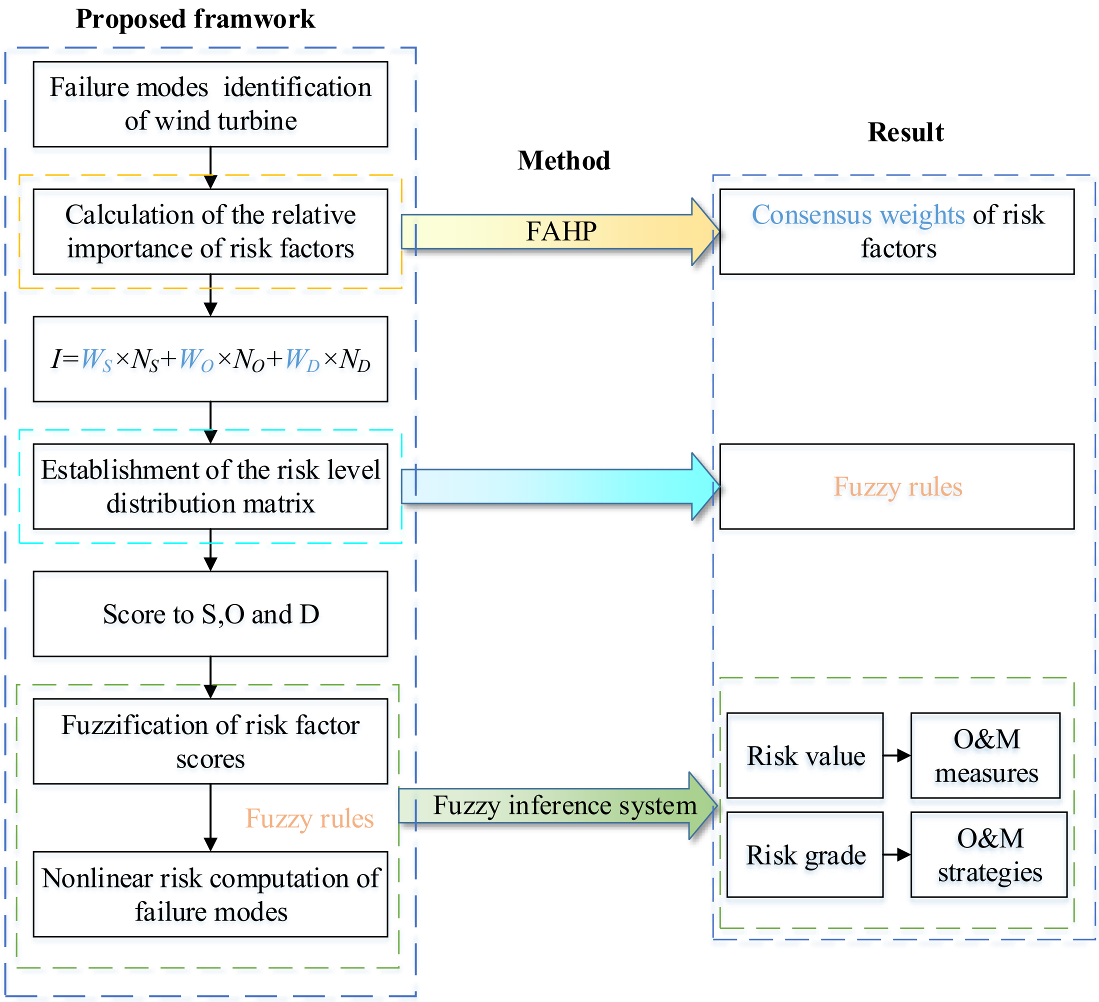


Fig. 1. Improved FMEA framework diagram

2.1.1 Methods for determining the weights of risk factors

As an extension of the AHP, the FAHP is a systematic method that integrates fuzzy set theory with hierarchical analysis[21]. Compared to traditional AHP, FAHP more accurately reflects human cognitive processes and is more capable of handling the uncertainty involved in mapping subjective perceptions of decision-makers into precise numerical values[22].This section adopts the FAHP proposed by Zeng et al.[23]to determine the weights of risk factors. In this method, experts initially employ a predetermined pairwise comparison scale to determine triangular fuzzy numbers representing the relative importance of the risk factors; the pairwise comparison scale is shown in Table 2. Then, the triangular fuzzy numbers are defuzzified, and the weights of the risk factors are calculated accordingly.

2.1.1.1 Determination and defuzzification of Triangular Fuzzy Numbers

Specifically, the triangular fuzzy number is composed of three parameters a, b, and c, denoted as $M\ (a,\ b,\ c)$[24]. In this notation, a represents the minimum possible value, b represents the most likely value, and c represents the maximum possible value.

Table 2 Two-by-two comparison scale

Scale	Define
1	Both are of equal importance
3	General importance
5	Higher importance
7	It's very important.
9	Absolutely important.
2,4,6,8	midpoint

For various applications, such as ranking and comparison, fuzzy numbers frequently need to be converted into crisp numbers. This conversion process is known as defuzzification[25]. In this paper, the geometric mean method is chosen for defuzzification[26]. The defuzzification formulas are listed in Equation (1).

$$P(M)=\frac{(a+4b+c)}{6} \tag{1}$$

After defuzzification, the preliminary pairwise comparison matrix of risk factors $A=(a_{ij})_{3\times3}$ is obtained. A is listed in Equation (2).

$$A=\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \tag{2}$$

2.1.1.2 Calculation of weights

Step 1: Normalized

The matrix is then normalized to obtain the new judgment matrix $B=(b_{ij})_{3\times3}$, with the normalization formula expressed as Equation (3):

$$b_{ij}=\frac{a_{ij}}{\sum_{i=1}^{3} a_{ij}} \tag{3}$$

Step 2: Obtain the weight

After normalization, the weights can be calculated using the formula shown in Equation (4):

$$AW_i=\frac{\sum_{j=1}^{3} b_{ij}}{3} \tag{4}$$

Step 3: Consistency test

The consistency test is conducted to ensure that the consistency of the judgment matrix is within acceptable limits. The Consistency Index (*CI*) serves as the measure for this test, and its formula is presented in Equation (5).

$$CI = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n\text{-}1}} \tag{5}$$

When CI < 0.1, the analysis is consistent and the consistency test is passed. Where $\lambda_{\max}$ is the maximum eigenvalue and n is the dimension of pairwise comparison matrix.

2.1.2 Methods for establishing a risk level distribution matrix

The risk level of a particular failure mode under various combinations of risk factors is displayed in the risk level distribution matrix. Its establishment relies on the weights of the risk factors calculated in section 2.1.1 and ultimately applies in section 2.1.3.

2.1.2.1Definition of the risk index

The S, O, and D are each divided into five levels: VL (Very Low), L (Low), M (Medium), H (High), and VH (Very High), with ascending integer values assigned accordingly. The assignment results of each risk factor are denoted as N_S, N_O, and N_D, respectively. Subsequently, these level parameters are integrated with the corresponding weights of the risk factors to compute the parameter *I*. The calculation method is shown in formula (6), where W_S, W_O, and W_D are the weights of S, O, and D, respectively:

$$I = N_s \times W_s + N_o \times W_o + N_d \times W_d \tag{6}$$

2.1.2.2 The establishment of risk level matrix

To construct the two-dimensional risk-level distribution matrix, this paper first fixes the S to a given level and then computes the *I* for each combination of O and D. This indicator divides failure modes into three risk categories: low, medium, and high. According to existing literature, based on the developed models and failure data collected from both onshore and offshore operators, the failure rate of components in floating offshore wind turbines is approximately 26% higher than that of onshore wind turbines[27]. It is therefore necessary to establish a high detection rate for high-risk scenarios and apply broader rule coverage to high-risk areas, thereby enhancing sensitivity to high risks. Hence, the proportions for low, medium, and high-risk levels are set to 3:3:4.

Accordingly, for each of the five distinct S levels, we constructed a 5×5 two-dimensional risk-level distribution matrix. Each matrix clearly visualizes the risk level of failure modes for every O and D combination under the given risk factor weights, thereby providing the foundation for the generation of fuzzy rules. Within the matrix, low, medium, and high-risk levels are color-coded as green, orange, and red, respectively, to facilitate visual identification and analysis.

2.1.3 Methods for determining the risk value and grade of failure modes

Based on the previous two sections, we will rank and categorize the failure modes. In this section, fuzzy inference system will be used to implement it. The flowchart for this section is shown in Fig. 2.

Fig. 2. Flowchart for Deriving Risk Value and Risk grade

2.1.3.1 Fuzzification

Within this model, four key linguistic variables are defined: S, O, D, and Risk grade (R). Prior to fuzzy inference, these variables are partitioned into fuzzy sets—a foundational concept in fuzzy inference system[28]. Considering that the scoring range of the risk factors is defined from 1 to 10, the corresponding fuzzy membership sets are constructed based on the principle of equal interval division to enhance the structural clarity of the fuzzy evaluation process. Furthermore, given that offshore wind turbines exhibit higher failure rates compared to their onshore counterparts, the numerical range assigned to the high level of risk fuzzy set is appropriately extended to improve the detectability of high-risk scenarios. The partitioning results are presented in Table 3. The use of fuzzy sets enables the integration of linguistically expressed terms with mathematical models, thereby facilitating the interpretation and processing of knowledge represented in linguistic form.

Table 3 Division of fuzzy sets

Language	Hierarchy	Numerical range
S	Very low impact (S_1)	1≤S<3
	Low impact (S_2)	3≤S<5
	Medium impact (S_3)	5≤S<7
	High impact (S_4)	7≤S<9
	Very high impact (S_5)	9≤S≤10
O	Very low (O_1)	1≤O＜3
	Low (O_2)	3≤O＜5
	Medium (O_3)	5≤O＜7
	High (O_4)	7≤O＜9
	Very high (O_5)	9≤S≤10
D	Very high (D_1)	1≤D＜3
	High (D_2)	3≤D＜5
	Medium (D_3)	5≤D＜7
	Low (D_4)	7≤D＜9
	Very low (D_5)	9≤S≤10
R	Low level of risk (R_1)	0≤R≤0.3
	Medium level of risk (R_2)	0.3＜R≤0.6

	High level of risk (R_3)	$0.6 < R \leq 1$

To preserve the inherent fuzziness and uncertainty in risk factor scores assigned by experts, this paper employs membership functions to fuzzify the scores and determine their degrees of membership across different fuzzy sets. Various types of membership functions are commonly used, including triangular, trapezoidal and Gaussian functions[29]. In this study, the Gaussian membership function is selected for the fuzzification of risk factor scores due to its ability to smoothly represent the probable range of values around the assigned score[30]. The mathematical expression of the Gaussian membership function is provided in Equation (7).

$$f(x,\sigma_{pn},\mu_{pn}) = \exp\left[-\frac{(x-\mu_{pn})^2}{2\sigma_{pn}^{\ 2}}\right] \tag{7}$$

Where σ_{pn} and μ_{pn} are the variance and mean of p when it is at level n, respectively, and the four membership functions are illustrated in Fig. 3.

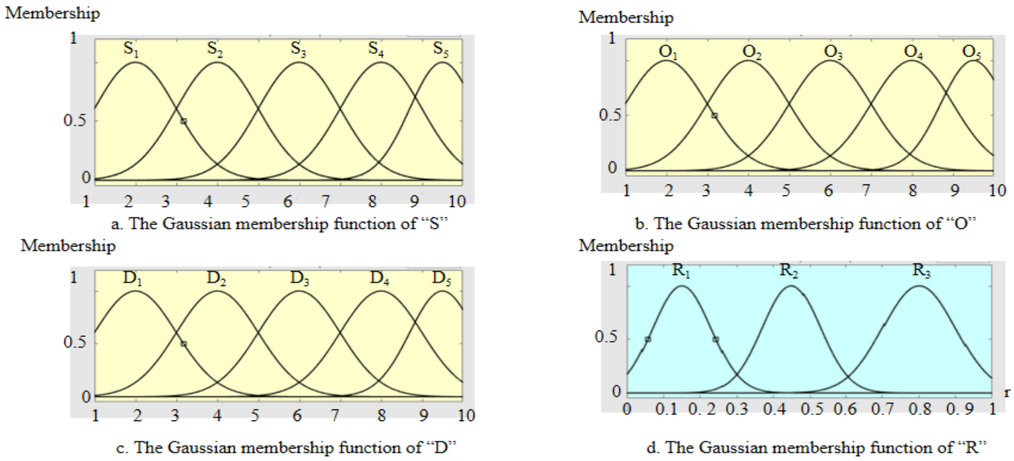


Fig. 3. Gaussian membership function a-d for each variable

2.1.3.2 Fuzzy inference

Fuzzy rules constitute the core components of the fuzzy inference system. These rules utilize linguistic variables of risk factors as antecedents and risk level as the consequent. The fuzzy inference system matches fuzzified input data with the rule antecedents to perform the inference process. The fuzzy rules are derived from the previously established risk level distribution matrix. Since each risk factor is divided into five levels, a total of 5×5×5=125 fuzzy rules are generated, covering all possible combinations of risk factor levels. The complete list of these 125 fuzzy rules is provided in Appendix 1. Each rule follows the standard if-then structure, which is formalized in Equation (8): If the S level is e, the O level is f, and the D level is g, then the risk level of the corresponding failure mode is h.

$$\textit{If } S \text{ is } S_{\mathrm{e}} \text{ and } O \text{ is } O_{\mathrm{f}} \text{ and } D \text{ is } D_{\mathrm{g}}\text{, then } R \text{ is } R_{\mathrm{h}} \tag{8}$$

After inputting the S, O, and D values of the risk factors into the fuzzy inference system for fuzzification, the corresponding fuzzy rules will be activated. To transform qualitative fuzzy rules into quantitative results, the Mamdani algorithm is used here[31].This algorithm aggregates the output fuzzy sets of each rule based on the max-min composition rule, thereby producing the risk level membership function. The formula of the Mamdani algorithm is listed as Equation (9). The inference process is as Fig. 4.

$$\mu_R(r) = \max\{\min \mu_l(S), \mu_l(O), \mu_l(D)\} \tag{9}$$

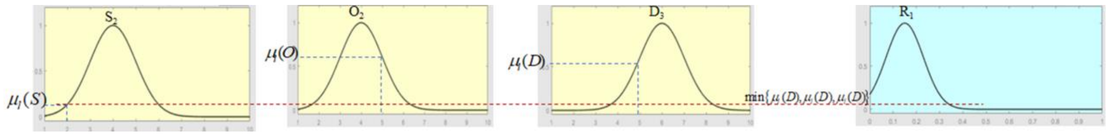


Fig. 4. Demonstration of the fuzzy inference process

In equation (9), $\mu_R(r)$ represents the risk level membership function, and l represents the rule number. $\mu_l(S)$ represents the membership degree of the input S value to a certain S fuzzy set in the l rule. $\mu_l(O)$, $\mu_l(D)$ mean the same as above.

2.1.3.3 Defuzzification

Currently, the principal defuzzification techniques include the centroid method, the mean of maxima, the computation by the center of gravity method, the center of means, and the midpoint of an area procedure[32]. The center of gravity method computes the center of gravity of the aggregated fuzzy set, thereby accounting for both the height and the spread of the output membership function and offering a desirable balance and consistency[33]. Consequently, this paper employs the center of gravity method to defuzzify and obtain r, the formula is presented in Equation (10).

$$\mathrm{r} = \frac{\int \mu_R(\mathrm{r})\ \mathrm{rdr}}{\int \mu_R(\mathrm{r})\ \mathrm{dr}} \tag{10}$$

In MATLAB, the r corresponds to the value determined by the membership function graph. Specifically, it represents the x-coordinate of the centroid of the area enclosed by the membership function curve and the x-axis. This centroid is illustrated as the center of gravity of the blue shape in Fig. 5.

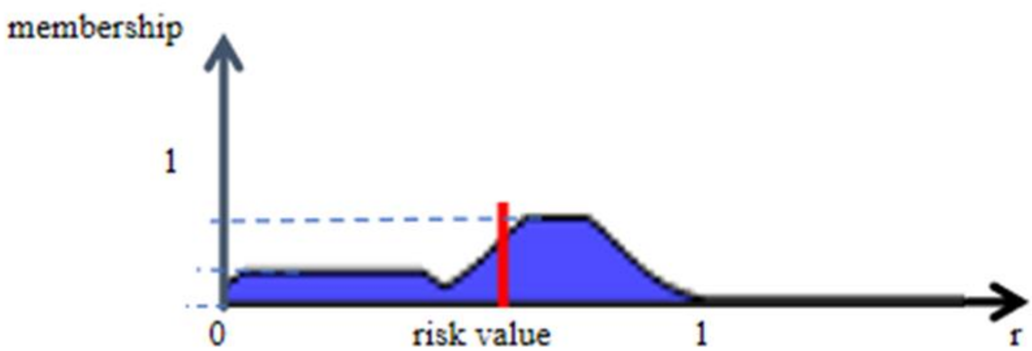


Fig. 5. Demonstration of defuzzification section

2.1.3.4 Risk grade of failure modes

After determining the r of the failure mode, it is substituted into the risk level membership function to calculate the degree of membership for each risk grade. The risk grade corresponding to the highest membership degree is then selected as the final risk classification of the failure mode.

2.2 Related methods in the framework

2.2.1Fuzzy Analytic Hierarchy Process (FAHP)

FAHP, as an extension of AHP, was first proposed by Van Laarhoven and Pedrycz in 1983[34]. Since its introduction, FAHP has been widely used in the field of risk management. For example, Kaewfak et al.[35] used FAHP for Multimodal transportation risk assessment. Spanidis et al.[36] used the FAHP method to determine the likelihood that natural hazards risk will take place in the form of weight factors and sub-factors.

The method comprises three variants: interval FAHP, triangular FAHP, and trapezoidal FAHP, which utilize interval fuzzy numbers, triangular fuzzy numbers, and trapezoidal fuzzy numbers, respectively, to represent the relative importance among the evaluated factors, rather than relying on crisp values as in the traditional AHP method[37].

2.2.2 Mamdani based fuzzy inference system

Fuzzy inference system was proposed by Lotfy Zadeh in 1965 to help address the problem of information fuzziness[38]. Mendel et al.[39] believed that a fuzzy inference system is a nonlinear mapping of input data (feature) vectors to scalar outputs (a decomposition of vector output cases into a collection of mutually independent multiple-input single-output systems). It can simultaneously handle numerical data and linguistic knowledge, cleverly linking the two by processing the degree of membership between them.

Nearly forty years after its conception, fuzzy logic is far less controversial than it used to be. Today, the widespread influence of fuzzy logic is evident. Lu et al.[40]combined fuzzy logic and protective layer analysis to reduce the uncertainty factor in the calculation process of traditional protective layer analysis method to analyze the risk of fire accidents in leaking pools of crude oil storage tanks and give a risky decision-making scheme. Kambalimath et al.[41] mentioned that problems related to hydrology often involve imprecision and ambiguity, and that models based on fuzzy logic can well deal with these problems.

The fuzzy inference system is the process of fuzzifying subjective knowledge, inference through fuzzy rules, and then outputting crisp values. The general process of a fuzzy logic inference is as follows:

（1）Defining linguistic variables and fuzzy sets
（2）Determine the membership function
（3）Creating a rule base
（4）Fuzzy inference based on Mamdani algorithm
（5）Defuzzification

The model of fuzzy inference system is shown in Fig. 6.

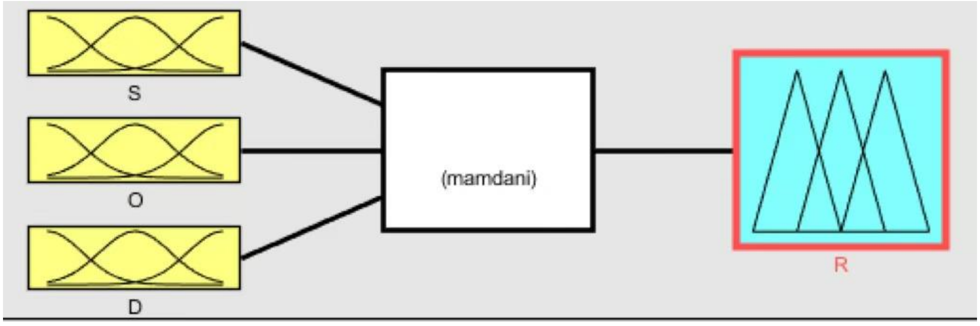


Fig. 6. Fuzzy inference system model

3. Case study

3.1 Case introduction

In this section, a case study of an offshore wind farm located off the eastern coast of China is presented to conduct a risk analysis of the key components of offshore wind turbines and to validate the proposed framework. The wind farm comprises 80 wind turbines, each with a rated capacity of 4.2 MW. The risk analysis focuses on critical components of the offshore wind turbines, including blades, bearings, generators, transformers, gearboxes, pitch systems, yaw systems, and electrical control systems.

3.2 Data acquisition

Five experts specializing in offshore wind power were invited to identify the failure modes and to evaluate the S, O, and D of each failure mode, with scores assigned on a scale from 1 to 10. Detailed information about the participating experts is provided in Table 4, while the individual scoring results are presented in Appendix 2. Based on the expert evaluations, the comprehensive values of S, O, and D are calculated using Equations (11), (12), and (13).

$$S=\sum_{\tau=1}^{5} W_{\tau} \cdot S^{\tau} \tag{11}$$

$$\mathrm{O}=\sum_{\tau=1}^{5} W_{\tau} \cdot O^{\tau} \tag{12}$$

$$D=\sum_{\tau=1}^{5} W_{\tau} \cdot D^{\tau} \tag{13}$$

Where S^{τ} is the evaluation value of expert τ to S, O^{τ} is the evaluation value of expert τ to O, D^{τ} is the evaluation value of expert τ to D. W_{τ} is the weight of expert τ, which is related to their position and work experience. Referring to the ISO 30414(Human Capital Reporting), the evaluation criteria of expert weight are shown in Table 5. The expert weight is calculated by Equation (14):

$$\mathrm{w}_{\tau}=\frac{P_{\tau}+E_{\tau}}{\sum_{\tau=1}^{5} P_{\tau}+E_{\tau}} \tag{14}$$

Where W_{τ} is the weight of expert τ. P_{τ} denotes the position score of expert τ, E_{τ} denotes the work experience score of expert τ.

Table 4 Detailed information of experts

Expert	Position	Experience
1	Engineer	8 years
2	Chief Engineer	16 years
3	R&D personnel	5 years

4	Professor	15 years
5	Operator	4 years

Table 5 Expert weight evaluation criteria

		Score
position	Engineer/R&D personnel/Operator	4
	Chief Engineer/Professor	6
Experience	<10 years	4
	Between 11 and 20 years	6

After the calculations were completed, the comprehensive values of the risk factors for each failure mode are shown in Table 6.

Table 6 Results of failure mode identification and evaluation

Serial number	Assemblies	Failure mode	S	O	D
FM1	Blade	Blades cracks	8	4	5
FM2		Slight corrosion	2	7	6
FM3	Main bearing	Bearing damage	9	4	6
FM4		Bearing vibration	8	6	4
FM5	Generate	Overheat	9	7	1
FM6		Winding failure	8	6	3
FM7	Transformer	Short circuit	8	4	2
FM8		Open circuit	8	4	3
FM9	Pitch system	Wrong pitch angle	6	4	2
FM10	Yaw system	Hydraulic leakage	6	5	2
FM11		Corrosion	5	5	5
FM12	Gearbox	Fractured gear teeth	9	2	3
FM13		Seized gears	9	4	4
FM14	Electrical controls	sensor accuracy degradation	3	4	3
FM15		Output voltage inaccuracy	5	6	6

3.3 Analysis of improved FMEA framework

3.3.1 Calculation of risk factor weights

The triangular fuzzy numbers represent the results of experts' pairwise comparisons of risk factors. Specifically, A_{SO}, A_{SD}, and A_{OD} represent the comparison results of S and O, S and D, and O and D, respectively. Based on the predetermined pairwise comparison scale, experts selected triangular fuzzy numbers to represent the relative importance of risk factors. Table 7 shows the calculation process of risk factors using the method proposed in 2.1.1.

Through the Delphi method, solicit expert opinions and provide feedback to them, repeating this process until a consensus is reached, that is, $A_{SO} = (1, 3, 5)$, $A_{SD} = (3, 5, 7)$, and $A_{OD} = (1, 3, 5)$. Using the geometric mean method to defuzzify yields a_{ij}, and a_{ji} is the reciprocal of a_{ij}. Finally, a preliminary pairwise comparison matrix $A=(a_{ij})_{3\times3}$ can be formed. For example, in A_{SO}, 1 is the smallest possible value after comparison, 3 is the most likely value, 5 is the maximum possible value, and 3 is the defuzzified value.

Table 7 Pairwise comparison matrix and consistency test

	S	O	D	Normalized	S	O	D	∑	AW
S	1	3	5	S	0.65	0.69	0.56	1.9	0.633
O	0.33	1	3	O	0.22	0.23	0.33	0.78	0.26
D	0.2	0.33	1	D	0.13	0.08	0.11	0.32	0.107
∑	1.53	4.33	9	∑	1	1	1	3	
	S*0.633	O*0.260	D*0.107	∑	λ_{max}				
S	0.633	0.78	0.535	1.948	3.032				
O	0.209	0.26	0.321	0.79					
D	0.127	0.086	0.107	0.320					

In the Table 7, the λ_{max} is 3.032, n is 3, and substituting into the consistency test formula gives a CI of 0.016, which is less than 0.1, indicating that the consistency test is passed. Therefore, the weights of the risk factors S, O, and D are 0.633, 0.26, and 0.107, respectively.

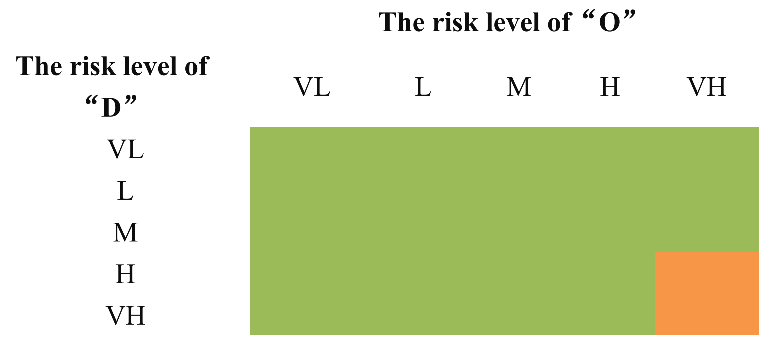
3.3.2 Risk level distribution matrix

Based on the weights calculated in the preceding steps, the formula for calculating I is presented in Equation (15).

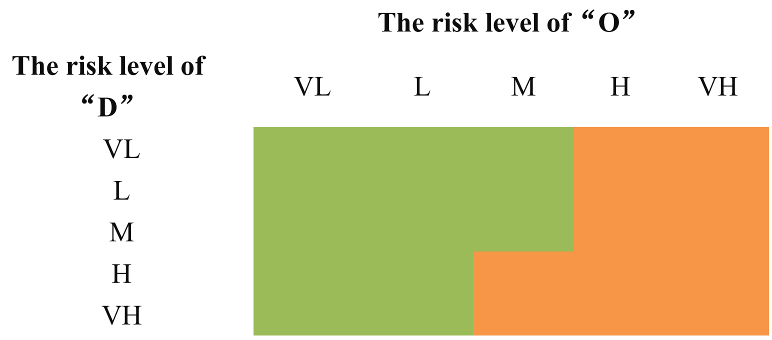
$$I = N_s \times 0.633 + N_O \times 0.26 + N_D \times 0.107 \tag{15}$$

Based on the size of I, the two-dimensional 5x5 risk level matrix has been formed under five different S levels:

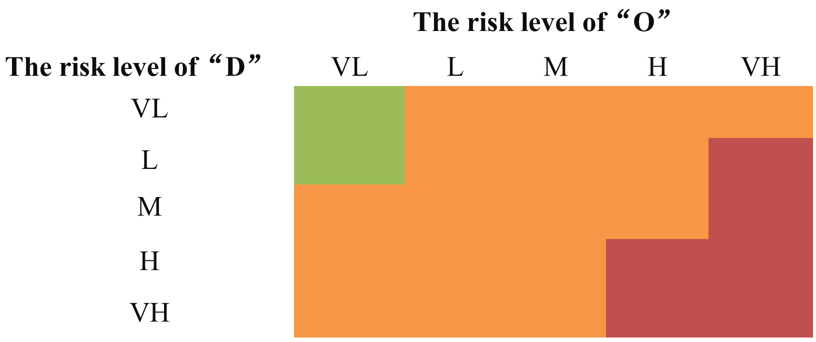
（1）When S is VL, the risk level distribution matrix is as follows:



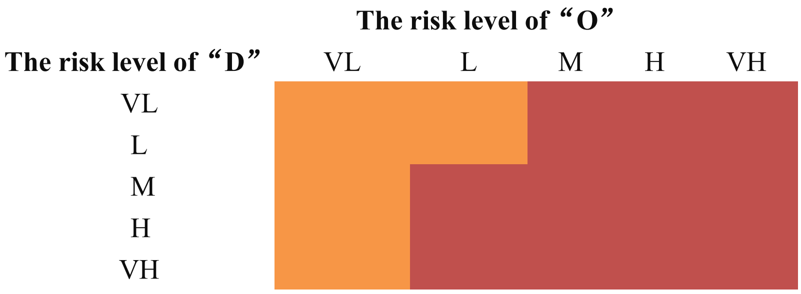
（2）When S is L, the risk level distribution matrix is as follows:



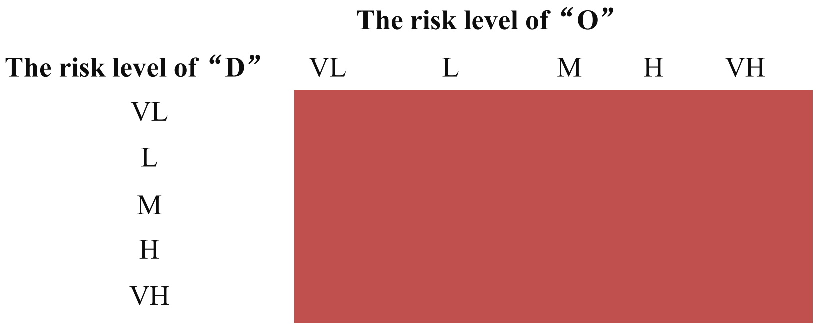
（3）When S is M, the risk level distribution matrix is as follows:



(4) When S is H, the risk level distribution matrix is as follows:



(5) When S is VH, the risk level distribution matrix is as follows:



The above five risk level matrices clearly and intuitively display the risk level distribution of failure modes under different combinations of risk factor levels. For example, it can be intuitively observed that when the levels of S, O and D are all classified as VL, the corresponding cell in the first matrix is highlighted in green, indicating a VL risk level. Accordingly, a complete fuzzy rule can be formulated as follows: If S is S_1 and O is O_1 and D is D_1, then R is R_1. All of the rules are listed in Appendix 1.

3.3.3 Improvement results and evaluation

Input the score into the fuzzy inference system, using MATLAB software to output the *r* and calculate the risk level membership degree, and then obtain the results as shown in Table 8.

Table 8 Improved FMEA results

Seria number	*r*	Degree of membership	Risk grade	Rank
FM1	0.593	R_1:0 R_2:20.240% R_3:11.765%	R_2	7
FM2	0.226	R_1:63.763% R_2:1.984%	R_1	14

		R_3:0		
FM3	0.732	R_1:0 R_2:0.193% R_3:79..421%	R_3	3
FM4	0.74	R_1:0 R_2:0.140% R_3:83.620%	R_3	2
FM5	0.786	R_1:0 R_2:0.015% R_3:99.025%	R_3	1
FM6	0.727	R_1:0 R_2:0.248% R_3:76.721%	R_3	4
FM7	0.49	R_1:0 R_2:0.248% R_3:76.721%	R_2	9
FM8	0.496	R_1:0.012% R_2:88.251% R_3:0.822%	R_2	8
FM9	0.474	R_1:0.027% R_2:95.602% R_3:0.493%	R_2	11
FM10	0.478	R_1: 0.002% R_2: 94.059% R_3: 0.560%	R_2	10
FM11	0.312	R_1:13.534% R_2:21.654% R_3:0	R_2	13
FM12	0.637	R_1: 0 R_2: 6.721% R_3:26.501%	R_3	6
FM13	0.652	R_1:0 R_2:4.150% R_3:33.641%	R_3	5
FM14	0.165	R_1:56.113% R_2:2.796% R_3:0	R_1	15
FM15	0.377	R_1:1.832% R_2:65.705% R_3:0	R_2	12

In this paper, 15 major failure modes were analyzed and ranked in terms of risk based on *r*. Among them, generator overheating, winding failure, and main bearing vibration and damage are recognized as extremely critical failure modes because their *r* exceeds 0.7. It suggests that the generator and main bearing are high-risk vital components. To avert the manifestation of these failure modes, they are analyzed individually:

(1) The probability of excessive temperature rise in offshore wind turbine generators is relatively high, primarily due to the cooling system tends to experience issues such as insufficient cooling medium and coolant blockages after prolonged operation, which impede timely heat dissipation. Additionally, abnormal electrical operation can also contribute to heat accumulation. This overheating phenomenon may not only result in the wind turbine shutdown, but also cause overload damage to downstream components, including transformers and cables. In response, it is recommended to design redundant cooling circuits and rapid disconnection protection, enforce regular and thorough maintenance of the cooling system, and establish an early warning temperature threshold of 75 °C for the generator housing.

(2) Main bearing vibration frequently results in severe oscillations throughout the machine and eccentric operation, negatively impacting operational safety and power production efficiency. In offshore environments, factors such as wave-induced impacts, moisture condensation, and salt spray corrosion can accelerate the degradation and failure of the main bearing lubrication system. To address these challenges, it is recommended to integrate intelligent lubrication units. By efficiently reducing oil emulsification and sludge formation, these systems may automatically replenish or replace lubricating grease depending on temperature and vibration thresholds, increasing system dependability and main bearing service life.

(3) Once a main bearing is damaged, it often induces severe vibrations of the entire system and may even result in uncontrolled shutdowns, posing significant safety risks. Due to prolonged exposure to alternating and impact loads, microcracks can readily develop on the surface of rolling elements and progressively propagate into macroscopic cracks during operation. Currently, most sensors are installed on the bearing housing, making it difficult to directly and effectively monitor the internal condition of the bearing, which leaves blind spots in fault detection. To address these issues, bearing steels with high corrosion resistance and fatigue strength can be employed, and nano-coatings can be applied to the raceway surfaces to enhance wear and corrosion resistance. In addition, embedding temperature and oil film thickness sensors within the bearing is recommended to enable real-time monitoring of lubrication status and frictional changes, thereby improving fault prediction capability and operational reliability.

(4) Generator winding faults typically manifest as insulation breakdown, partial short circuits, or winding burnout. In severe cases, such faults may necessitate shutdowns and factory-level repairs, incurring high maintenance costs and potential damage to downstream electrical equipment, thereby causing additional losses. In offshore environments, high humidity and salt spray conditions can accelerate the aging of insulation materials. However, early-stage partial discharges and internal hotspots are often difficult to detect due to limitations in current monitoring technologies. To address these issues, it is recommended to use insulation materials with enhanced

moisture resistance and higher thermal ratings, and to strengthen online monitoring and insulation health assessment methods.

Besides ranking the failure modes, the risk levels of the failure modes can also be categorized via the calculated membership degrees. The results presented in Table 8 indicate that FM3, FM4, FM5, FM6, FM12, and FM13 are classified as high-risk failure modes; FM1, FM7, FM8, FM9, FM10, FM11, and FM15 are categorized as medium risk; and FM2 and FM14 are identified as low risk. Given the high O&M costs, limited accessibility and short maintenance windows of offshore wind farms, adopting differentiated O&M strategies based on the risk classification of failure modes can effectively improve maintenance efficiency and support coordinated management. Currently, O&M strategies for offshore wind power include corrective maintenance, preventive maintenance, condition-based maintenance, and opportunistic maintenance[42][43]. Therefore, for high-risk failure modes, a hybrid model of condition - based and predictive maintenance is recommended; For medium risk failure modes, opportunistic maintenance is a good choice; For low-risk failure modes, corrective maintenance is acceptable.

3.4 Sensitivity analysis

In this paper, the weights of risk factors are initially reflected in the risk level matrix, and fuzzy rules are derived from the risk matrix for fuzzy inference, ultimately affecting the output of the failure mode. Therefore, the weights of risk factors are the critical part of the method proposed in this paper.

The weights of risk factors are derived using the FAHP method, which relies on experts making pairwise comparisons of risk factors and selecting triangular fuzzy numbers to represent the relative importance between them. However, this process is based on the subjective judgment of experts, and inviting different groups of experts may yield different weight results. Sensitivity analysis of the weights can explain the extent to which changes in the weight values of relevant risk factors affect the calculation results.

When the weights fluctuate, the changing weight is $W'_i = \partial W_i$, and $0 \leqslant Wi \leqslant 1$, the remaining weights are reversed in equal parts and normalized so that the weighted total following the weight fluctuations is 1.The weight Ki of the S and D is changed by the parameter ∂ times, making the original weight value fluctuate within the range of $\pm$10%, the values of ∂ are 0.9 and 1.1. Update the weights of S, O and D, and recalculate the risk value of the failure modes. The calculation results are shown in Table 9.

Table 9 Result calculation comparison

Failure mode	This paper		-10%		+10%	
	Risk value	rank	Risk value	Rank	Risk value	Rank
FM1	0.593	7	0.593	7	0.593	7
FM2	0.226	14	0.226	14	0.226	14
FM3	0.732	3	0.732	3	0.732	3
FM4	0.74	2	0.74	2	0.74	2
FM5	0.786	1	0.786	1	0.786	1

FM6	0.727	4	0.727	4	0.727	4
FM7	0.49	9	0.49	9	0.49	9
FM8	0.496	8	0.496	8	0.496	8
FM9	0.474	11	0.474	11	0.474	11
FM10	0.478	10	0.478	10	0.478	10
FM11	0.312	13	0.312	13	0.312	13
FM12	0.637	6	0.637	6	0.637	6
FM13	0.652	5	0.652	5	0.652	5
FM14	0.165	15	0.165	15	0.165	15
FM15	0.377	12	0.377	12	0.377	12

From Table 9, it can be seen that when S and D change by 10%, it does not affect the magnitude of the final output risk value. This is because within this range of change, the fuzzy rules remain unchanged. Therefore, within this range, the calculation results are not sensitive to changes in the weights of the risk factors.

Within the previously defined fluctuation range, S remains the dominant factor influencing the risk levels of failure modes. To further investigate the sensitivity of the risk assessment to weight variations, a weight perturbation experiment is conducted by decreasing the weight of S and increasing the weight of D. The adjusted weights for S, O, and D are set to 0.253, 0.104, and 0.643, respectively. Based on these adjusted weights, the *r* is recalculated and the failure modes are re-ranked. The results are then compared with those obtained using the original weighting scheme proposed in this study, as illustrated in Fig. 7. In Fig. 7, Weight Group 1 represents the results derived from the original weights, while Weight Group 2 reflects the outcomes based on the adjusted weighting scheme.

As shown in Fig. 7, when the risk factor weights are assigned according to Weight Group 2, most failure modes undergo noticeable changes. Among these, FM5 exhibits the most significant variation, primarily due to the increased weight of D in this weighting scheme. Since FM5 has a D score of only 1, its overall risk level decreases accordingly.

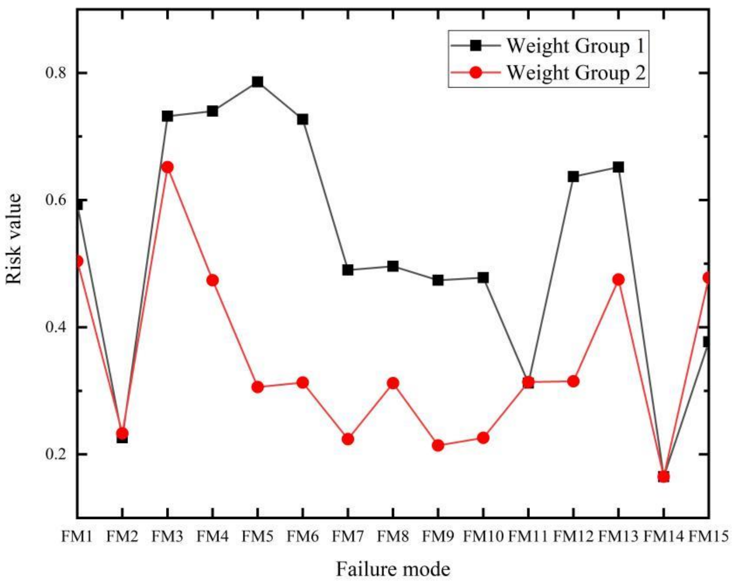


Fig.7. Comparison of Weight Perturbation Experimental Results

3.5 Comparison analysis

In this section, to verify the rationality and effectiveness of the proposed framework, a quantitative comparison is conducted between the proposed method and traditional FMEA as well as Weighted FMEA originated from literature [17], as shown in Table 10. The normalized scoring results used in the Weighted FMEA method are detailed in Appendix 3.

Table 10 Summary of Calculation Results

Failure mode	Traditional FMEA		Weighted FMEA		proposed framework	
	RPN	Rank	Weightd-RPN	Rank	*r*	Rank
FM1	160	4	0.1077	6	0.593	7
FM2	84	9	0.0690	14	0.226	14
FM3	216	1	0.1191	2	0.732	3
FM4	192	2	0.1169	3	0.74	2
FM5	63	11	0.1259	1	0.786	1
FM6	144	5	0.1150	5	0.727	4
FM7	64	10	0.1019	9	0.49	9
FM8	96	8	0.1038	7	0.496	8
FM9	48	14	0.0829	13	0.474	11
FM10	60	12	0.0884	11	0.478	10
FM11	125	7	0.0847	12	0.312	13
FM12	54	13	0.1024	8	0.637	6
FM13	144	5	0.1153	4	0.652	5
FM14	36	15	0.0564	15	0.165	15
FM15	180	3	0.0923	10	0.377	12

According to Table 10, the failure mode rankings derived from traditional FMEA serve as a reference. For each failure mode, the rankings obtained via the Weighted FMEA method and the proposed method are compared against this reference to calculate the differences in their ranking positions. If a risk ranking is increased, the deviation is recorded as a positive value. A corresponding line chart illustrating these deviations is presented in Fig. 8.

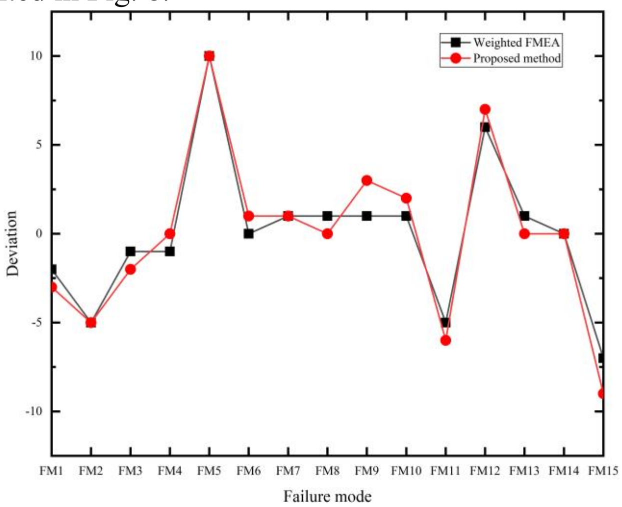


Fig. 8. Comparison of failure mode risk ranking deviations (Using traditional FMEA as the

Baseline)

As shown in the visualized results in Fig. 8, the ranking of failure modes changes significantly under the influence of risk factor weights. Notably, FM2, FM5, FM11, FM12, and FM15 exhibit more pronounced changes in ranking. It is worth noting that the fluctuation trends of the two methods are generally consistent, which to some extent validates the rationality of embedding risk factor weights into the fuzzy rules in this study. Furthermore, Fig.8 indicates that the proposed method yields larger overall ranking deviations. This is mainly attributed to the fuzzy inference system, which maps experts' quantitative ratings into continuous membership intervals through membership functions, thereby effectively preserving and revealing the fuzzy and uncertain information that is compressed in crisp-value quantification.

A comparison of the ranking results in Table 10 between the proposed method and the Weighted FMEA model reveals that, in the Weighted FMEA approach, FM9 (incorrect pitch angle) is ranked three positions lower than FM15 (inaccurate output voltage), whereas in the proposed method, FM9 is ranked one position higher than FM15. From the perspective of post-failure repair difficulty and associated costs, FM9 typically requires on-site inspection and maintenance by professional technicians, which increases both the complexity and cost of repair. In contrast, FM15 is usually caused by improper controller parameter settings, sensor faults, or external disturbances. These issues can generally be resolved through software adjustments, parameter optimization, or replacement of faulty components, making the repair process relatively simple and cost-effective. Therefore, it is reasonable for FM9 to be assigned a higher risk priority than FM15, and it should receive greater attention.

Furthermore, FM1 and FM12 also exhibit notable differences in their risk rankings. In the Weighted FMEA method, FM1 (blade crack) is ranked two positions higher than FM12 (Fractured gear teeth), whereas in the proposed method, FM1 is ranked one position lower than FM12. From the perspective of repair difficulty and cost, the gearbox—located inside the nacelle—typically requires the use of large-scale lifting equipment for disassembly and repair or replacement, which includes not only the cost of replacement parts, but also expenses related to crane rental, transportation, labor, and power generation losses due to downtime. In contrast, FM1 can often be addressed through various methods such as on-site repair or blade replacement. Minor cracks can usually be repaired in situ, avoiding the need for large equipment. As such, the repair cost is comparatively lower than that of gearbox failures. Therefore, assigning a higher risk priority to FM12 over FM1 is reasonable, and FM12 should receive greater attention.

4.Discussion

4.1 Validation and reliability of the results

4.1.1Validity analysis

In order to verify the effectiveness of the proposed improved framework, this paper adopts the validation method proposed by Wang and Triantaphyllou[44]. This validation method includes three test criteria to evaluate the effectiveness of the method, as detailed below.

Test criterion 1: Upon introducing an inferior alternative to a less-than-ideal one, an effective MCDM technique should not influence the indication of the optimal option, provided that the relative significance of each decision criterion remains constant.

Test criterion 2: An effective MCDM approach ought to adhere to transferability.

Test criterion 3: When decomposing an MCDM problem into sub-problems and ranking alternatives within each sub-problem using the same method, the aggregated ranking of all alternatives must be consistent with their ranking in the original non-decomposed problem.

We create the design program in accordance with the three rules:

Test solution 1: We decide to modify FM4 in order to confirm Test criteria 1. Additionally, FM′4 is a representation of the modified FM4. The precise risk value for FM4 and FM′4 are listed in Table 11.

The ranking outcome of the offshore wind turbine risk assessment problem can be obtained using the enhanced FMEA framework that we put out in this study. The initial ranking outcome is displayed as follows.

FM5>FM4>FM3>FM6>FM13>FM12>FM1>FM8>FM7>FM10>FM9>FM15>FM11>FM2>FM14

We can get a new ranking result by substituting FM4 with FM′4 using the suggested enhanced risk assessment FMEA method. The following is the new ranking result.

FM5>FM3>FM6>FM13>FM12>FM1>FM8>FM7>FM10>FM9>FM15>FM11>FM2>FM14>FM′4

It is evident that the optimal FM has remained consistent, confirming that the model put out in this work satisfies Test criteria 1.

Test solution 2 &3:

We separate the entire FM sets into two subsets in order to validate Test Criterion 2 and 3. Ω = {FM1, FM2, FM3, FM4, FM5, FM6, FM7, FM8, FM9, FM10, FM11, FM12, FM13, FM14, FM15} is one way to express the entire set. The subset O can be expressed as O= {FM2, FM3, FM4, FM5, FM7, FM10, FM11, FM14, FM15}, while P = {FM1, FM2, FM3, FM4, FM5, FM6, FM7, FM8, FM9}. We can determine the corresponding ranking outcomes of the two subsets of FMs using the suggested enhanced risk assessment FMEA approach.

Following computation, the subset O ranking result is displayed as follows:

FM5>FM4>FM7>FM10>FM15>FM11>FM2>FM14

Following computation, the subset P ranking result is displayed as follows:

FM3>FM6>FM13>FM12>FM1>FM8>FM7>FM9

The ranking results of two subsets are shown to be consistent with the ranking results of the entire set, confirming that the model put forth in this study satisfies Test Criterion 2 & 3.

Table 11 The *r* of initial and modified FM1.

	S	O	D	*r*
FM4	8	6	4	0.740
FM′4	1	1	1	0.156

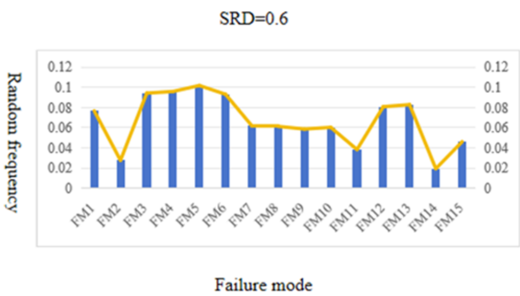
4.1.2 Reliability analysis

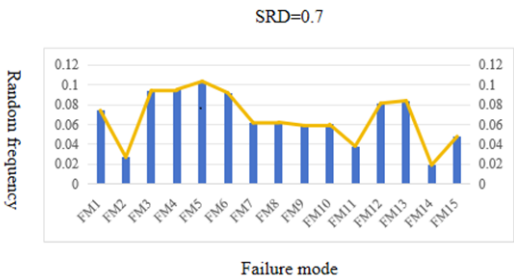
The simulation experiment was designed using the Monte Carlo method, grounded in statistical principles, to verify the validity of the proposed approach.

Experiment: Comprehensive evaluation values were assigned to the 15 failure modes to represent their respective risk levels. Random sequences of these failure modes were then generated to simulate their occurrence order. During each simulation, if the risk level of a failure mode exceeded the system risk degree (SRD)—set at 0.6—the system was deemed to have collapsed. Additionally, whenever the cumulative risk of sequentially occurring failure modes reached or exceeded 0.6, the simulation terminated and the triggering failure mode was recorded. This process was repeated multiple times to determine the frequency with which each failure mode precipitated system collapse.

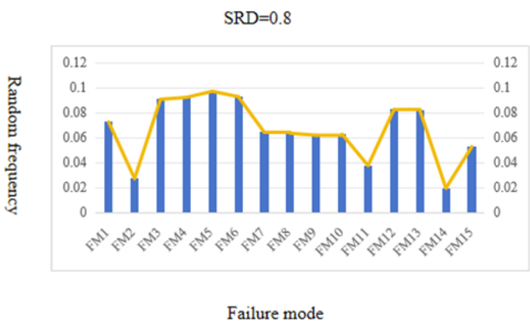
At the same time, the fault tolerance of the system, represented by the SRD must also be considered. A higher SRD indicates that the system can tolerate more failure modes (FMs), reflecting lower sensitivity to failures. Conversely, a lower SRD suggests limited fault tolerance and higher sensitivity to failures. To investigate the impact of SRD levels, the experiment was conducted with SRD values ranging from 0.6 to 0.9.

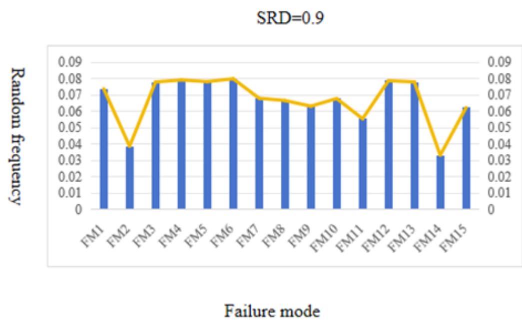
Therefore, based on the experimental concept, this paper simulated the case. On the basis of 200,000 simulations, statistically significant data were obtained, which represented the random frequency of each failure mode under different SRDs in Appendix 4. To more clearly reflect the results, we presented the data in the form of charts, as shown in Fig. 9. We can see that the ranking results based on the random frequency of each frequency modulation are the same as those obtained by the proposed method, proving the reliability of the proposed method.





a. Random frequency of Each FM at SRD = 0.6 b.Random frequency of Each FM at SRD = 0.7





c. Random frequency of Each FM at SRD = 0.8 d. Random frequency of Each FM at SRD = 0.9

Fig. 9. The random frequency of each FM under different SRD(a-d)

4.2 The superiority of the framework

In response to the shortcomings of classic FMEA, this paper proposes a framework for an improved FMEA method and applies it to offshore wind turbine. In this section, we analyze the advantages of this improved framework from the following aspects.

4.2.1 In terms of the treatment of risk factor scores

Risk factor scores are derived from the expertise and judgment of invited specialists, inherently involving a degree of uncertainty. Compressing these evaluations into precise numerical values may overlook the inherent fuzziness and uncertainty in the assessment process. To address this, Gaussian membership functions are employed in this study to fuzzify the risk factor scores. This function allows for a smooth representation of the probable range around the assigned scores and effectively maps them to the membership degrees of different fuzzy sets, thereby preserving the uncertainty and imprecision inherent in expert evaluations.

4.2.2 In terms of the generation of fuzzy rules

Fuzzy rules are core to fuzzy inference system, and their generation is highly vital. Most current studies rely on integrating the experience of multiple domain experts to construct a comprehensive fuzzy rule base. However, this process becomes inefficient when dealing with a large number of fuzzy rules. This paper innovatively embeds risk factor weights into the fuzzy rules by compressing expert knowledge of overall risk perception into 3 core parameters (the weights of S, O and D), rather than 125 independent rules, thereby improving the efficiency of rule generation, as reflected in reduced expert workload and streamlined opinion aggregation, as detailed in Table 12. According to Table 12, incorporating risk factor weights into fuzzy rules enhances the efficiency of rule generation by up to 40 times in terms of workload, thus substantially reducing the time required for the fuzzy rule development process.

Table 12 Comparison of the Workload between the Two Methods

Dimension	Multi-rule integration method	Weight embedding method
Expert workload	Each expert provides 125 rules	Each expert provides 3 assessments regarding the relative importance of S, O and D.
Opinion aggregation	Handling 125 N rules (N represents the number of experts)	Handling 3N assessments concerning the weights

4.2.3 In terms of ranking and classifying the failure mode

In current FMEA-based risk analysis studies for offshore wind farms, most research focuses on determining the risk priority of failure modes and then proposing corresponding maintenance suggestions. However, offshore wind farm is characterized by significant accessibility constraints, which pose substantial challenges for effective maintenance. To address this, this paper not only ranks the risks of failure modes but also further classifies their risk levels. By developing differentiated O&M strategies for each category, the paper aims to enhance the overall efficiency of O&M work.

5. Conclusion and prospect

5.1 Conclusions

To address the inherent limitations of traditional FMEA and the research gaps identified in existing literature, this paper proposes a novel improved FMEA framework for risk analysis of offshore wind turbines. The conclusions are as follows:

(1) The weights of risk factors are implicitly embedded into fuzzy rules to optimize the efficiency of fuzzy rule generation. Based on this, fuzzy inference system is first employed to fuzzify the risk factor scores, which then enables the nonlinear computation of overall risk. The resulting output value r is used for risk prioritization, and the corresponding membership degree of r is applied to classify risk levels.

(2) The case study results indicate that generator overheating (with an r of 0.786), winding faults (0.727), main bearing vibration (0.740), and main bearing failure (0.732) are the most critical failure modes. To mitigate the occurrence of these failure modes, efforts can be directed toward four key areas: equipment selection and material optimization, intelligent monitoring and fault prediction, O&M with system redundancy design, and enhanced structural reliability and environmental adaptability. Furthermore, it is recommended to adopt tiered maintenance strategies for failure modes based on their respective risk levels. Specifically, a combination of condition-based maintenance and predictive maintenance strategies is recommended for high-risk failure modes. For medium risk modes, an opportunistic maintenance strategy can be adopted, while low risk modes may be managed using a corrective maintenance strategy.

(3) A quantitative comparison is performed between the results obtained from the proposed improved framework and those derived from the Weighted FMEA method. The deviations between both methods and the traditional FMEA results are used to validate the rationale for implicitly incorporating risk factor weights into the fuzzy rules. The underlying reasons for the discrepancies in the deviation are also analyzed. In addition, the differences in ranking results are examined considering the difficulty and cost of fault repair, further confirming the reasonableness and effectiveness of the proposed framework.

5.2 Limitations and future work

The following summaries the limitations of the proposed FMEA model:

(1) In this study, the scoring of failure mode risk factors relies on expert judgment, and involving different groups of experts can lead to varying results. In future research, we plan to adopt expert clustering methods to assess the impact of this effect.

(2) Once the risk factor weights are established based on expert consensus, the rule base is consequently defined. Although this design enhances the efficiency of system construction, it inherently limits the robustness of the fuzzy rule base. Therefore, future studies may consider introducing dynamic weighting and adaptive rule optimization strategies to improve the system's responsiveness and robustness.

(3) In practical engineering applications, the design and processes of offshore wind turbines are continuously optimized throughout their lifecycle. Each time a change is introduced, the FMEA should be re-evaluated. However, due to project schedule constraints, FMEA updates are often delayed, resulting in assessments that may no longer accurately reflect the current failure risks of the product. In the future, a

unified FMEA database and knowledge management system can be developed to integrate design change records, operational data, and maintenance history, thereby enabling dynamic management and enhancing the adaptability of FMEA throughout the entire product lifecycle.

CRediT authorship contribution statement

Erhong Chen: Methodology, Data curation, Writing-Original draft. **Xiaofang Luo:** Validation, Supervision, Conceptualization. **Xiandong Ma:** Resources, Validation,. **Xu Bai:** Layout design, Resources, Funding acquisition. **Jiaxuan Luo:** Writing-review & editing, Validation.

Declaration of competing interest

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

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Appendix

Appendix 1 Fuzzy rule base

If S is S_1 and O is O_1 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_1
If S is S_1 and O is O_2 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_1
If S is S_1 and O is O_3 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_1
If S is S_1 and O is O_4 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_1
If S is S_1 and O is O_5 and D is D_1 or D_2 or D_3, then R is R_1
If S is S_2 and O is O_1 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_1
If S is S_2 and O is O_2 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_1
If S is S_2 and O is O_3 and D is D_1 or D_2 or $D_{3,}$ then R is R_1
If S is S_3 and O is O_1 and D is D_1 or D_2, then R is R_1
If S is S_1 and O is O_5, D is D_4 or D_5, then R is R_2
If S is S_2 and O is O_3 and D is D_4 or D_5, then R is R_2
If S is S_2 and O is O_4 and D is D_1 or D_2 or D_3 orD_4 or D_5, then R is R_2
If S is S_2 and O is O_5 and D is D_1 or D_2 or D_3 orD_4 or D_5, then R is R_2
If S is S_3 and O is O_1 and D is D_3 orD_4 or D_5, then R is R_2
If S is S_3 and O is O_2 and D is D_1 or D_2 or D_3 orD_4 or D_5, then R is R_2
If S is S_3 and O is O_3 and D is D_1 or D_2 or D_3 orD_4 or D_5, then R is R_2
If S is S_3 and O is O_4 and D is D_1 or D_2 or D_3, then R is R_2
If S is S_3 and O is O_5 and D is D_1, then R is R_2
If S is S_4 and O is O_1 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_2
If S is S_4 and O is O_2 and D is D_1 or D_2, then R is R_2
If S is S_4 and O is O_2 and D is D_1 or D_2, then R is R_2
If S is S_3 and O is O_4 and D is D_4 or D_5, then R is R_3
If S is S_3 and O is O_5 and D is D_2 or D_3 or D_4 or D_5, then R is R_3
If S is S_4 and O is O_2 and D is D_3 or D_4 or D_5, then R is R_3
If S is S_4 and O is O_3 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_3
If S is S_4 and O is O_4 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_3
If S is S_4 and O is O_5 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_3
If S is S_5 and O is O_1 or O_2 or O_3 or O_4 or O_5 and D is D_1 or D_2 or D_3 or D_4 or D_5, then R is R_3

Appendix 2 The scoring results of each expert

	Expert 1			Expert 2			Expert 3			Expert 4			Expert 5		
	S	O	D	S	O	D	S	O	D	S	O	D	S	O	D
FM1	8	4	7	9	4	5	7	5	4	8	3	4	8	3	5
FM2	2	8	5	3	8	6	2	7	4	2	5	7	3	6	5
FM3	9	4	6	9	4	7	9	4	6	8	4	6	8	4	6
FM4	8	5	4	7	6	4	7	7	4	9	6	4	8	7	3
FM5	9	8	1	10	5	1	9	7	1	9	7	1	10	7	1
FM6	7	6	2	9	6	3	8	5	3	8	3	6	8	5	3

FM7	8	4	3	8	3	2	8	4	2	8	4	3	8	4	1
FM8	8	4	3	8	3	3	8	5	3	7	2	3	8	5	3
FM9	4	4	2	6	4	3	6	4	2	6	4	2	6	3	2
FM10	6	4	2	5	6	2	6	5	2	6	5	2	6	5	2
FM11	5	5	6	4	5	5	4	3	5	5	5	4	5	5	5
FM12	10	1	4	9	2	4	9	2	4	9	2	4	9	3	3
FM13	9	3	4	9	4	5	9	3	5	9	4	3	8	4	4
FM14	3	4	2	4	4	2	2	4	3	3	4	3	3	4	3
FM15	5	6	6	6	6	6	5	6	6	5	7	6	4	7	6

Appendix 3 The normalized value

Serial number	Raw value	Normalized value
FM1	(8, 4, 5)	(0.120, 0.085, 0.090)
FM2	(2, 7, 6)	(0.030, 0.148, 0.108)
FM3	(9, 4, 6)	(0.135, 0.085, 0.108)
FM4	(8, 6, 4)	(0.120, 0.128, 0.072)
FM5	(9, 7, 1)	(0.135, 0.148, 0.018)
FM6	(8, 6, 3)	(0.120, 0.128, 0.054)
FM7	(8, 4, 2)	(0.120, 0.085, 0.036)
FM8	(8, 4, 3)	(0.120, 0.085, 0.054)
FM9	(6, 4, 2)	(0.090, 0.085, 0.036)
FM10	(6, 5, 2)	(0.090, 0.106, 0.036)
FM11	(5, 5, 5)	(0.075, 0.106, 0.090)
FM12	(9, 2, 3)	(0.135, 0.043, 0.054)
FM13	(9, 4, 4)	(0.135, 0.085, 0.072)
FM14	(3, 4, 3)	(0.045, 0.085, 0.054)
FM15	(5, 6, 6)	(0.075, 0.128, 0.108)

Appendix 4 The RF under different SRD_S

	SRD=0.6	SRD=0.7	SRD=0.8	SRD=0.9
the RF of FM1	0.076835	0.074185	0.072605	0.07372
the RF of FM2	0.02761	0.02698	0.027395	0.03861
the RF of FM3	0.09437	0.09423	0.09072	0.07788
the RF of FM4	0.096025	0.09535	0.09224	0.07912
the RF ofFM5	0.101985	0.103625	0.09709	0.078105
the RF of FM6	0.093195	0.092015	0.092785	0.07987
the RF of FM7	0.06187	0.06171	0.06432	0.06795
the RF of FM8	0.06136	0.06225	0.06361	0.06655
the RF of FM9	0.058685	0.058955	0.061955	0.06308
the RF of FM10	0.060385	0.060025	0.062785	0.06777
the RF of FM11	0.038355	0.03808	0.037735	0.055405
the RF of FM12	0.08092	0.08144	0.082585	0.07867
the RF of FM13	0.082965	0.08406	0.08169	0.077935

the RF of FM14	0.01929	0.01914	0.01969	0.033135
the RF of FM15	0.04615	0.047955	0.052795	0.0622