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A real-time inspection and opportunistic maintenance strategies for floating offshore wind turbines

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ABSTRACT

This paper proposes an FMEA-BN model to determine the inspection and opportunistic maintenance strategies of floating offshore wind turbines. A mapping algorithm is proposed to establish a mirrored Bayesian Network (BN) model from a given failure mode and effect analysis (FMEA) structure to realize the FMEA-BN modelling, which is efficient to consider common cause failures. The failure probabilities of items of floating offshore wind turbines are first updated by the BN sub-model, in which, various operation scenarios are considered. The updated failure probabilities are then imported to the FMEA sub-model to determine the items of the floating offshore wind turbines that are to be inspected and to which the opportunistic maintenance action would be applied. With the FMEA-BN model, inspection and opportunistic maintenance strategies for a floating offshore wind turbine are suggested under several commonly occurring operation scenarios. The validation of the results is illustrated by the failure rate of the floating offshore wind turbine predicted by the BN sub-model, the uncertainty of which is lower than 3%. Overall, the presented FMEA-BN model supports real-time inspection and opportunistic maintenance strategies determination of complicated systems like floating offshore wind turbines.

1. Introduction

Floating offshore wind energy has newly emerged. The development of such a new concept has incomparable advantages over the maturely installed onshore wind: (i) Flexible in construction. The floating wind is more suitable for the construction of large wind farms and does not occupy land space (Dincer, 2000; Díaz and Guedes Soares, 2020a); (ii) Higher electricity generation efficiency. Generally, the electricity generation efficiency of floating offshore wind can be up to 1.5 to 2 times that of onshore ones (Sinha and Steel, 2015; Li et al., 2020b); (iii) Higher capacity factor. The higher speed and more stable wind profile at sea are expected to push the capacity factor of floating offshore wind turbines up to more than 50%, which is much higher than that of onshore wind turbines, which is about 34% based on American wind energy statistics during the past three years (U.S. Energy Information Administration, 2021); (vi) It is more suitable for stepping into deeper (above 50 m) and farther waters (above 40 km from the coast) (Uzunoglu et al., 2016; Díaz and Guedes Soares, 2020b). Hence, the wind market, to some extent, has been turned from onshore wind to bottom-fixed types and is now inclining towards floating wind (Bagbanci et al., 2012; Díaz and Guedes Soares, 2020a).

However, large-scale wind turbine designed (Roddier et al., 2010; Bento and Fontes, 2019; Uzunoglu and Guedes Soares, 2020), extreme wind farm environments (Zhang et al., 2014; Martins et al., 2015; Karmakar et al., 2016; Reder et al., 2018; Ioannou et al., 2019; Sobral et al., 2019), limited maintenance resources (Nielsen and Sørensen, 2011; Santos et al., 2015; Shafiee and Sørensen, 2019; Yeter et al., 2020), and lack of operational experience (Rinaldi et al., 2017; Kausche et al., 2018; Li et al., 2021a,b) have brought certain obstacles to the development of floating offshore wind turbines and the construction of floating offshore wind farms, including but not limited to: floating offshore wind electricity price is still higher than thermal power (Sinha and Steel, 2015; Kausche et al., 2018); failure rates of floating offshore wind turbines as a whole and their key components are higher than onshore structures (Carroll et al., 2016; Li et al., 2020a; Li and Guedes Soares, 2021).

Operation and maintenance are the efforts associated with the daily operations and normal repairs of floating offshore wind turbines so that it continues to provide electricity and achieve their expected life. Compared to design, manufacturing, and installation, operation and maintenance last longer and is costly. For instance, operation and

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maintenance costs of onshore and bottom-fixed offshore wind turbines accounting for 20%–30% of their overall economic benefits, which can be compared to 35% that of floating ones (in some wind farms) (Sinha and Steel, 2015; Castro-Santos et al., 2016, 2017, 2020). Therefore, the development of floating offshore wind turbines relies heavily on higher reliability, availability, and energy production efficiency, which further resorts to effective inspection and maintenance strategies.

One of the cores of operation and maintenance is the maintenance technique. Overall, corrective maintenance, preventive maintenance, and condition-based maintenance (CBM) are three types of maintenance for engineering systems like floating offshore wind turbines (Barata et al., 2002; Sinha and Steel, 2015; Santos et al., 2016). Corrective maintenance starts when failure occurs. Preventive maintenance is performed according to a predetermined time interval to avoid potential failures. CBM is a relatively up-to-date technique that dynamically determines maintenance activities according to the health state of the system that has been analysed (Kang et al., 2019b).

However, the maintenance of floating offshore wind turbines and floating offshore wind farms are much more complicated. First, the low availabilities of maintenance vessels and uncertain weather windows (Martins et al., 2015) result in low accessibility to floating wind farms, which degrades the possibility of maintenance and the maintenance must be finalized at a limited period (Myhr et al., 2014; Santos et al., 2018; Pandit et al., 2020; Elusakin et al., 2021). Second, the maintenance of floating offshore wind turbines is costly especially when the cost of vessels is considered (Santos et al., 2015b; Taboada et al., 2021). Hence, under the double pressures of maintenance possibility and cost, the maintenance crew of the floating offshore wind sector is expected to carry out inspections and some minor preventive maintenance after corrective maintenance had been done, which is a combined maintenance strategy of corrective and preventive maintenance, taking all advantage of opportunistic maintenance (Erguido et al., 2017; Zhang et al., 2017, 2019; Kang et al., 2019a; Li et al., 2020c; Kang and Guedes Soares, 2020).

The opportunistic maintenance strategy is urgently needed by the floating offshore wind turbines and can be extended to the floating offshore wind farm level (Abdollahzadeh et al., 2016; Atashgar and Abdollahzadeh, 2016; Li et al., 2021c), as this new strategy contributes to maintenance cost saving and no additional weather window delay and employment of vessels are needed (Kang and Guedes Soares, 2020). To this end, Li et al. (2020c) proposed an opportunistic maintenance schedule for offshore wind turbines considering degradation of components and economic dependencies among multiple parts, the result indicates that the determined opportunistic maintenance schedule has a potential of reducing 6.3% of overall maintenance cost of the offshore wind turbine. To take the imperfect maintenance of wind turbines into account, Zhang et al. (2017) proposed a reliability-based opportunistic maintenance schedule for wind turbines, concluded that the reliability threshold for initializing the opportunistic maintenance of the wind turbine is 0.9825. Furtherly, they accessed the impact of weather windows and spare parts inventory management on the maintenance cost of wind turbines, and constructed an opportunistic maintenance strategy for the wind turbines, which can potentially decline over 18% maintenance cost of wind turbines compared with the conventional maintenance strategies (Zhang et al., 2019).

The opportunistic maintenance is stepping from wind turbines to wind farms level where the modelling scale becomes larger and more items, wind turbines, or elements of a wind turbine are taken into account. To be specific, Atashgar and Abdollahzadeh (2016) formulated an opportunity maintenance model to determine the redundancy level of wind farms with multiple types of wind turbines by considering the number of wind turbines, maintenance delay, and the limitation of the maintenance crew, the results indicated that the achieved opportunity maintenance strategy has a superior performance in both maintenance cost-saving (about 22%) and reliability improvement of wind turbines (over 29%). Moreover, to reflect the multiple failure modes of wind turbines and their effects on wind farms, Erguido et al. (2017) created an opportunity maintenance model by considering the multiple failure modes of wind turbines and the reliability threshold of activating maintenance, which contributes to the maximizing the availability and reducing life cycle cost of wind farms. More recently, Kang and Guedes Soares (2020) determined an opportunity maintenance strategy for offshore wind farms, in which the imperfect maintenance and the uncertainty of maintenance effectiveness are considered. A comparison of the state-of-the-art researches and the presented one is listed in Table 1.

However, the mentioned opportunistic maintenance strategies have several practical restrictions: (i) With the target of cost-saving, these models neglect other factors affecting maintenance of floating offshore wind turbines such as operational risk; (ii) The existing models plan deterministic opportunistic maintenance strategies and are unable to update the components that to be inspected according to the real-time operational state of floating offshore wind turbines; (iii) The modelling basis of such models are at the components level and are unable to consider furtherly the failure modes and the failure cause of components. To this end, this paper presents a real-time risk-based inspection and opportunistic maintenance model for floating offshore wind turbines, which can update, in a real-time pattern, the inspection and opportunistic maintenance strategies for floating offshore wind turbines according to the variable environmental situations and operational states. The novel contributions of this paper are as follows:

(1) Propose a FMEA-BN model to update the inspection and opportunistic maintenance strategies according to variable environmental situations and operational states of floating offshore wind turbines.
(2) Propose, for the first time, a risk-based criterion to achieve real-time suggestions of components that are to be inspected for floating offshore wind turbines.
(3) Deepen the inspection and opportunistic maintenance strategies modelling into the failure modes and the failure causes level.

The remainder of this paper is arranged as follows. Section 2 introduces the FMEA-BN model. Section 3 demonstrates the configuration of the floating offshore wind turbines and the data source. Section 4 lists

Table 1
Components considered in the inspection and opportunistic maintenance strategy of wind turbines.

Reference	Components	Type of the Model	Factors Considered
[i]	Rotor, Main Bearing, Generator, Gearbox	Cost-based	Redundancy
[ii]	Gearbox, Pitch, Yaw, Blades	Cost-based	Reliability threshold
[iii]	Rotor, Main Bearing, Generator, Gearbox	Cost-based	Imperfect maintenance
[iv]	Rotor, Main Bearing, Generator, Gearbox	Cost-based	Weather conditions
[v]	Electrical system, Drive train, Generator, Blade, Hub, Yaw, Control	Cost-based	Maintenance interval of subcomponents
[vi]	Blade, Hub, Generator, Gearbox, Pitch, Converter, Transformer	Cost-based	Imperfect maintenance
[vii]	26 components including moorings and the floating foundation	Risk-based	Operation conditions

[i] : Atashgar and Abdollahzadeh (2016).
[ii] : Erguido et al. (2017).
[iii] : Zhang et al. (2017).
[iv] : Zhang et al. (2019).
[v] : Li et al. (2020c).
[vi] : Kang and Guedes Soares (2020).
[vii] : This paper.

the results, discussions, and comparisons. The conclusion of this paper is provided in Section 5.

2. Methodology

The maintenance crew of floating offshore wind farms expects to finalize as many as possible maintenance tasks in one arrival to a wind farm, as the accessibility to where is low and costly. Hence, it is necessary to conduct additional checks and inspections to components (except for the failed ones). However, floating offshore wind turbines are complicated systems with multiple components that suffer various failures (Santos et al., 2015a; Li and Guedes Soares, 2019; Scheu et al., 2019; Li et al., 2021a,b). To this end, the FMEA-BN model is to provide a recommendation of candidates from the numerous components, elements, structures, and failures of a floating offshore wind turbine that are to be inspected and the preventive maintenance can be then implemented after corrective maintenance would be done.

The FMEA is a predictive methodology that uses objective indices generally including severity, occurrence, and detection to construct risk priority numbers (RPNs) as a basis to find out critical failures of systems (Gandhi and Agrawal, 1992; Price and Taylor, 2002; Kim and Zuo, 2018). Severity is the consequence of failures. Detection numerically represents difficulties of a failure to be observed in advance of its happening. Occurrence denotes the likelihood of failures like failure probability. Normally, failures of the system are collected from maintenance records (if any) or from specialists working in the area if the maintenance record is not available. Various extensions of the approach are available (Carmignani, 2009; Peeters et al., 2017).

BNs are probabilistic models to standardize the causality between elements and systems, by which the performance of systems and failure properties of subsystems, components, until each failure is expected to be modeled by employing failure probabilities of basic failure items (Langseth and Portinale, 2007; Langseth et al., 2009). BNs can probabilistically update posterior probabilities of failures by the given evidence such as operational conditions of floating offshore wind turbines. The primary idea of the FMEA-BN model proposed is to extend the FMEA methodology by evidence updating capability so that it can reflect the impact of operational conditions on reliability issues.

Methodologically, the FMEA-BN model composes of two sub-models, which are FMEA and BN, and both share failure probabilities of basic failures. The BN sub-model updates probabilities of failures by actual operational conditions and transfers the updated posterior evidence to the FMEA sub-model as a basis to recompute the Risk Priority Number (RPN) of each failure, by which the inspection and opportunistic maintenance strategies of floating offshore wind turbines can be determined.

Initially, constructing a BN model from an FMEA structure is required. Let the elements in FMEA be $\mathbf{V} = (\mathbf{N}, \mathbf{L})$, and:

$$\mathbf{N} = \left\{N^{\mathrm{FOWT}}, \mathbf{X}^{\mathbf{SYST}}, \mathbf{X}^{\mathbf{COMP}}, \mathbf{X}^{\mathbf{FM}}, \mathbf{X}^{\mathbf{FE}}, \mathbf{X}^{\mathbf{FC}}\right\} \tag{1}$$

$$\mathbf{L} = \{L_1, L_2, \cdots, L_i, \cdots, L_n\} \tag{2}$$

In Eqs (1) and (2), $\mathbf{N}$ represents failure items and $\mathbf{L}$ denotes affiliations between failure items such as the hierarchical structure of failure behaviour (Li et al., 2021b) that is “floating offshore wind turbine-system-component-failure mode-failure cause”. N^{FOWT} is the top level of the FMEA model reflecting the floating offshore wind turbine, $\mathbf{X}^{\mathbf{SYST}}$, $\mathbf{X}^{\mathbf{COMP}}$, $\mathbf{X}^{\mathbf{FM}}$, $\mathbf{X}^{\mathbf{FE}}$, and $\mathbf{X}^{\mathbf{FC}}$ are node sets at the system level (e.g. wind turbine system), the component level (e.g. generator), the failure mode level (e.g. broken mooring lines), the failure effect level (e.g. wind turbine shutdown), and the failure cause level (e.g. fatigue), respectively. L_i is the affiliation of nodes, which exists only between levels, mathematically say:

$$\forall L_i \in \mathbf{L} st. X^i \Leftrightarrow X^j, i \neq j \tag{3}$$

where, i and j demonstrate node levels, $X^i \Leftrightarrow X^j$ reflects affiliations between nodes.

Different from the existing BN mapping algorithms from FMEA structures that process limitations on mapping common cause failures such as Brahim et al. (2019), Kulkarni et al. (2020), this paper proposes a new procedure with an item aggregation mechanism to map a BN model from a FMEA structure. Knowing that a BN can be illustrated by $\mathbf{G} = (\mathbf{I}, \mathbf{E})$, in which $\mathbf{I}$ and $\mathbf{E}$ are node set and arc set. Accordingly, a BN model can be constructed from a FMEA structure by the following steps.

Step 1: Nodes Mapping. Mapping nodes of the BN model according to items of the FMEA structure, including items in $\mathbf{X}^{\mathbf{SYST}}$, $\mathbf{X}^{\mathbf{COMP}}$, $\mathbf{X}^{\mathbf{FE}}$, $\mathbf{X}^{\mathbf{FC}}$, and N^{FOWT}, see Fig. 1(a).

Step 2: Nodes States Determination. For $\forall X_j^{\mathrm{COMP}} \in \mathbf{X}^{\mathbf{COMP}}$, identifying the failure modes of the component X_j^{COMP}, say X_i^{FM}, mathematically illustrated by:

$$\forall L_i \in \mathbf{L}, st. X_i^{\mathrm{FM}} \rightarrow X_j^{\mathrm{COMP}} \tag{4}$$

where L_i represents X_i^{FM} is one of the failure modes of the component X_j^{COMP} in the FMEA model, $X_i^{\mathrm{FM}} \rightarrow X_j^{\mathrm{COMP}}$ denotes X_i^{FM} is a state of the component X_j^{COMP} in the BN model.

Holistically, $N + 1$ states of each component are considered including N failure modes and the working state, which assumes that the component X_j^{COMP} either works normally (working state) or is failed (can be represented by a known failure mode X_i^{FM}), see Fig. 1(b).

Step 3: Arcs Mapping. Connect all nodes of failure behaviour (system-component-failure cause) by directed arcs in the bottom-up mechanism that is an arc starts from failure cause and points to the system level, see Fig. 1(c), mathematically represented by:

$$X_i^{\mathrm{FC}} \Rightarrow X_j^{\mathrm{COMP}} \Rightarrow X_k^{\mathrm{SYST}} \Rightarrow N^{\mathrm{FOWT}} \tag{5}$$

In Eq. (5), $\Rightarrow$ reflects the direction of arcs and $X_i^{\mathrm{FC}} \in \mathbf{X}^{\mathrm{FC}}$, $X_j^{\mathrm{COMP}} \in \mathbf{X}^{\mathbf{COMP}}$, $X_k^{\mathrm{SYST}} \in \mathbf{X}^{\mathbf{SYST}}$.

For the node X_j^{COMP} with external impacts, distribute a directed arc that starts with X_j^{COMP} and points to its corresponding effect $X_i^{\mathrm{FE}} \in \mathbf{X}^{\mathbf{FE}}$, repeat this schedule to the overall BN model. Specifically, the circle avoidance principle is expressed by:

$$X_i \nleftarrow Parent(X_i) \tag{6}$$

where, $\nleftarrow$ is the prohibition symbol denoting that node X_i does not directly or indirectly point to its parent node(s) $Parent(X_i)$. Eq. (6) applies to nodes in $\mathbf{X}^{\mathbf{COMP}}$ and $\mathbf{X}^{\mathbf{SYST}}$ indicating that directed arcs only point to a node in higher levels to avoid directed cycles in the BN model.

Step 4: Node Aggregation. Aggregate the same nodes in failure cause set $\mathbf{X}^{\mathbf{FC}}$ and failure effect set $\mathbf{X}^{\mathbf{FE}}$. It is worth mentioning that the aggregation of the nodes should not change the failure behaviour and the failure transmission paths. For example, the reason of bearings' and gears' wear of generators are unsuitable initial preload and installation error, respectively, accordingly, no aggregation is needed. On the other hand, the merging of nodes should not delete the directed arcs of the aggregated nodes including those start from or point to the known nodes, also understood as that the node aggregation should not change the presented physical failure properties, see Fig. 1(d).

Step 5: Failure Probabilities of Root Nodes Determination. The failure probabilities of root nodes can be approximated by their failure frequencies after long-term observation or by analysing maintenance records of systems. The constant failure rate model is applicable to map relationships among failure rates, failure probabilities, and mean time to failures (MTTFs) of elements since

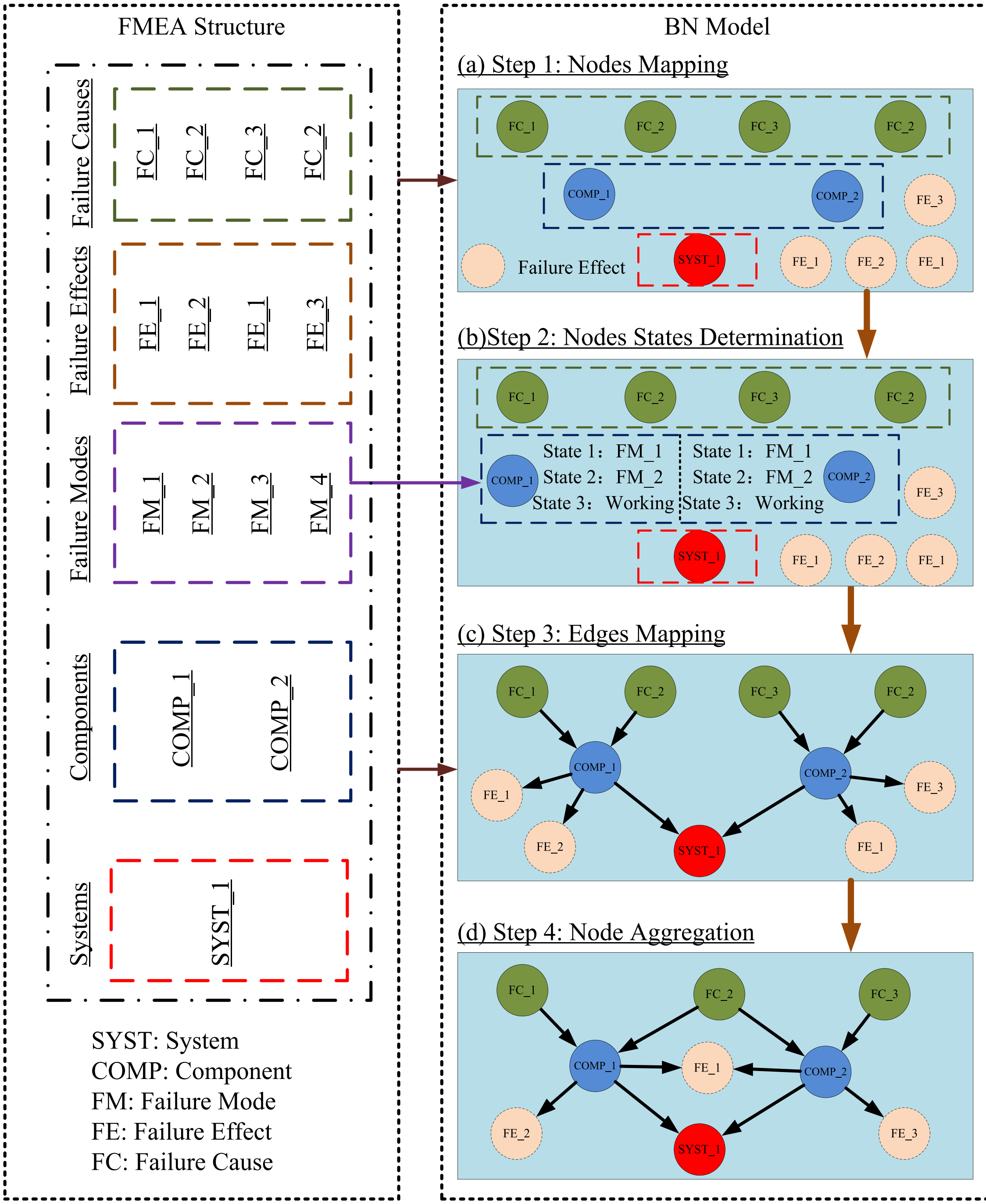

Fig. 1. Mapping procedure of the FMEA-BN model.

available failure data is always insufficient to fit life distributions for all failure causes especially in the design stage of floating offshore wind turbines. In general, the MTTF of a failure cause can be reflected by:

$$MTTF_i^{FC} = \frac{t_i - \sum_j tr_j}{N} \tag{7}$$

where, $MTTF_i^{FC}$ is the MTTF of failure cause i, t_i denotes the observation period of failure cause i, tr_j represents the repair time for the failure j, N reflects the number of failures had occurred during the observation period. The occurrence rate of failure cause i (λ_i^{FC}) can be converted by MTTF, as:

$$\lambda_i^{FC} = \frac{1}{MTTF_i^{FC}} \tag{8}$$

Hence, the failure probability of failure cause i ($P_i^{FC}(t)$) is expressed by:

$$P_i^{FC}(t) = 1 - e^{-\lambda_i^{FC} t} \tag{9}$$

For failure causes with insufficient failure data, this paper provides an analogy model to approximate failure rates from the occurrence of failure causes (occurrence of each failure cause is required by the FMEA schedule). Specifically, decompose the occurrence vector of failure causes to be:

$$\mathbf{O}=\left[\mathbf{O}_{\mathbf{i}}^{\boldsymbol{\alpha}} \quad \mathbf{O}_{\mathbf{j}}^{\boldsymbol{\beta}}\right]=\left[O_1^{\alpha} \quad \cdots \quad O_{\alpha}^{\alpha} \quad O_1^{\beta} \quad \cdots \quad O_{\beta}^{\beta}\right] \tag{10}$$

Define the failure rate vector of failure causes as:

$$\boldsymbol{\lambda}^{\mathbf{FC}}=\left[\boldsymbol{\lambda}_{\boldsymbol{\alpha}\mathbf{i}}^{\mathbf{FC}} \quad \boldsymbol{\lambda}_{\boldsymbol{\beta}\mathbf{j}}^{\mathbf{FC}}\right]=\left[\lambda_{\alpha 1}^{\mathrm{FC}} \quad \cdots \quad \lambda_{am}^{\mathrm{FC}} \quad \lambda_{\beta 1}^{\mathrm{FC}} \quad \cdots \quad \lambda_{\beta h}^{\mathrm{FC}}\right] \tag{11}$$

In Eqs. (10) and (11), $\mathbf{O}_{\mathbf{i}}^{\boldsymbol{\alpha}}$ and $\boldsymbol{\lambda}_{\boldsymbol{\alpha}\mathbf{i}}^{\mathbf{FC}}$ are occurrence vector and failure rate vector of failure causes with known failure rate (see Eqs. (7)-(9)), $\mathbf{O}_{\mathbf{j}}^{\boldsymbol{\beta}}$ and $\boldsymbol{\lambda}_{\boldsymbol{\beta}\mathbf{j}}^{\mathbf{FC}}$ are those with unknown failure rates and which are to be determined.

Define an analogy index as:

$$\varpi=\sum_{j=1}^{h} O_i^{\beta} \Big/ \sum_{j=1}^{m} O_i^{\alpha} \tag{12}$$

Accordingly, the inferred failure rate of failure causes can be computed by:

$$\boldsymbol{\lambda}_{\boldsymbol{\beta}}^{\mathbf{FC}}=\varpi \times \boldsymbol{\lambda}_{\boldsymbol{\alpha}\mathbf{i}}^{\mathbf{FC}}=\frac{\sum_{j=1}^{h} O_i^{\beta} \times \boldsymbol{\lambda}_{\boldsymbol{\alpha}\mathbf{i}}^{\mathbf{FC}}}{\sum_{j=1}^{m} O_i^{\alpha}} \tag{13}$$

The analogy method infers failure rates of failure causes by comparing the differences between their occurrence that are given by specialists. With the differences and integrated with known failure rates of failure causes, the failure probabilities of the rest failure causes can be calculated. However, the most relevant failure items should be selected to carry on the comparison, for instance, when inferring the failure rate of a gearbox's failure, the failure items of the gearbox should be considered first instead of those of other components with different failure mechanisms like towers and blades.

Step 6: Conditional Probability Tables (CPTs) Determination. The CPTs of nodes in the BN model can be gained from maintenance records of floating offshore wind turbines (if any) or experts' opinions. For the former, assume that parents of node i in the BN model contain h states, and the parents' state set ($\boldsymbol{\tau}$) is arranged to be:

$$\boldsymbol{\tau}=\{\tau_1, \tau_2, \cdots, \tau_j, \cdots, \tau_h\} \tag{14}$$

Accordingly, the conditional probability of node i works in the state k is reflected by:

$$p_i^k=p\left(x_i=\mathrm{Sta}(k) \middle| \tau_j\right)=\frac{N\left(\mathrm{Sta}(k), \tau_j\right)}{N(\mathrm{Sta}(k))} \tag{15}$$

where p_i^k represents the probability of node i works in the state k and its parent node j works in the state τ_j, $N(\mathrm{Sta}(k))$ is the frequency that node i works in the state k, $N(\mathrm{Sta}(k), \tau_j)$ denotes the frequency of node i works in the state k at the same time its parent node j works in the state τ_j. $N(\mathrm{Sta}(k))$ and $N(\mathrm{Sta}(k), \tau_j)$ can be reached from maintenance records of floating offshore wind turbines.

The failure probability of a root failure cause of a floating offshore wind turbine can be updated by its known operational conditions by the diagnostic support information propagation of the BN model:

$$P\left(X_i \middle| X_j\right)=\frac{P\left(X_i, X_j\right)}{P\left(X_j\right)}=\frac{P\left(X_j \middle| X_i\right) P\left(X_i\right)}{P\left(X_j\right)}=\frac{P\left(X_j \middle| X_i\right) P\left(X_i\right)}{\sum_i P\left(X_j \middle| X_i\right) P\left(X_i\right)} \tag{16}$$

where, $X_1, X_2, \cdots, X_n$ are independent variables, $P(X_1, X_2, \cdots, X_n)$ is their joint probability distribution illustrated by:

$$P(X_1, X_2, \cdots, X_n)=\prod_{i=1}^{n} P(X_i | parents(X_i)) \tag{17}$$

where, $parents(X_i)$ represents parent nodes of X_i.

Subsequently, conditional RPN of a failure cause can be updated by:

$$RPN^{\mathrm{FC}}=\alpha S \times \beta P^{Post.} \times \gamma D \tag{18}$$

where, RPN^{FC} represents the risk priority number of a failure cause, S and D are severity and detection of the failure cause given by specialists, $P^{Post.}$ denotes the posterior failure probability of the failure cause. α, β, and γ are weights of severity, posterior failure probability, and detection of the failure cause.

Accordingly, RPNs of a failure mode is expressed by the summation of its corresponding failure causes, as:

$$RPN^{\mathrm{FM}}=\sum RPN^{\mathrm{FC}} \tag{19}$$

Similarly, RPN of components (RPN^{COMP}) and systems (RPN^{SYST}) of the floating offshore wind turbine are calculated by:

$$RPN^{\mathrm{COMP}}=\sum RPN^{\mathrm{FM}} \tag{20}$$

$$RPN^{\mathrm{SYST}}=\sum RPN^{\mathrm{COMP}} \tag{21}$$

The framework of mapping a BN model from an FMEA structure is shown in Fig. 2.

3. The floating offshore wind turbine considered and data sources

Floating offshore wind turbines are functionally integrated by a selection of components that are either independent to or auxiliary to others. The floating offshore wind turbine considered in this study is shown in Fig. 3 (Li et al., 2021b), which consists of four primary modules: wind turbine, tower and transition piece, floating foundation, and mooring system. Among others, the wind turbine is analogous to the onshore concept that accomplishes the energy generation function by assembled blades, the gearbox, the generator, and several more mechanical and electrical assembling.

Moreover, the rest including the tower and transition piece, floating foundation, and mooring system (Xu et al., 2019) are unique systems of the floating offshore wind turbine than onshore ones, designed to locate in a selected sea space where the wind profile is typically higher. Overall, the design, operation, and maintenance of elements within the nacelles of the floating equipment are comparable to those of onshore ones. Hence, experience, methods, standards, and techniques accumulated from the onshore sector can be applied to today's new floating concept. However, transition pieces, floating foundations, and mooring systems are particularly designed for floating offshore wind turbines. Elements of the floating offshore wind turbine modules are listed in Table 2.

Overall, 42 failure modes with 104 failure causes (see Appendix A) were collected from the employed five specialists in China and Spain, see in Table 3 (Li et al., 2021b). Failure rates of the root failure causes are partly reviewed from (Kang et al., 2019c), and the rest are inferred by the proposed analogy model, see Eqs. (10)–(12). CPTs, the casualties among failures, of the BN model are partly inferred from the maintenance records of four onshore wind farms located in China. For the failures that were not covered by the maintenance records, experts' opinion was applied. Weights of severity, posterior failure probability, and detection of failure causes, exactly α, β, and γ, are the same as that what been concluded in Li et al. (2021b). The constructed FMEA-BN model is illustrated in Fig. 4.

4. Results and discussion

4.1. Recommendations for inspection and opportunistic maintenance

Theoretically, the FMEA-BN model constructs RPNs of failure items

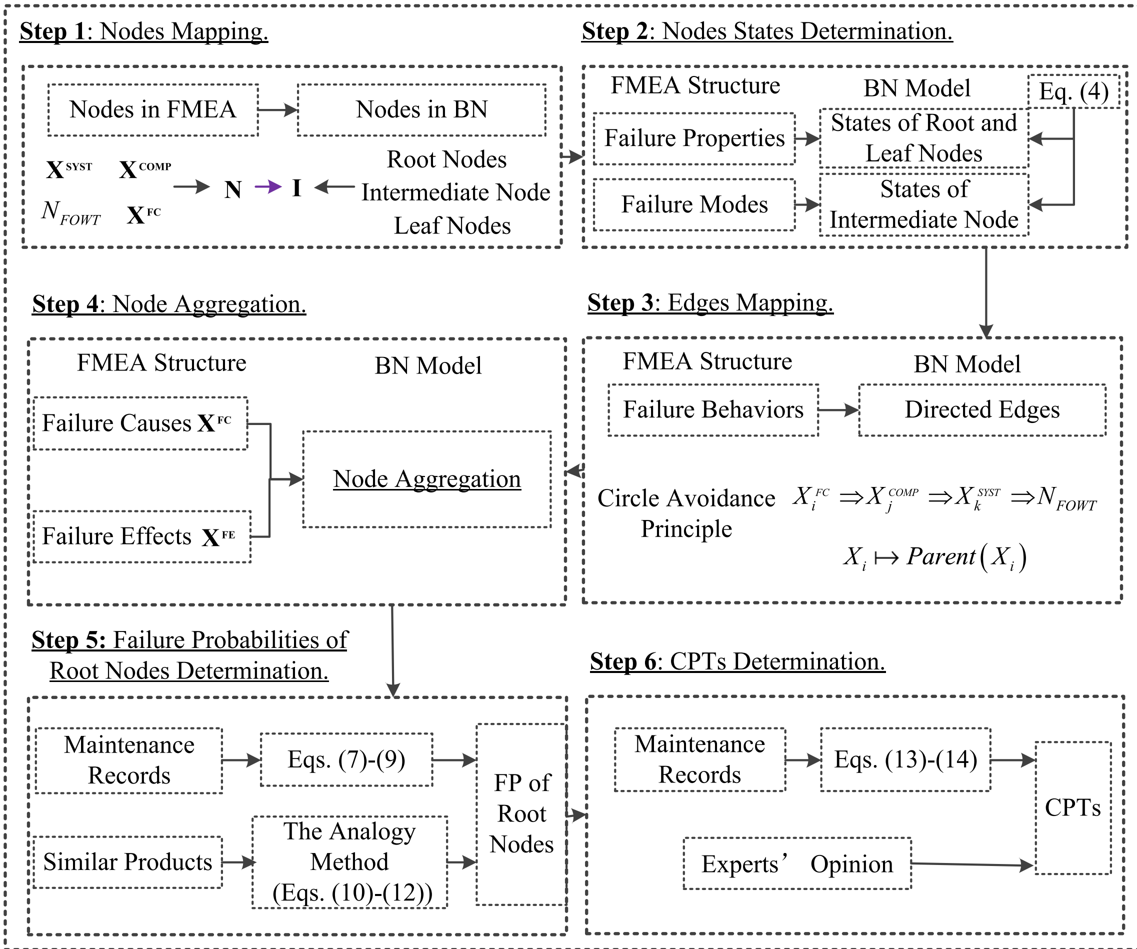

Fig. 2. The framework of mapping a BN model from an FMEA structure/FP: Failure Probability; CPT: Conditional Probability Table.

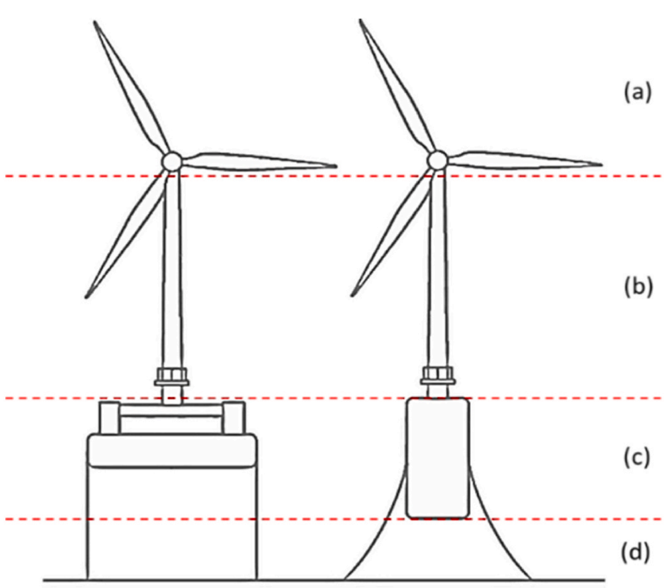

Fig. 3. Floating offshore wind turbine/(a) Wind turbine; (b) Tower and transition piece; (c) Floating foundation; (d) Mooring system.

Table 2
Main components of the floating offshore wind turbine (Li et al., 2021b).

System		Component
Code	System	
WT	Wind Turbine	Blade (BL), Hub (HB), Main Bearing (MB), Main Shift (MSH), Generator (GE), Gearbox (GB), Converter (CV), Transformer (TR), Pitch Subsystem (PS), Yaw Subsystem (YS), Controller and Electrical Facilities (CE)
TT	Tower and Transition Piece	Tower (TO), Transition Piece (TP)
FF	Floating Foundation	Pipe (PP), Pillar (PL), Lights (LT), Helicopter Assistance Equipment (HAE), Handrails (HD), Ladders (LD), Vents (VE), Sensors (SS), Manholes (MH)
MS	Mooring System	Mooring Lines (ML), Fairlead (FL), Anchor (AC), Rests (RE)

by multiplying severity, failure probability (rather than occurrence), and detection. The application of the BN model makes it possible to determine the posterior failure probability of failure items under special operating conditions and to update RPNs of failure items. The results of the FMEA-BN model under operational conditions are listed in Appendix B.

Table 3
Specialists involved in failure collection of floating offshore wind turbines/FOWTs: Floating Offshore Wind Turbines.

Code	Employer	Duty	Working Period	Country	Reason of Employment
<1>	Wind Energy Company	System Design	4 Years	China	Specialized in systems design
<2>	Wind Energy Company	Components Design	3 Years	China	Specialized in components design
<3>	Wind Energy Company	Quality Engineer	4 Years	China	Experienced in quality issues
<4>	University	Researcher	6 Years	China	Experienced in failure analysis of FOWTs, with several publications related
<5>	Wind Energy Company	Technical Officer Chief	11 Years	Spain	Experienced in the operation of FOWTs, especially in the maintenance sector

On the other hand, in practice, the FMEA-BN model provides recommendations of the components, elements, structures, and their corresponding failures that are to be inspected and then opportunistic maintenance can be implemented by identifying the most critical failure items under various operational conditions. The maintenance crew is suggested to have inspections on the failure items with a higher risk of failure under practical operation situations, for instance:

(i) Periodical preventive maintenance. It is to determine the order of failure items that are to be inspected and also provide a guide to normal preventive maintenance.
(ii) Practical operation scenario. It is to update the order of failure items that to be inspected in the case of the practical operation scenario is observed such as long-term unstable electricity output (UO) which is a frequently happened abnormal state of wind turbines. In the UO state of wind turbines, the wind turbine works in the rated wind condition (the wind speed is higher than the cut-in wind speed) but the output power is lower than the designed rated one. However, no failures are reported by the monitoring system like SCADA or CMS.
(iii) Specific maintenance applied. It is to update the order of failure items that to be inspected in the case of specific corrective maintenance had been applied to some components. For example, the order of the components to be inspected can be determined after corrective maintenance has been done for the generator.
(iv) Dangerous weather conditions. It is to update the order of failure items that are to be inspected after dangerous weather conditions happen like typhoons or storms, which can occur several times in a given sea area.

4.1.1. Inspection and opportunistic maintenance strategy without operational condition

The results of the FMEA-BN model support the understanding of the failure properties of the floating offshore wind turbines under the situation that no operational condition is considered. With the results, the wind turbine system with the RPN of 0.44 (44% of the total) is to be inspected preferentially, followed by the mooring system (24%), the tower and transition piece system (16%), and the floating foundation (15%).

At the components level, the inspection of components in decreased order is mooring facilities (24%), floating foundation elements (15%), the gearbox (12%), the tower (11%), the generator (7%), the transition piece (6%), the converter (5%), the transformer (4%), the yaw system (4%), the pitch system (3%), blades (2%), the main shaft (2%), the hub (2%), the main bearing (2%), as well as controller and electrical elements (1%). It is worth pointing out that mooring facilities, floating foundation elements, the gearbox, the tower, and the generator are critical components of the floating offshore wind turbine, which numerically account for 20% components of the entire equipment but contribute to nearly 70% of RPN.

Regarding the critical components already mentioned, "broken and

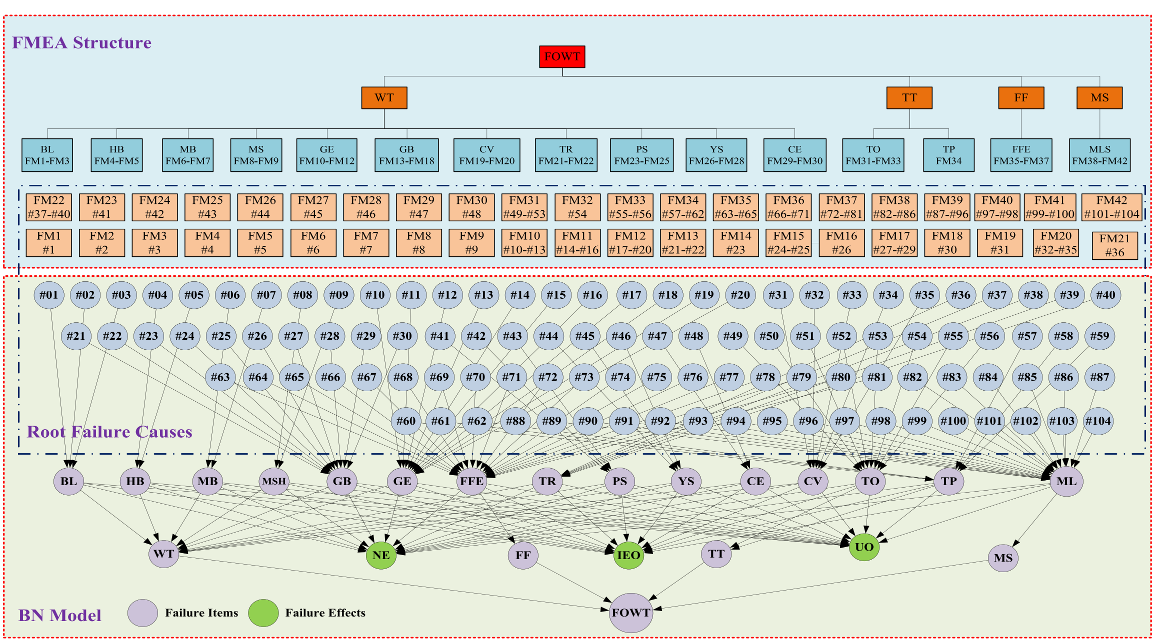

Fig. 4. The FMEA-BN model of the floating offshore wind turbine, see Appendix A/FFE: Floating Foundation Elements; NE: No Electricity; IEO: Insufficient Electricity Output; UO: Unstable Electricity Output.

abnormal mooring lines" are the two critical failures of mooring facilities, the former is caused primarily by accumulator failure, connectors failure, mooring interface structure failure, and transitional chain wear, which can be compared with "abnormal mooring lines" that resulted from abnormal stress and ineffective maintenance.

Another failure namely "abnormal mooring system functions", caused mainly by harsh sea conditions, calls for special attention of designers and operators, which indicates that catastrophic failures can occur. "Watertight fault" is a typical failure of the floating foundation, the root reason of which can be tracked to fouling of the platform. Leaking and lubrication dried out are the main reasons for "gearbox overheat" as direct friction of metal parts such as bearings (between elements and internal and external rings) and gears (between surfaces) are inevitable at such conditions, which furtherly bring additional heat to the gearbox.

"Tower collapse" as a consequence of strong wind/wave and ice storm (in some wind farms) as well as "transition piece crack" resulting from strong wind or wave are two dangerous failures. The criticalities of generator's failures including "bearing deformation", "overheat", and "winding failures" are comparable, which are consequences of improper grease, cooling system failure, and winding corrosion.

4.1.2. Inspection and opportunistic maintenance strategy with operational conditions

As illustrated in Table 4, the criticalities and their ranks of failure causes were updated given the UO state of the floating offshore wind turbine. Table 4 lists failure causes whose criticality ranks changed the most, compared with that of in the working state, given the floating offshore wind turbine works in the UO state. It indicates that the wind turbine system and the mooring system are more sensitive to the UO state than the remaining systems.

Operators and maintenance crew of the floating offshore wind turbine should firstly pay attention to the pitch subsystem after the UO state is observed. Moreover, lubrication problems of the main bearing, generator bearings, sensors failure of floating foundations, mooring lines defects like corrosion and wear are to be checked given the UO state. These new suggestions, which result from the present approach, cannot be obtained by conventional studies.

However, several failures (mostly hard failures) would no longer be crucial for the floating offshore wind turbine than ever under the UO states, for instance, "blades cracks", "main shaft fracture", and "tower collapse" resulting from the lightning strike, transition piece crack, and failure causes of the mooring system like friction chain wear and anchor pickup device damage. The mentioned failures would cause either shutdown (e.g. "tower collapse") or minor consequences (e.g. "transition piece crack") rather than UO of the floating offshore wind turbine, which meets the updated results of the FMEA-BN model that concluded decreased criticality rankings to such failures.

Similarly, the corresponding conclusions and suggestions for the inspection and opportunity maintenance under various operational conditions can be easily achieved by the FMEA-BN model, for instance, specific maintenance applied and dangerous weather conditions happened. Those easy results are not listed in this paper, however, it is worth pointing out that:

(i) The sensitivities of failures to different operational conditions vary a lot. For instance, the criticality ranks of mooring lines corrosion (MS-ML-FM38-#84), main bearing lubrication (WT-MB-FM7-#7), mooring lines wear (MS-ML-FM38-#82), and sensors for platform monitoring (FF-FFE-FM37-#80) changed significantly given the UO state, which can be compared to those without changing including navigation and work lights fail (FF-FFE-FM37-#72), the handrails corrosion (FF-FFE-FM37-#74), and ladders corrosion (FF-FFE-FM37-#75);
(ii) At the components level, some components are only sensitive to certain conditions, such as structures exposed to harsh marine environments are more sensitive to the marine environments (such as strong wind and waves), generator maintenance only affects the generator itself and have limited impact on other parts;
(iii) As the failure reaches a level, the reactions (or sensitivities) of failure causes to operation conditions are different despite they may failure causes of the same component, for instance, given the UO state, the criticality of "abnormal mooring lines" are increased as a consequence of the shape growing of failure likelihoods (e.g. MS-ML-FM38-#82, MS-ML-FM38-#83, MS-ML-FM38-#84), on the contrary, the criticality of broken mooring lines (e.g. MS-ML-FM39-#88, MS-ML-FM39-#91) goes down.

The above results indicate that considering operational conditions into the inspection and opportunistic maintenance of complicated systems like floating offshore wind turbines benefits for gaining convincing and close-to-practice results.

The inspection and opportunistic maintenance of floating offshore wind turbines considering operations and maintenance actions are systemic and complicated schedules, involving combinations of several operational conditions such as extreme weather (e.g. strong wind) and particular working conditions (e.g. UO state). The mentioned factors may happen at the same time. The suggestions of the inspection and opportunistic order under the combined operational conditions can be reached by appealing to the diagnostic support reasoning of the BN model by giving a selection states of corresponding nodes. For example, the combination of the cooling system failure and UO state reflects the situation that the floating offshore wind turbine generates unstable electricity during or after the cooling system failed. The posterior probabilities of root failure causes would be updated by the BN model assigning the states of the cooling system failures (nodes WT-GE-FM11-#15 and WT-CV-FM20-#35) and the UO (node UO) both to be true. Accordingly, conditional RPNs of failure items under such a condition can be determined.

More actual and useful conclusions of the floating equipment work in other operating conditions can be reached by analysing the results in Appendix B in a similar way. This paper, however, will not discuss such conditions and the combinations of multiple conditions in detail. More particular results call for extensive analysis to enhance the body of inspection and opportunistic maintenance strategies of floating offshore wind turbines.

Table 4
Criticalities comparison of failure causes under the working and UO states.

Failure causes	Criticalities Changes		Failure causes	Criticalities Changes	
	Amount	De/In-crease		Amount	De/In-crease
WT-BL-FM1-#1	10	↓	TT-TP-FM34-#58	13	↑
WT-MB-FM7-#7	26	↑	FF-FFE-FM35-#63	10	↓
WT-MSH-FM9-#9	11	↑	FF-FFE-FM37-#80	24	↑
WT-GE-FM11-#15	13	↑	MS-ML-FM38-#82	17	↑
WT-CV-FM20-#35	13	↑	MS-ML-FM38-#83	10	↑
WT-TR-FM22-#39	10	↑	MS-ML-FM38-#84	31	↑
WT-PS-FM23-#41	16	↑	MS-ML-FM39-#88	10	↓
WT-PS-FM25-#43	12	↑	MS-ML-FM39-#91	10	↓
TT-TO-FM31-#50	10	↓	↑/↓: Increased/Decreased		

4.2. Reliability prediction and model verification

With the BN model constructed from the FMEA structure (see Fig. 4), the failure rate of the floating offshore wind turbine is predicted to be 8.08 failures/wind turbine/year with the MTTF of 1084 h.

A comparison between the results of this paper and those reached by other models is illustrated in Fig. 5. Compared with the failure rate (or MTTF) obtained from the data collection (some 350 offshore wind turbines installed around the European continent with a totally of 15.5 million operating hours) and those predicted by other mature models, the FMEA-BN model proposed in this paper holds a lower relative error (less than 3%). The low error predicted supports the correctness of the results calculated, accordingly, which also indicates the correctness of the posterior probabilities reasoned by the FMEA-BN model given specific operating conditions of the floating offshore wind turbine.

Overall, the better performance of the FMEA-BN model over the existing ones (see Fig. 5) is the consequence of the following aspects:

(i) More failures considered. Exactly 42 failures with 104 failure causes and in total 127 nodes are considered to model the failure configuration of the floating offshore wind turbine, which is more comprehensive than the existing models such as Li et al. (2020a), Kang et al. (2019c), and Zhang et al. (2021), in which only 80 failure causes and altogether 116 nodes/events are involved.

(ii) More data collected. Complicated system assumption is applied in constructing the BN model, to be specific, this assumption holds that relations between failures are unterminated and cannot be expressed by series and parallel systems. Hence the probabilities in CPTs of the BN model are determined by the statistical analysis of maintenance records of wind turbines and the rest that are not covered by the maintenance records are designed by specialists within the scope of [0, 1]. This type of modelling significantly improved the reliability modelling forms under simple system assumption that believes a failure either has no or has an inevitable impact on others.

Overall, the proposed FMEA-BN model predicts a lower relative error than those calculated by conventional BN and FTA models but the results of fuzzy FTA are closer to the statical data with a relative error of less than 1%. It is worth mentioning that, the failure data reported by Carroll et al. (2016) is based on 350 offshore wind turbines with bottom-fixed structure, which differs from floating offshore wind turbines in this paper and there is no obvious evidence that can rank the performances of the mentioned theoretically predicted results. However, the comparison demonstrates that the proposed FMEA-BN model has the capability of predicting failure rates of components of floating offshore wind turbines and the results are convincing as which close to both collected and theoretically predicted ones.

The FMEA-BN model proposed in this paper is an integration of maturely used FMEA as well as BN methodologies. To be specific, the FMEA constructs an easy deductive schedule for complex system configuration identification and modelling, at the same time, the BN model, mapped from the FMEA structure by the prosed mapping algorithm, supports the probabilistic failure analysis of the FMEA schedule. Finally, by the integrated FMEA-BN model, operational conditions of complicated systems can be reasonably modeled. The presented methodology is not limited to the inspection and opportunistic maintenance of floating offshore wind turbines but would be feasible for other complicated systems.

5. Conclusions

A risk-based inspection and opportunistic maintenance strategy determination technique namely the FMEA-BN model is proposed. The model is able to determine the order of failure items to be inspected given operating conditions. For instance, systems (e.g. wind turbine), components (e.g. mooring lines), and failure causes (e.g. wear and fatigue) that are to be checked under the UO state of the floating equipment are suggested. The superiority of the proposed risk-based method over the existing cost-based ones is that it can update the order of failure items to be inspected according to the operational situations and the working states of floating offshore wind turbines so that a real-time inspection and opportunistic maintenance stagey can be obtained. The correctness of the FMEA-BN model is validated by the precisely predicted failure rate (8.08 failures/wind turbine/year) and MTTF (1084 h), specifically, the relative error is less than 3% compared with the filed data collected. However, combining the proposed risk-based method and the existing cost-based models to construct a risk-and-cost integrated inspection and opportunistic maintenance model to achieve a comprehensive opportunistic maintenance strategy is the future work following this paper.

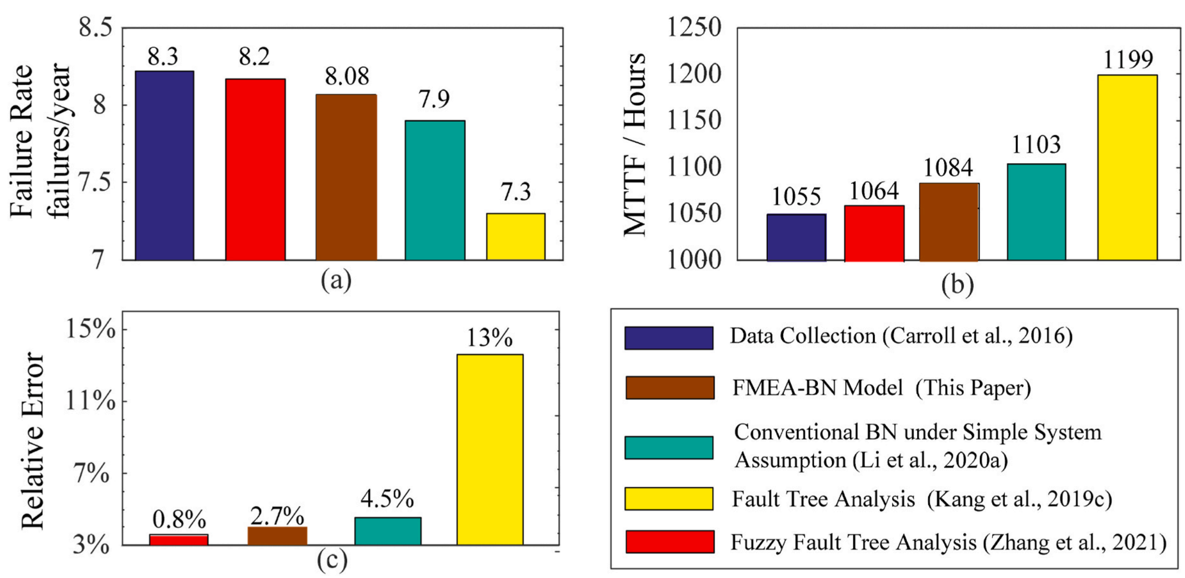

Fig. 5. Comparison of results/(a) Comparison in failure rates; (b) Comparison in MTTFs; (c) Comparison in relative errors.

CRediT authorship contribution statement

He Li: Methodology, Formal analysis, Writing – original draft, Visualization. **Cheng-Geng Huang:** Writing – original draft. **C. Guedes Soares:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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Appendix A. Failure modes and causes of the floating offshore wind turbine

Failure Mode Level			Failure Cause Level	
Code	Failure Modes	End Effects	Code	Failure Causes
WT-BL-FM1	Blades cracks	Wind turbine stop working	#1	Manufacturing error
WT-BL-FM2	Delamination	Wind turbine stop working	#2	Insufficient lighting protection
WT-BL-FM3	Gear teeth slip	Blades fail to attack wind properly	#3	Wear, fatigue, etc.
WT-HB-FM4	Fracture in the shell	Rotor break	#4	Manufacturing error
WT-HB-FM5	Error in positioning	Blades break away from the hub	#5	Manufacturing error and/or fitting error
WT-MB-FM6	Bearing damage	Wind turbine stop working	#6	Wear, fatigue, etc.
WT-MB-FM7	Bearing vibration	Abnormal working condition	#7	Substandard lubrication
WT-MSH-FM8	Cracks	Collapse of wind turbine	#8	Welding defects
WT-MSH-FM9	Fracture	Collapse of wind turbine	#9	Fatigue
WT-GE-FM10	Bearing deformation	No, abnormal or unbalanced electricity generation	#10	Improper grease
			#11	Over tighten
			#12	Electric corrosion of rollaway nest
			#13	Shaft wear deformation
WT-GE-FM11	Overheat (GE)	Offshore wind turbine shutdown	#14	Turbine overload
			#15	Cooling system failure
			#16	Partial short circuit on stator winding
WT-GE-FM12	Winding failure	No, abnormal or unbalanced electricity generation	#17	Cable insulation failure
			#18	Connecting plug fall off
			#19	Interturn short circuit
			#20	Winding corrosion
WT-GB-FM13	Wear gears	Exceeded vibration or unstable electricity output	#21	Wear, fatigue
			#22	Dirty or lacking lubrication
WT-GB-FM14	Seized gears	No electricity output	#23	Sudden shock exceed limitation
WT-GB-FM15	Fractured gear teeth	Exceeded vibration or unstable electricity output	#24	Sudden shock exceed limitation
			#25	Fatigue
WT-GB-FM16	Wear bearing	Exceeded vibration	#26	Fatigue
WT-GB-FM17	Overheat (GB)	Offshore wind turbine shutdown	#27	Wear
			#28	Lubrication dried out
			#29	Leaking
WT-GB-FM18	Shift crack	Offshore wind turbine shutdown	#30	Fatigue
WT-CV-FM19	Short circuit	Converter shutdown	#31	Over heat
WT-CV-FM20	Open circuit	Disconnect to grid	#32	Load mutation
			#33	Invert power input fault
			#34	Overload
			#35	Cooling system fault
WT-TR-FM21	Short circuit	Transformer shutdown	#36	Over heat
WT-TR-FM22	Open circuit	Disconnect to grid	#37	Constant overload
			#38	Iron core corrosion
			#39	Overcurrent
			#40	Overvoltage
WT-PS-FM23	Wrong pitch angle	Decrease of electricity output	#41	Poor calibration
WT-PS-FM24	Pitting Gears	Vibration increase	#42	Wear, fatigue
WT-PS-FM25	Misalignment bearings	Decrease of electricity output	#43	Wear, excessive vibration
WT-YS-FM26	Seizure bearings	Over heat	#44	Poor lubrication
WT-YS-FM27	Corrosions	Pitting of raceways	#45	Presence of corrosive substances
WT-YS-FM28	Hydraulic leakage	Rotor fails to stop	#46	Wear or degradation on hydraulic lines
WT-CE-FM29	Short circuit	Offshore wind turbine shutdown	#47	Moisture penetration
WT-CE-FM30	Open circuit	Offshore wind turbine shutdown	#48	Lightning strike
TT-TO-FM31	Tower collapse	Failure of whole facility and vast economic loses	#49	Strong wind/wave
			#50	Lightning Strike
			#51	Hit by blades
			#52	Ice storm
			#53	Braking system failed

(*continued on next page*)

(*continued*)

Failure Mode Level			Failure Cause Level	
Code	Failure Modes	End Effects	Code	Failure Causes
Failure Mode Level			Failure Cause Level	
Code	Failure Modes	End Effects	Code	Failure Causes
TT-TO-FM32	Abnormal vibration	Potential collapse	#54	Resonance
TT-TO-FM33	Crack	Potential collapse	#55	Faulty welding of Tower
			#56	Material fatigue
TT-TP-FM34	Transition piece crack	Potential collapse	#57	Material fatigue
			#58	Corrosion
			#59	Plastic deformation
			#60	Cyclic degradation
			#61	Strong wind/wave
			#62	Faulty welding
FF-FF-FM35	Hit by dropped objects	Damage to the facility, vast economic loses	#63	Planes crash
			#64	Biological collision
			#65	Strong wind/wave
FF-FF-FM36	Watertight fault	Potential failure	#66	Inefficient detection
			#67	Pipe joint corrosion
			#68	Pipe joint weld defect
			#69	Pipe joint fatigue
			#70	Pillar damage
			#71	Excessive fouling of platform
FF-FF-FM37	Additional structures fail	Potential failure	#72	Navigation and work lights fail
			#73	Helicopter assistance equipment fail
			#74	Handrails corrosion
			#75	Ladders corrosion
			#76	Dynamic umbilical connection fail
			#77	Towing brackets/bollards fail
			#78	Vents fail
			#79	Bilge piping/pumps fail
			#80	Sensors for platform monitoring fail
			#81	Manholes fail
MS-ML-FM38	Abnormal mooring lines	Mooring line strength decrease or broken	#82	Mooring lines wear
			#83	Mooring lines fatigue
			#84	Mooring lines corrosion
			#85	Abnormal stress
			#86	Not effective maintenance
MS-ML-FM39	Broken mooring lines	Malfunction of the whole system, the facility cannot locate in water	#87	Transitional chain wear
			#88	Friction chain wear
			#89	Mooring winch failure
			#90	Buoys friction chain wear
			#91	Anchor pickup device damage
			#92	Hydraulic motor failure
			#93	Accumulator failure
			#94	Over pressure
			#95	Connectors failure
			#96	Mooring interface structure failure
MS-FL-FM40	Fairlead failure	The anchor cannot be dropped and lift	#97	Fairlead corrosion
			#98	Fairlead fatigue
MS-AC-FM41	Anchor failure	Anchor failure	#99	Abnormal working conditions
			#100	Cyclic degradation
MS-RE-FM42	Abnormal functions	Anchoring accuracy decrease	#101	Poor operation environment
			#102	Insufficient emergency measurement
			#103	Human Error
			#104	Analysis and calculation fault

Appendix B. Analysis of failure causes

Failure Causes	RPN & RPN Rank				Failure Causes	RPN & RPN Rank			
	WC	WF	UO	GM		WC	WF	UO	GM
WT-BL-FM1-#1	81.79(68)	81.79(78)	81.79(78)	81.79(72)	WT-GE-FM12-#19	58.65(93)	58.75(98)	58.76(98)	58.69(93)
WT-BL-FM2-#2	77.74(74)	77.75(85)	77.75(84)	77.75(77)	WT-GE-FM12-#20	76.36(78)	80(81)	80.46(81)	77.72(79)
WT-BL-FM3-#3	72.63(83)	78.68(84)	79.27(83)	76.52(82)	WT-GB-FM13-#21	81.48(72)	85.37(71)	85.95(69)	80.16(74)
WT-HB-FM4-#4	59.11(92)	59.44(97)	59.62(97)	59.23(92)	WT-GB-FM13-#22	205.46(1)	270.55(3)	278.64(5)	197.59(3)
WT-HB-FM5-#5	123.52(18)	144.59(19)	139.82(22)	131.47(17)	WT-GB-FM14-#23	89.48(52)	96.6(52)	97.68(52)	86.9(62)
WT-MB-FM6-#6	90.2(51)	90.27(61)	90.47(60)	90.22(55)	WT-GB-FM15-#24	98.74(38)	104.37(37)	105.22(38)	96.71(43)
WT-MB-FM7-#7	86.65(60)	94.74(53)	111.72(34)	88.29(60)	WT-GB-FM15-#25	98.47(39)	100.74(45)	101(46)	98.38(41)
WT-MSH-FM8-#8	105.34(29)	111.33(33)	116.52(30)	107.19(33)	WT-GB-FM16-#26	76.34(79)	80.59(79)	81.28(80)	74.42(83)
WT-MSH-FM9-#9	101.42(33)	101.55(43)	101.61(44)	101.45(39)	WT-GB-FM17-#27	77.18(76)	79.19(82)	79.38(82)	77.46(81)
WT-GE-FM10-#10	75.44(82)	82.56(76)	83.54(75)	77.64(80)	WT-GB-FM17-#28	171.85(8)	213.06(8)	216.51(9)	181.88(8)
WT-GE-FM10-#11	67(87)	68.62(88)	68.85(88)	67.44(87)	WT-GB-FM17-#29	190.59(2)	248.56(4)	255.68(6)	184.3(7)
WT-GE-FM10-#12	68.64(86)	71.25(87)	71.61(87)	69.45(86)	WT-GB-FM18-#30	95.47(44)	99.05(49)	99.51(49)	94.93(46)
WT-GE-FM10-#13	67(88)	68.42(89)	68.61(89)	67.44(88)	WT-CV-FM19-#31	109.05(23)	152.71(16)	148.98(19)	118.16(22)
WT-GE-FM11-#14	63.17(89)	63.99(91)	64.07(91)	63.56(90)	WT-CV-FM20-#32	87.91(56)	101.28(44)	94.09(54)	94.65(47)
WT-GE-FM11-#15	91.16(48)	107.56(36)	110.08(35)	94.93(45)	WT-CV-FM20-#33	83(64)	93.59(56)	87.87(64)	88.31(59)
WT-GE-FM11-#16	62.93(91)	63.74(92)	63.82(92)	63.31(91)	WT-CV-FM20-#34	88.55(54)	104.01(40)	93.73(56)	94.3(48)
WT-GE-FM12-#17	56.89(95)	57.06(99)	57.08(99)	56.93(95)	WT-CV-FM20-#35	97.53(41)	128.4(24)	118.55(28)	104.67(34)
WT-GE-FM12-#18	55.92(96)	56.14(100)	56.16(100)	56(97)	WT-TR-FM21-#36	82.51(65)	91.46(59)	87.81(65)	85.28(63)

Failure Causes	RPN & RPN Rank				Failure Causes	RPN & RPN Rank			
	WC	WF	UO	GM		WC	WF	UO	GM
WT-TR-FM22-#37	75.49(81)	79.02(83)	77.61(85)	77.75(78)	TT-TO-FM33-#55	107.74(26)	115.58(29)	117.19(29)	109.54(28)
WT-TR-FM22-#38	81.78(69)	87.91(67)	84.45(72)	84.65(65)	TT-TO-FM33-#56	117.97(20)	127.1(25)	128.77(24)	120.8(20)
WT-TR-FM22-#39	75.71(80)	87.42(68)	85.68(70)	78.41(76)	TT-TP-FM34-#57	91.01(49)	101.96(41)	103.2(41)	93.53(50)
WT-TR-FM22-#40	76.47(77)	88.89(66)	87.02(67)	79.34(75)	TT-TP-FM34-#58	87.09(58)	100.03(48)	101.49(45)	90.07(56)
WT-PS-FM23-#41	99.41(36)	138.24(21)	144.2(20)	108.41(30)	TT-TP-FM34-#59	83.47(62)	89.75(62)	90.51(59)	84.62(66)
WT-PS-FM24-#42	117.2(21)	165.74(13)	173.44(13)	127.16(18)	TT-TP-FM34-#60	83.04(63)	83.65(74)	83.7(74)	83.27(69)
WT-PS-FM25-#43	105.08(30)	145.7(17)	151.93(18)	114.49(25)	TTTP-FM34-#61	125.2(17)	176.43(11)	186.62(11)	136.51(15)
WT-YS-FM26-#44	129.65(15)	152.85(15)	155.7(17)	142.43(13)	TTTP-FM34-#62	88.8(53)	97.14(51)	98.14(51)	90.4(54)
WT-YS-FM27-#45	106.05(28)	123.52(27)	125.69(26)	115.59(23)	FF-FFE-FM35-#63	97.97(40)	98.49(50)	98.49(50)	98.36(42)
WT-YS-FM28-#46	133.47(11)	163.07(14)	166.71(16)	149.77(11)	FF-FFE-FM35-#64	86.39(61)	88.97(65)	89.01(63)	88.35(58)
WT-CE-FM29-#47	77.29(75)	83.08(75)	83.43(76)	80.86(73)	FF-FFE-FM35-#65	187.4(3)	274.85(2)	292.24(3)	206.7(1)
WT-CE-FM30-#48	69.48(85)	80.37(80)	81.71(79)	71.78(85)	FF-FFE-FM36-#66	81.59(71)	82.25(77)	82.25(77)	81.94(70)
TT-TO-FM31-#49	182.82(4)	238.17(5)	249.18(7)	195.03(5)	FF-FFE-FM36-#67	97.53(42)	109.82(34)	109.93(36)	102.12(37)
TT-TO-FM31-#50	131.58(13)	134.29(23)	134.55(23)	133.31(16)	FF-FFE-FM36-#68	91.82(46)	100.28(47)	100.33(48)	96.41(44)
TT-TO-FM31-#51	125.57(16)	126.1(26)	126.18(25)	125.82(19)	FF-FFE-FM36-#69	86.83(59)	89.02(64)	89.04(62)	87.89(61)
TT-TO-FM31-#52	176.23(6)	204.08(10)	207.78(10)	189.62(6)	FF-FFE-FM36-#70	82.18(67)	86.51(70)	86.55(68)	83.95(67)
TT-TO-FM31-#53	119.8(19)	120.69(28)	120.78(27)	120.37(21)	FF-FFE-FM36-#71	178.06(5)	233.45(6)	233.86(8)	204.92(2)
TT-TO-FM32-#54	107.49(27)	114.58(30)	116.18(31)	108.56(29)	FF-FFE-FM37-#72	45.41(102)	54.42(102)	54.53(102)	46.78(102)

Failure Causes	RPN & RPN Rank				Failure Causes	RPN & RPN Rank			
	WC	WF	UO	GM		WC	WF	UO	GM
FF-FFE-FM37-#73	52.69(99)	59.59(95)	59.67(96)	53.73(99)	MS-ML-FM39-#89	99.32(37)	101.63(42)	101.76(43)	101.51(38)
FF-FFE-FM37-#74	42.3(103)	51.69(103)	51.8(103)	43.73(103)	MS-ML-FM39-#90	88.54(55)	89.75(63)	89.82(61)	89.68(57)
FF-FFE-FM37-#75	42.3(104)	51.69(104)	51.8(104)	43.73(104)	MS-ML-FM39-#91	91.79(47)	93.4(57)	93.5(57)	93.32(51)
FF-FFE-FM37-#76	48.03(101)	55.68(101)	55.77(101)	49.19(101)	MS-ML-FM39-#92	96.5(43)	100.32(46)	100.73(47)	99.96(40)
FF-FFE-FM37-#77	53.61(98)	61.75(94)	61.85(94)	54.85(98)	MS-ML-FM39-#93	129.89(14)	141.24(20)	142.47(21)	140.16(14)
FF-FFE-FM37-#78	50.58(100)	59.59(96)	59.7(95)	51.94(100)	MS-ML-FM39-#94	82.35(66)	84.95(72)	85.23(71)	84.71(64)
FF-FFE-FM37-#79	55.47(97)	63.12(93)	63.21(93)	56.63(96)	MS-ML-FM39-#95	108.81(24)	113.96(31)	114.51(33)	113.47(26)
FF-FFE-FM37-#80	63.17(90)	87.36(69)	87.66(66)	66.83(89)	MS-ML-FM39-#96	101.68(31)	104.1(38)	104.36(39)	103.87(36)
FF-FFE-FM37-#81	57.06(94)	65.2(90)	65.3(90)	58.29(94)	MS-FL-FM40-#97	90.84(50)	93.84(55)	94.57(53)	93.2(52)
MS-ML-FM38-#82	101.59(32)	135.07(22)	166.86(15)	107.25(31)	MS-FL-FM40-#98	108.32(25)	113.42(32)	114.67(32)	112.33(27)
MS-ML-FM38-#83	109.52(22)	145.06(18)	178.83(12)	115.53(24)	MS-AC-FM41-#99	149.05(9)	169.14(12)	171.85(14)	166.76(9)
MS-ML-FM38-#84	79.92(73)	91.18(60)	101.87(42)	81.82(71)	MS-AC-FM41-#100	72.61(84)	72.74(86)	72.76(86)	72.73(84)
MS-ML-FM38-#85	141.77(10)	226.66(7)	307.44(2)	155.99(10)	MS-RE-FM42-#101	172.49(7)	290.85(1)	399.21(1)	196.05(4)
MS-ML-FM38-#86	132.22(12)	210.93(9)	285.84(4)	145.4(12)	MS-RE-FM42-#102	87.4(57)	92.02(58)	92.84(58)	91.31(53)
MS-ML-FM39-#87	101.14(34)	104.07(39)	104.24(40)	103.91(35)	MS-RE-FM42-#103	81.65(70)	83.85(73)	84.23(73)	83.51(68)
MS-ML-FM39-#88	91.88(45)	93.89(54)	94.01(55)	93.78(49)	MS-RE-FM42-#104	100.91(35)	108.42(35)	109.75(37)	107.25(32)

A(B): RPN(Rank); WC: Without Condition; WF: Floating Offshore Wind Turbine Failure; UO: Unstable Electricity Output; GM: Generator Maintenance

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