A Fuzzy-FMEA Risk Assessment Approach for Offshore Wind Turbines

F. Dinmohammadi[1], M. Shafiee[2]*

[1] *Renewable Energy Organization of Iran (SANA), Tehran, Iran*
[2] *School of Applied Sciences, Cranfield University, Cranfield, Bedfordshire, MK43 0AL, United Kingdom*

mahsha@chalmers.se

Abstract

Failure Mode and Effects Analysis (FMEA) has been extensively used by wind turbine assembly manufacturers for risk and reliability analysis. However, several limitations are associated with its implementation in offshore wind farms: (i) the failure data gathered from SCADA system is often missing or unreliable, and hence, the assessment information of the three risk factors (i.e., severity, occurrence, and fault detection) are mainly based on experts' knowledge; (ii) it is rather difficult for experts to precisely evaluate the risk factors; (iii) the relative importance among the risk factors is not taken into consideration, and hence, the results may not necessarily represent the true risk priorities; and etc. To overcome these drawbacks and improve the effectiveness of the traditional FMEA, we develop a fuzzy-FMEA approach for risk and failure mode analysis in offshore wind turbine systems. The information obtained from the experts is expressed using fuzzy linguistics terms, and a grey theory analysis is proposed to incorporate the relative importance of the risk factors into the determination of risk priority of failure modes. The proposed approach is applied to an offshore wind turbine system with sixteen mechanical, electrical and auxiliary assemblies, and the results are compared with the traditional FMEA.

1. Introduction

Offshore wind energy has experienced an extensive and worldwide growth during the past several years. For instance, of the 9,616 MW installed wind energy capacity in the EU in 2011, 866 MW (i.e., 9%) was offshore, which increased the EU's offshore wind power capacity to 3,810 MW—less than one percent of the total electricity demand (EWEA, 2012). Certain forecasts indicate that the share of offshore wind power in EU's electricity demand will reach up to 14% by 2030.

Comparing with onshore wind power, offshore winds tend to flow at higher speeds, thus it allows turbines to produce more electricity (Bilgili, Yasar and Simsek, 2011). However, a wind power system located on sea comes with higher failure rate, lower reliability, and higher operation and maintenance (O&M) costs. So, with the development of wind farms in remote areas, the need for efficient tool to identify and then limit or avoid risk of failures is of increasing importance.

Failure Mode and Effects Analysis (FMEA) has been extensively used by wind turbine assembly manufacturers for analyzing, evaluating, and prioritizing the potential failure modes (Andrawus, 2008). FMEA is a structured, bottom-up approach that starts with potential/known failure modes at one level and investigates the effect on the next sub-system level (Kumar and Kumar, 2005). Hence, a complete FMEA analysis of a system often spans all the levels in the hierarchy from bottom to top (see Fig. 1).

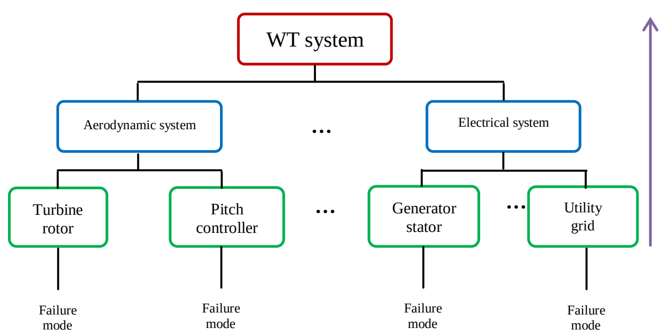


Fig. 1– Hierarchical structure of a typical wind turbine system.

A failure mode is defined as the way in which a component, subsystem or system could potentially fail to perform its desired function. Examples of failure modes in wind turbine systems are: material fatigue, deterioration, deformation, strips, fracture, detachment, blockage, misalignment, collapse, and etc. (Tavner, Xiang and Spinato, 2007).

A failure cause is defined as a weakness that may result in a failure. Typical causes of failures in wind turbine systems are: using incorrect material, poor welding, corrosion, assembly error, calibration error, over stressing, overheating, icing, maintenance fault, forming of cracks, being out of balance, connection failure, and etc.

The failure modes are usually detected through visual inspection, *online* condition monitoring techniques – such as oil analysis and ultrasonic testing (for more see Márquez, Tobias, Pérez and Papaelias, 2012), and time-based preventive maintenance actions. For each identified failure mode, their ultimate effects need to be determined by a cross-functional team which is usually formed by specialists from various functions (e.g., design, operation and maintenance, and power production). A failure effect is defined as the result of a failure mode on the function of the system as perceived by the user. Some of the effects of a failure in wind turbine systems are loss of electricity production, poor power quality to the grid, and a significant audible noise. Also, the effects of a failure in one component can be the cause of a failure mode in another component.

As outlined by Pillay and Wang (2003), the process for carrying out an FMEA can be divided into several steps as shown in Fig. 2.

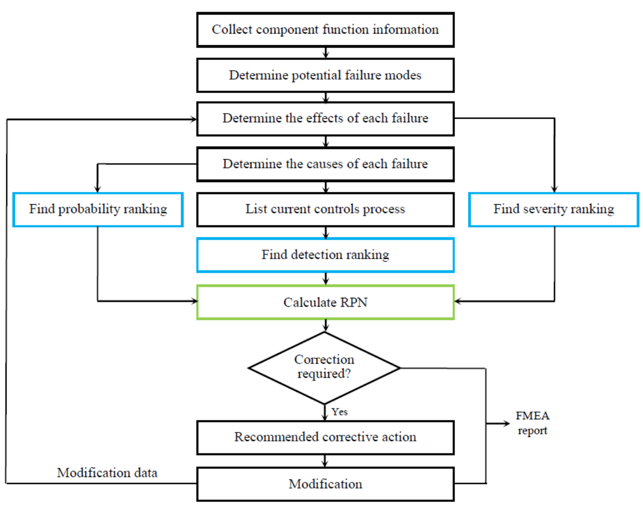


Fig 2– FMEA process.

Basically, each failure mode in the FMEA technique is evaluated by three factors as severity (S), likelihood of occurrence (O), and the difficulty of detection (D). A number between 1 and 10 (with 1 being the best and 10 being the worst case) is given for each of the three factors, and a risk-priority-number (RPN) is obtained, which is RPN = $S \times O \times D$. The RPN value helps the FMEA team to identify the components or subsystems that need the priority actions for improvement. Depending on the wind farm manager's decision, different criteria are used to trigger the improvement actions. For instance, action could be required if the overall RPN exceeds a predefined threshold, or for the highest RPN regardless of a threshold. Finally, at the last step, some hardware, software or design modifications are made in the system to minimize the failure effects.

Even though FMEA is probably the most popular tool for reliability and failure mode analysis in wind turbine systems, several limitations are associated with its implementation in offshore wind farms:

(i) The failure data gathered from inspectors, vibration sensors, and the SCADA system is often missing or unreliable. Hence, the assessment information of three risk factors (severity, occurrence, and detection) is mainly based on experts' knowledge and expertise;

(ii) Comparing with onshore wind power, the history of offshore wind power generation is fairly recent. Hence, it is difficult or even impossible for experts to precisely evaluate the three risk factors S, O and D. The risk factors are often expressed in a linguistic way (such as 'likely' , 'important', 'very high' and etc);

(iii) In the traditional FMEA methodology, the three risk factors are assumed to have the same importance (Braglia, 2000). However, it is observed that many O&M experts give more preference to the 'fault detection' factor.

So, the results of the traditional FMEA methodology may not necessarily represent the true risk priorities in offshore wind turbine systems, and this can entail a waste of resources and time.

To overcome the above drawbacks and improve the effectiveness of the traditional FMEA methodology, we develop a fuzzy-FMEA approach to determine the effects of failure on offshore wind turbine systems. Firstly, a fuzzy inference approach is considered to represent the assessment information using linguistic terms. Then, by using the weight vector of three risk factors, a grey theory analysis is proposed to rank the failure modes. To our knowledge, this paper is the first attempt to make the traditional FMEA methodology more applicable for offshore wind turbine systems, especially when the failure data is unavailable or unreliable.

The rest of this paper is organized as follows. In Section 2, we give a brief overview of FMEA methodology so as to set the background for the main contribution of the paper. Section 3 describes the wind turbine system considered in this paper. In section 4, the proposed fuzzy approach which utilizes the fuzzy IF–THEN rules and grey relation analysis. Finally, in section 5, the results obtained from the proposed approach are compared with the traditional FMEA.

2. FMEA: AN OVERVIEW

FMEA as a formal system analysis methodology was first proposed by NASA in 1963 for their obvious reliability requirements. Then, it was adopted and implemented by

Ford Motor in 1977 (Gilchrist, 1993). Since then, it has become a powerful tool extensively used for risk and reliability analysis of systems in a wide range of industries, including automotive, construction, aerospace, nuclear, and electro-technical.

2.1. FMEA in Wind Turbines

A brief review of the literature shows that only a few researchers have worked on improving the traditional FMEA methodology to make it more practical for wind turbine systems. Arabian-Hoseynabadi, Oraee and Tavner (2010) presented a design-stage FMEA methodology for prioritization of failures in a 2-MW wind turbine system (named as R80) within the RELIAWIND project. The authors' methodology used four-point scales for severity rating (Table 1), occurrence rating (Table 2), and detection of a failure (Table 3) to represent the risk of the 64 possible severity–occurrence–detection combinations.

Table 1– Severity rating scale for wind turbine FMEA.

Scale #	Description	Criteria
1	Category IV (minor)	Electricity can be generated but urgent repair is required.
2	Category III (marginal)	Reduction in ability to generate electricity.
3	Category II (critical)	Loss of ability to generate electricity.
4	Category I (catastrophic)	Major damage to the Turbine as a capital installation.

Table 2– Occurrence rating scale for wind turbine FMEA.

Scale #	Description	Criteria
1	Level E (extremely unlikely)	A single failure mode probability of occurrence is less than 0.001.
2	Level D (remote)	A single failure mode probability of occurrence is more than 0.001 but less than 0.01.
3	Level C (occasional)	A single failure mode probability of occurrence is more than 0.01 but less than 0.10.
5	Level A (frequent)	A single failure mode probability of occurrence is greater than 0.10.

Table 3– Detection rating scale for wind turbine FMEA.

Scale #	Description	Criteria
1	Almost certain	Current monitoring methods almost always will defect the failure.
4	High	Good likelihood current monitoring methods will detect the failure.
7	Low	Low likelihood current monitoring methods will defect the failure.
10	Almost impossible	No known monitoring methods available to detect the failure.

From the scales that they assign to the three risk factors, the following results can be concluded:

(i) The proposed methodology gives importance weights of (0.21, 0.26, 0.53) to (S, O, D). This implies that their methodology gives more preference to the fault detection factor.

(ii) From the existing sixty-four combinations, only thirty-nine different RPN values can be obtained, which they are heavily distributed at the bottom of the scale from 1 to 100 (see Fig. 3).

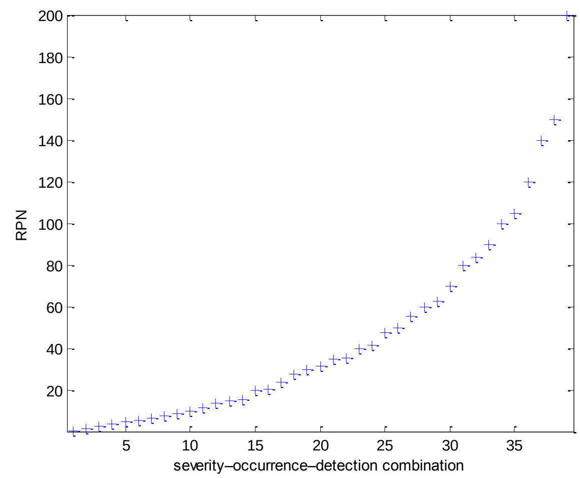


Fig 3–The RPN values for the sixty-four 'occurrence–severity–detection' combinations

Kahrobaee and Asgarpoor (2011) proposed a cost-priority-number (CPN) approach, in which the system's risk is calculated as C × P × N, where C is the cost consequences of each failure, P is the probability of occurrence, and N is the possibility of not detection. This approach has been recently extended in Dinmohammadi and Shafiee (2013) by incorporating all the costs associated with each failure (corrective replacement, spare parts, transportation, manpower, and production loss) in calculating the CPN value. Also, a quantitative study is carried out on two the same type of onshore and offshore wind turbines, and some useful comparisons are made.

2.2. Fuzzy FMEA

Fuzzy logic is a tool for transforming the vagueness of human feeling and recognition into a mathematical formula. It also provides meaningful representation of measurement for uncertainties and vague concepts expressed in natural language. In line with this, there has been a growing trend in FMEA literature to use fuzzy linguistic terms for describing the three risk factors S, O, and D. Readers can refer to Yang, Bonsall, and Wang (2008); Keskin and Özkan (2009); Gargama and Chaturvedi (2011) as good sources of fuzzy-FMEA approach. Most of the existing studies in the fuzzy FMEA literature have concerned with the fuzzy rule-base approach by using 'If–Then' rules. Fig. 4 shows an overall view of the fuzzy rule base technique, in which there are three major steps to carry out the assessment (Chin, Chan and Yang, 2008):

(i) *Fuzzification* process uses linguistic variables to convert the three risk factors S, O and D into the fuzzy representations. Using the linguistic variables and their definitions, ranking three risk factors can be made in a scale basis. These inputs are then fuzzified to determine the degree of membership in each input class.

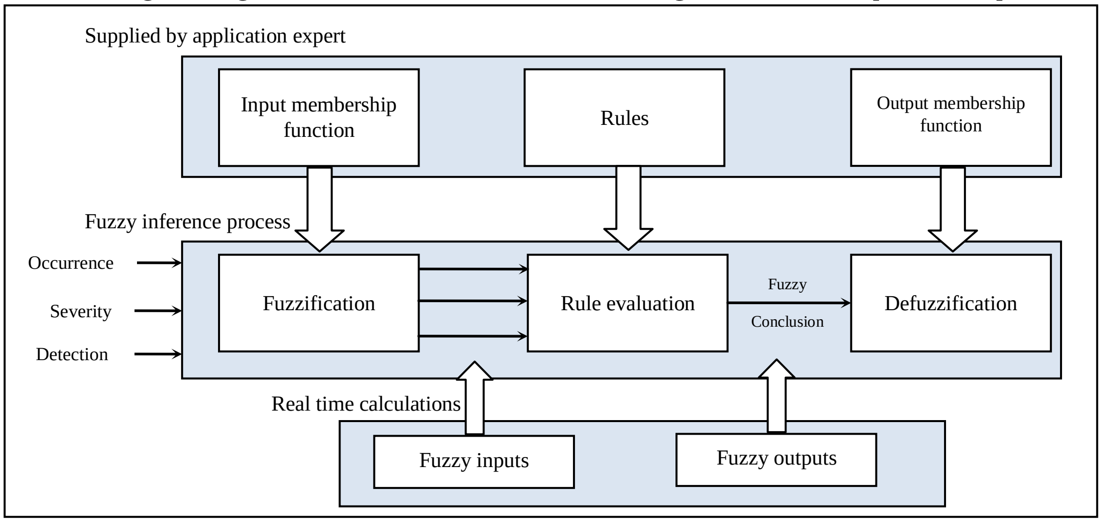


Fig 4–Overall view of the fuzzy-FMEA approach

(ii) *Rule evaluation* consists of the expert knowledge about the interactions between various failure modes and effect that is represented in the form of fuzzy if–then rules. Such rules are usually more conveniently formulated in linguistic terms than in numerical terms. The outputs of the fuzzy inference system are variously named as 'riskiness', 'critically failure mode', 'priority for attention', and 'fuzzy RPN' in the fuzzy FMEA studies.

(iii) *Defuzzification* process creates a crisp ranking from the fuzzy RPN to give the prioritization level for the failure modes.

3. WIND TURBINE SYSTEM CONSIDERED IN THIS STUDY

Nowadays, many kinds of wind turbine systems compete in the market. According to Li and Chen (2008), wind turbines can be categorized by their generator, gearbox, and their power converter types.

Fixed speed wind turbines which operate with constant speed 'Danish concept' were produced until the late 1990s with the power ratings below 1-MW. They used a multi-stage gearbox, and a standard squirrel-cage induction generator directly connected to the grid through a transformer. From the late 1990s, fully variable speed wind turbines were introduced in wind power industry. The first generation of fully variable speed wind turbines (with power ratings approximately 1-MW) used a multi-stage gearbox, a relatively low-cost standard wound rotor induction generator, and a power electronic converter feeding the rotor (Carlin, Laxson and Muljadi, 2003). The doubly fed induction generator (DFIG) technology is currently the most widely used in the wind turbine industry because of its low investment cost and good energy yield (Muller, Deicke and De Doncker, 2002). Since 1991, there have also been variable speed wind turbines with gearless generator systems which are equipped with a direct-drive generator and a fully-rated power electronic converter. The brushless doubly fed induction generator (BDFIG) is a well known drive technology which eliminates the need for brushes and slip rings, increases the lifetime of the machine, and ultimately reduces the maintenance costs (Carlson, Voltolini, Runcos and Kuo-Peng, 2006).

This paper focuses on a 5-MW REpower MM92 wind turbine system (Fig. 5), which is available in both onshore and offshore types. This wind turbine system features a non-integrated drive train with a rotor shaft supported by two bearings, a combined planetary/spur wheel gearbox, and a double-fed asynchronous generator. The three-blade rotor with a diameter of 126 meters is also equipped with an electrical blade angle adjustment and a cast iron rotor hub.

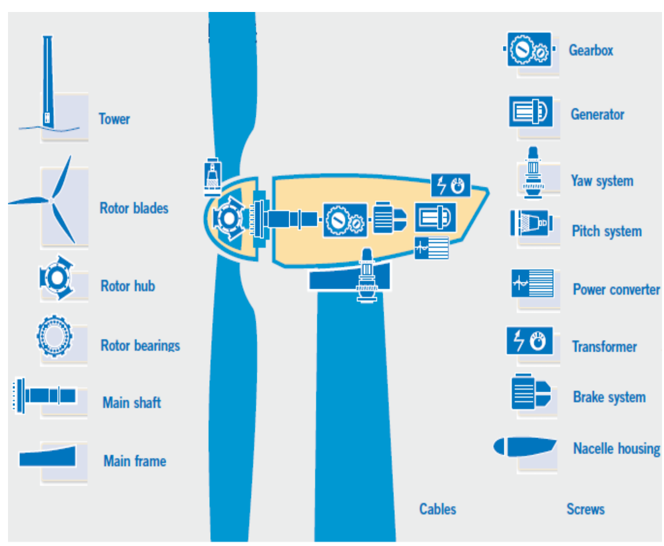


Fig. 5– 5MW REpower MM92 wind turbine system (http://www.REpower.de/)

After recognizing the wind turbine type, we define a general set of the sub-assemblies and main parts. In this study, sixteen sub-assemblies and components with higher failure probabilities and serious consequences have been considered as presented in Table 4. It may be apparent that not all of these components may be available in some types of wind turbine systems.

Table 4– The sixteen sub-assemblies considered in this study (listed in alphabetical order).

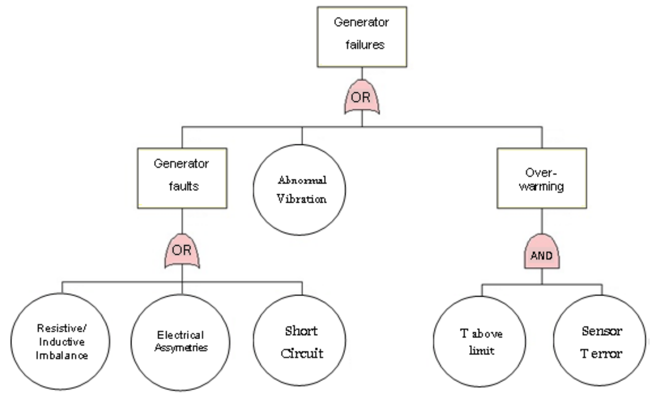
ID	Sub-assemblies	Some components
1	Brake system	Brake disk, Spring, Motor
2	Cables	
3	Gearbox	Toothed gear wheels, Pump, Oil heater/cooler, Hoses
4	Generator	Shaft, Bearings, Rotor, Stator, Coil
5	Main frame	
6	Main shaft	Shaft, Bearings, Couplings
7	Nacelle housing	Nacelle
8	Pitch system	Pitch motor, Gears
9	Power converter	Power electronic switch, cable, DC bus
10	Rotor bearings	
11	Rotor blades	Blades
12	Rotor hub	Hub, Air brake
13	Screws	
14	Tower	Tower, Foundation
15	Transformer	Controllers
16	Yaw system	Yaw drive, Yaw motor

After subdivision of the wind turbine system, the potential failure modes of the sub-assemblies are identified using the information gathered from four experts. These experts have experience within the reliability, availability, maintainability and safety (RAMS) of the wind energy industry, ranging from three to six years. The experts used the 'fault tree analysis (FTA)' to describe the complete set of potential system failures (for more see Andrews and Moss, 1993). The FTA is one of the most popular and diagrammatic techniques to analyze the undesired states of a system that uses AND gate (the output occurs only if all inputs occur) and OR gate (the output occurs if any input occurs). Fig. 6 depicts the fault tree diagram for two important sub-assemblies of the wind turbine system: generator and tower.

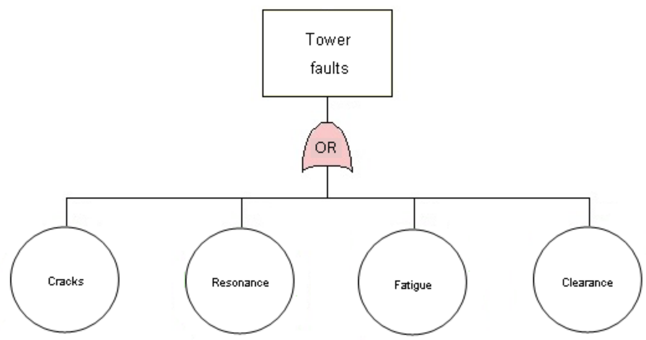
4. PROPOSED FUZZY-FMEA APPROACH

In this section, a new proposed approach which utilizes the fuzzy IF–THEN rules and grey relation theory is presented. The linguistic terms describing the 'inputs' are *Remote* (R), *Low* (L), *Moderate* (M), *High* (H) and *Very High* (VH), and for 'output' are *Unnecessary* (U), *minor* (mi), *very-low* (vl), *low* (l), *moderate* (mod), *high* (h), *Moderate-high* (Mh), *Very-high* (Vh), *necessary* (n) and *Absolutely-necessary* (A-n).

By using the interpretations of the linguistic terms described in Table 5, the experts were requested to define the membership functions. After receiving the feedback from the experts, the membership function of the linguistic terms defined by triangular fuzzy number (a,b,c) expressing the proposition 'close to b'. Making use of the fuzzy logic toolbox simulator of MATLAB®, the membership functions for the linguistic variables of severity, occurrence, detection, and fuzzy RPN are graphically represented in Fig. 7.



(a)



(b)

Fig. 6– Fault tree diagram for (a) #4: Generator (b) #14: Tower.

Table 5– Interpretations of the linguistic terms for developing the fuzzy rule system (Guimarães and Lapa, 2007).

Linguistic term	Probability of occurrence	Severity	Detection
Remote	It would be very unlikely for these failures to be observed even once	A failure that has no effect on the system performance, the operator probably will not notice	Defect remains undetected until the system performance degrades to the extent that the task will not be completed
Low	Likely to occur once, but unlikely to occur more frequently	A failure that would cause slight annoyance to the operator, but that cause no deterioration to the system	Defect remains undetected until system performance is severely reduced
Moderate	Likely to occur more than once	A failure that would cause a high degree of operator dissatisfaction or that causes noticeable but slight deterioration in system performance	Defect remains undetected until system performance is affected
High	Near certain to occur at least once	A failure that causes significant deterioration in system performance and/or	Defect remains undetected until inspection or test is carried out

		leads to minor injuries	
Very high	Near certain to occur several times	A failure that would seriously affect the ability to complete The task or cause damage, serious injury or death	Failure remains undetected, such a defect would almost certainly be detected during inspection or test

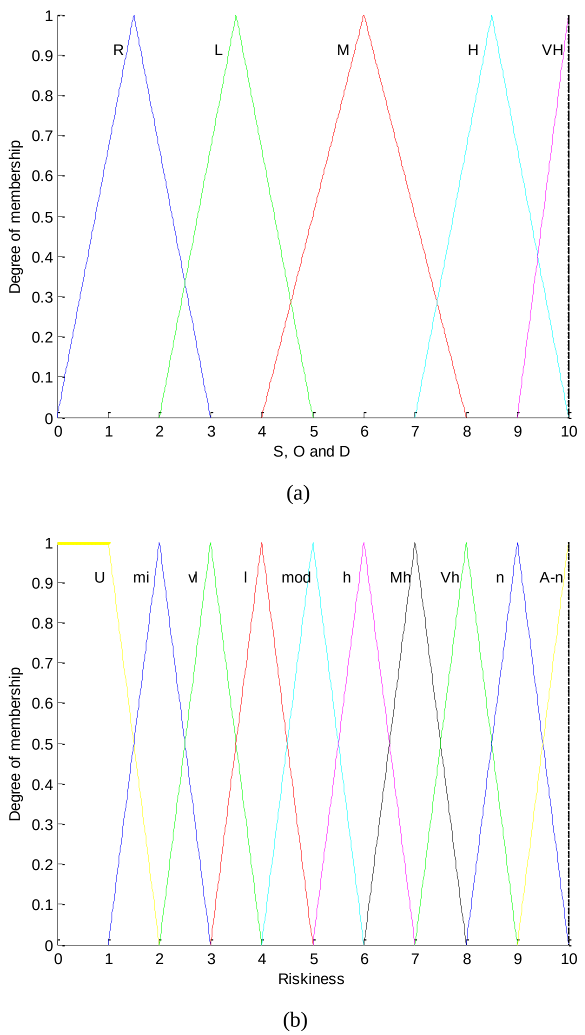


Fig. 7– Membership functions for (a) severity, occurrence, and detection, and (b) riskiness.

4.1. Fuzzy Rule Base

The membership functions derived from the experts are used to generate the fuzzy rule base. A total of $5\times5\times5$ = 125 rules are generated. However, these rules are combined (where possible) and the total number of rules in the fuzzy rule base is reduced to 35 rules. The Rule Viewer of the MATLAB that opens during the simulation can be used to access the ‘Membership Function Editor’ and the ‘Rule Editor’. Through ‘Simulator’ many results can be evaluated and rules can be removed. For example, consider these three rules:

Rule 1: if Severity is H, Occurrence is M, and Detection is M, then Riskiness is M–h.
Rule 2: if Severity is M, Occurrence is H, and Detection is H, then Riskiness is M–h.
Rule 3: if Severity is H, Occurrence is H, and Detection is M, then Riskiness is M–h.

Rules 1, 2 and 3, can be combined to produce: ‘‘if Severity is H, Occurrence is M, and Detection is M, then Riskiness is M–h’’ or any combination of the three linguistic terms assigned to these variables, then Riskiness is M–h.
The results of the fuzzy rule base are then defuzzified using the *centroid* method (see Cheng, 1998) to obtain the crisp value of ‘riskiness’ for ranking the failure modes. The defuzzified crisp numbers of ten output linguistic terms are given in Table 6.

Table 6–The defuzzified crisp numbers of output linguistic terms

U	mi	vl	l	Mod	h	M-h	V-h	n	A-n
0.81	2.03	3.02	4.01	5.01	6.01	7.01	8.01	9.01	9.67

Fuzzy inference functions used in this application are:
name: ‘FMEA_WT’
type: ‘Mamdani’
andMethod: ‘min’
orMethod: ‘max’
defuzzMethod: ‘centroid’
impMethod: ‘min’
aggMethod: ‘max’

4.2. Grey Relational Analysis

In the proposed rule base reduction, the three risk factors S, O and D are assumed to have the same importance. To assign different weights to the three risk factors, grey theory approach is suggested within the FMEA framework. Grey theory was first proposed and developed by Deng (1989) to deal with making decisions characterized by *incomplete* information. Indeed, it provides a measure to analyze relationship between discrete quantitative and qualitative series. The process for carrying out a grey relation analysis in FMEA involves several steps as shown in Fig. 8 (Liu, Liu, Bian, Lin, Dong and Xu, 2011).

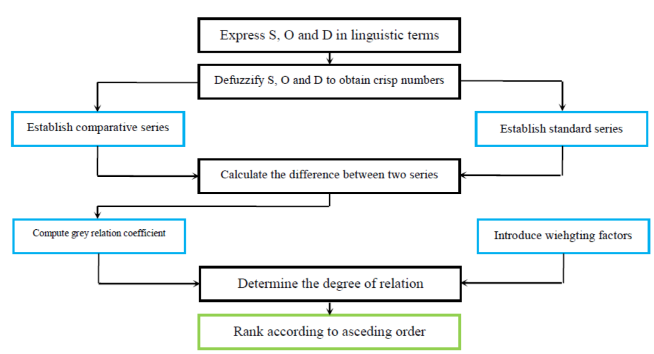


Fig 8–Grey relation analysis in FMEA

(i) Express S, O and D by linguistic terms and the membership functions as shown in Fig. 7(a).

(ii) Defuzzify S, O and D using Chen and Klien's method (1997) for obtaining the crisp number of a fuzzy set as shown in Eq. (1).

As an example, consider the defuzzification of the linguistic term *Low* in Fig. 9. This linguistic term can be defuzzified to

$$K(x) = \frac{\sum_{i=0}^{n}(b_i - c)}{\sum_{i=0}^{n}(b_i - c) - \sum_{i=0}^{n}(a_i - d)}, \qquad (1)$$

$$\frac{[5-0]+[3.5-0]}{\{[5-0]+[3.5-0]\}-\{[2-10]+[3.5-10]\}} = 0.370$$

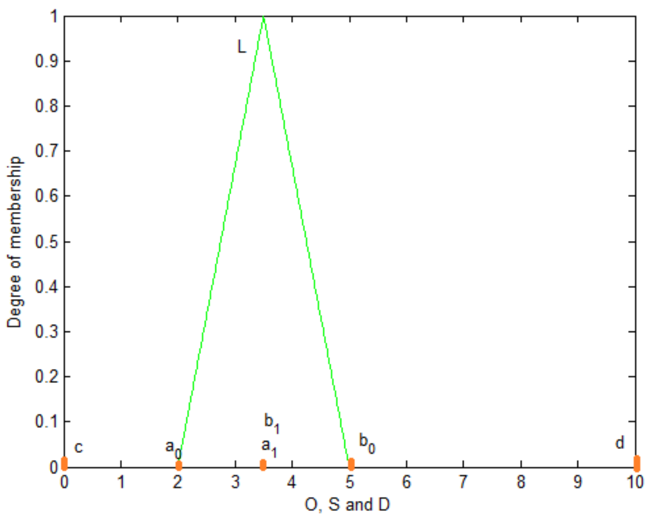


Fig. 9– Defuzzification of the linguistic term *Low*

The defuzzified crisp numbers of five linguistic terms are given in Table 7.

Table 7. The defuzzified crisp numbers of input linguistic terms

R	L	M	H	VH
0.196	0.370	0.583	0.804	0.952

(iii) Establish comparative series, which reflects the various linguistic terms and decision factors of the study. This can be represented in the form of a matrix, X as

$$X = \begin{pmatrix} x_1^1 & x_1^2 & x_1^3 \\ x_2^1 & x_2^2 & x_2^3 \\ .. & .. & .. \\ x_n^1 & x_n^2 & x_n^3 \end{pmatrix}, \qquad (2)$$

where n is the number of the failure modes, x_i^1, x_i^2 and x_i^3 are the crisp numbers of three risk factors for i^{th} failure mode. For example, for sub-assembly 6 (main shaft), x_6^1, x_6^2 and x_6^3 are assigned, respectively, 0.370, 0.370 and 0.583.

(iv) Establish standard series, which reflects the ideal or desired level of all the decision factors. This can be represented in a form of a matrix, Y as

$$Y = \begin{pmatrix} y_1^1 & y_1^2 & y_1^3 \\ y_2^1 & y_2^2 & y_2^3 \\ .. & .. & .. \\ y_n^1 & y_n^2 & y_n^3 \end{pmatrix}, \qquad (3)$$

where y_i^1, y_i^2 and y_i^3 represent the crisp numbers of the lowest level of three risk factors for i^{th} failure modes. Here, we have $y_i^j = 0.196$, for any $i \in \{1,2,...,n\}$ and $j \in \{1,2,3\}$.

(v) Calculate the difference between the comparative series and standard series. This can be represented in a form of a matrix, D, as

$$D = \begin{pmatrix} d_1^1 & d_1^2 & d_1^3 \\ d_2^1 & d_2^2 & d_2^3 \\ .. & .. & .. \\ d_n^1 & d_n^2 & d_n^3 \end{pmatrix}, \qquad (4)$$

where $d_i^j = \left| x_i^j - y_i^j \right|$, for any $i \in \{1,2,...,n\}$ and $j \in \{1,2,3\}$.

(vi) Compute the grey relation coefficient using the following equation (Chang, Wei and Lee, 1999):

$$\gamma_i^j = \frac{D_{\mathbf{min}} + \zeta D_{\mathbf{max}}}{d_i^j + \zeta D_{\mathbf{max}}}, \qquad (5)$$

where $D_{\min} \equiv \min_i \min_j d_i^j$, $D_{\max} \equiv \max_i \max_j d_i^j$, and $\zeta \in [0,1]$ is an identifier which only affects the relative value of risk without any change in priority. Here, we have $D_{\min} = 0$, $D_{\max} = 0.756$, and ζ is assumed to be 0.5.

(vii) Introduce the weight vector of three risk factors ($\beta_1, \beta_2, \beta_3$), where $0 < \beta_1, \beta_2, \beta_3 < 1$, and $\beta_1 + \beta_2 + \beta_3 = 1$. Weight vector of risk factors can be obtained by either directly assigning or indirectly using pair-wise comparisons (Kutlu and Ekmekçioğlu, 2012). Here, we consider the weights vector as in Arabian-Hoseynabadi, Oraee and Tavner (2010), i.e., (0.21, 0.26, 0.53) for (S, O, D).

(viii) Determine the degree of relation using $\Gamma_i = \beta_1 \gamma_i^1 + \beta_2 \gamma_i^2 + \beta_3 \gamma_i^3$ for each failure mode incorporating the weighted variables.

(i) Rank the priority of risk: the stronger the degree of relation, the smaller is the effect of the cause.

5. ANALYSIS OF RESULTS

In this Section, a comparative study is carried out using the traditional and the proposed fuzzy-FMEA methodologies applied to an offshore wind turbine system. The same experts have been surveyed for two methodologies to enable comparisons of the results. Our field failure data has been collected from 10-minute SCADA database, automated fault logs, operation and maintenance reports. Fig. 10 represents the failure rate of the sixteen sub-assemblies of the offshore wind turbine, where the average failure rate of the system (i.e., the expected number of failures per year) is equal to 1.38/year.

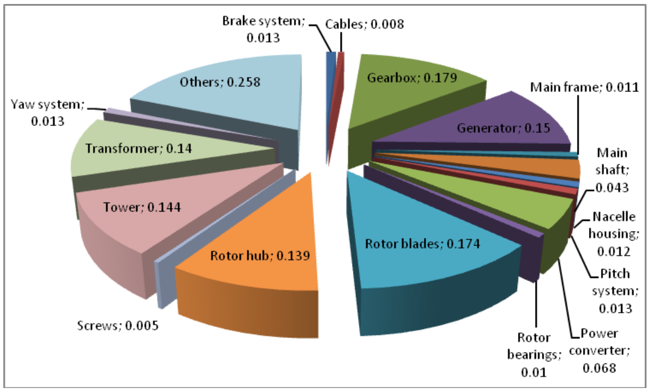


Fig. 10–The failure rates of the sub-assemblies of the offshore wind turbine system (sub-assemblies are listed in alphabetical order).

As shown, the gearbox, rotor blades, generator, tower and the transformer have the highest failure rates.

5.1. Traditional FMEA

On the basis of real data collected from an offshore wind farm database, and the criteria explained in tables 1–3, the traditional FMEA methodology is applied to the offshore wind turbine system. Table 8 gives the RPN values for the sixteen wind turbine sub-assemblies that considered in this study.

Table 8– The RPN values for wind turbine sub-assemblies

ID	Sub-assemblies	S	O	D	RPN	Rank
1	Brake system	2	2	7	28	11
2	Cables	3	2	1	6	14
3	Gearbox	3	5	7	105	2
4	Generator	2	5	7	70	5
5	Main frame	4	2	4	32	10
6	Main shaft	2	3	7	42	8
7	Nacelle housing	3	2	1	6	14
8	Pitch system	4	2	7	56	7
9	Power converter	4	3	7	84	4
10	Rotor bearings	3	2	4	24	12
11	Rotor blades	3	5	7	105	2
12	Rotor hub	2	5	4	40	9
13	Screws	1	2	1	2	16
14	Tower	4	5	7	140	1
15	Transformer	3	5	4	60	6
16	Yaw system	2	2	4	16	13

The results show that the tower (sub-assembly #14) is the most critical and the screws (sub-assembly #13) are the least critical parts in the offshore wind turbine system with the RPN values of 140 and 2, respectively.

From Table 8, the values of S, O and D for both the sub-assemblies of gearbox (sub-assembly #3) and rotor blades (sub-assembly #11) are the same. Hence, the traditional method puts the gearbox and rotor blades as having the same priority in offshore wind turbine systems. However, all the four experts believe that the *hidden* risk implications of these two failure modes are different in practice. One reason for this event is the existing limited number of the severity–occurrence–detection combinations for assigning to the three risk factors. This difference is obvious when the fuzzy rule base method and grey theory is applied.

5.2. Fuzzy FMEA

The results obtained from the proposed fuzzy approach are presented in Table 9.

Table 9– Ranking for proposed approach

ID	Sub-assemblies	Fuzzy rule base	Grey theory	Ranking (Fuzzy rule base)	Ranking (grey theory)
1	Brake system	1.405	0.937	11	12
2	Cables	1.288	0.941	16	16
3	Gearbox	4.873	0.829	3	3
4	Generator	2.032	0.917	6	6
5	Main frame	1.840	0.923	7	7
6	Main shaft	1.492	0.932	9	9
7	Nacelle housing	1.396	0.936	12	11
8	Pitch system	1.798	0.925	8	8
9	Power converter	2.503	0.902	4	4
10	Rotor bearings	1.366	0.939	14	14
11	Rotor blades	7.660	0.739	2	2
12	Rotor hub	1.492	0.935	9	10
13	Screws	1.312	0.940	15	15
14	Tower	8.890	0.700	1	1
15	Transformer	2.077	0.916	5	5
16	Yaw system	1.375	0.938	13	13

Table 9 shows a noticeable similarity between the results obtained from the two 'fuzzy rule base' and 'grey theory' methods. For instance, both approaches are in agreement about the tower (sub-assembly #14) being the most critical, and the cables (sub-assembly #2) being the least critical parts of the offshore wind turbine system. Also, the ranking order of the rotor blades (sub-assembly #11) is obtained higher than the gearbox (sub-assembly #3) in both the methods. The main reason for this event is that the blades are 'stressed' in a harsh maritime environment and extreme weather conditions, and they suffer from different types of external damages (including seasonal affects such as icing and thunderstorms) (Shafiee, Patriksson and Strömberg, 2013).

It should be noted that the ranking order produced by the fuzzy rule base method does not differentiate failure modes that have the same combination of linguistic terms describing the three risk factors. For example, S, O and D for the main shaft (sub-assembly #6) and rotor hub (sub-assembly #12) are assigned, respectively, as 'low/low/moderate' and 'low/moderate/low'. Hence, the defuzzified ranking is obtained the same for these sub-assemblies. This entails that the main shaft and rotor hub should be given the same priority for attention, and it could be misleading. The effects of the weighting coefficient introduced in the grey theory method can be clearly seen in this case. When using the grey theory method, the grey relation ranking is 0.932 and 0.935 for the main shaft and rotor hub, respectively. This entails that the main shaft should be given a higher priority compared to the rotor hub.

5.3. Comparison

In this section, a comparison is made between the ranking orders of the traditional FMEA, fuzzy rule base and grey theory approaches. In Table 10, the results obtained for the offshore wind turbine system from the traditional FMEA using the RPN method is compared with the results obtained from the proposed fuzzy FMEA using the rule base and grey relation methods.

Table 10–Ranking comparisons between the traditional and the fuzzy-FMEA approaches

Rank	Traditional	Fuzzy rule base	Grey theory
1	Tower	Tower	Tower
2	Gearbox / Rotor blades	Rotor blades	Rotor blades
3		Gearbox	Gearbox
4	Power converter	Power converter	Power converter
5	Generator	Transformer	Transformer
6	Transformer	Generator	Generator
7	Pitch system	Main frame	Main frame
8	Main shaft	Pitch system	Pitch system
9	Rotor hub	Main shaft/ Rotor hub	Main shaft
10	Main frame		Rotor hub
11	Brake system	Brake system	Nacelle housing
12	Rotor bearings	Nacelle housing	Brake system
13	Yaw system	Yaw system	Yaw system
14	Nacelle housing / Cables	Rotor bearings	Rotor bearings
15		Screws	Screws
16	Screws	Cables	Cables

As can be seen, the main problem in the traditional FMEA methodology is that it puts two critical sub-assemblies of the gearbox and the rotor blades as having the same priority. The nacelle housing and the cables are also placed at the same ranking level. But, applying the proposed methodology reveals that there is a noticeable difference between their ranking orders.

On the other side, there is some noticeable difference between the ranking orders of some sub-assemblies (such as main frame and nacelle housing) using the traditional and the Fuzzy FMEA methods. This shows that a more accurate ranking can be achieved by the application of the fuzzy rule base and grey theory to FMEA.

6. CONCLUSIONS AND TOPICS FOR FUTURE RESEARCH

The advantages of the proposed fuzzy rule base and grey theory approach for application to FMEA of offshore wind turbine systems can be summarized as follows:

a. The proposed fuzzy-FMEA approach provides an organized framework to combine the qualitative (expert experience) and quantitative (SCADA field data) knowledge for use in an FMEA study;
b. The proposed fuzzy-FMEA approach can be useful when the failure data is unavailable or unreliable;
c. The use of linguistic terms in the analysis enables the experts to express their judgments more realistically and hence improving the applicability of the FMEA technique in offshore wind farms;
d. The relative importance weights of risk factors are taken into consideration in the process of prioritization of failure modes, which makes the proposed FMEA more realistic, more practical and more flexible.

The proposed fuzzy rule base method (without the weighting vector of the risk factors) could be suitable for use in 'risk screening' phase, or during the 'design' stage of a new wind turbine configuration. During the risk-screening phase, only a relative ranking order is needed. This will distinguish the failure modes with a high risk level from those with a low-risk level. The proposed grey theory approach (with the weighting vector of the risk factors) would be suitable for use in 'risk analysis and evaluation' phase, or during the 'operation' stage. At this stage, a more detailed analysis of each failure mode is required to produce a ranking order that would determine the allocation of the limited resources. As the proposed method provides the analyst with the flexibility to decide which factor is more important to the analysis, the outcome of the analysis will provide valuable information for the wind farm managers or the wind turbine manufacturers.

Still, there is a wide scope for future research in improving the traditional FMEA methodology to make it more practical for wind turbine systems. Some of the possible extensions are:

(a) The proposed fuzzy-FMEA approach in this paper has no limitation on the number of risk factors and can be applied to any number of risk factors.
(b) Sometimes, it is observed that the FMEA team members, because of their different expertise and backgrounds have different opinions. The diversity and uncertainty of FMEA team members' assessment information will be considered in our future research.

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