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Research paper

Cost-based dynamic risk analysis of offshore wind turbines

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ABSTRACT

This paper proposes a cost-based dynamic risk model for offshore wind turbines, leveraging reliability and maintenance data from real offshore wind farms. The model integrates information on wind farm configurations into failure cost modelling and as a basis of that quantifies time-varying failure probabilities and consequences of onsite failures. The model enables dynamic and comparable risk assessment among various offshore wind farms. Results reveal that the auxiliary system represents the highest economic risk, particularly during winter months, and that increasing the distance to the onshore maintenance base leads to a greater rise in system and component risk than simply increasing turbine capacity. The feasibility and advantages of the proposed method are validated through systematic comparative analysis with existing approaches. Overall, this research provides a robust framework for cost-based dynamic risk analysis, supporting economically informed decision-making and season-specific maintenance strategies for offshore wind farms.

1. Introduction

In recent years, the offshore wind sector has undergone remarkable expansion, driven by advances in turbine technology and the implementation of supportive government policies (Barter et al., 2023). To improve the economic performance of offshore wind farms until it is comparable to that of onshore wind projects, the sector has engaged in developing larger turbines (from 2MW to 6MW and now moving to 20+MW) and construction at mega far offshore wind farms, expecting to increase the profitability of offshore wind projects by (large) scale effect (Xu, 2025).

Large-scale turbines and far-offshore wind farms are becoming increasingly dependent on reliability and maintainability strategies (Li et al., 2022). The adoption of larger turbines, however, introduces high failure likelihood, extended maintenance durations, and potential emergent hazards (Donnelly et al., 2024). These challenges highlight the critical need for rigorous risk analysis to mitigate hazardous events and associated financial losses.

Risk analysis estimates root causes, likelihoods, and consequences of adverse events, as well as their potential impacts on the entire systems by subjective index like Risk Priority Number (RPN) or objective index like Cost Priority Number (CPN) (Li et al., 2020). RPN represents the possible effects of events on structures, human safety, and the environment using Severity (S), Occurrence (O), and Detection (D). Specifically, severity represents the hazard level of an event; occurrence indicates the likelihood of the potential event; and detection denotes the possibility of observing an event before it occurs (Kong et al., 2024). RPN, the product of severity, occurrence, and detection, is then

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Abbreviations: $P_i(t)$, Failure probability of component i during time t; C_i, Total failure consequence of component i; $C_{i,f}$, Failure costs of component i; $C_{i,d}$, Downtime costs of component i; $C_{i,r}$, Repair cost of component i; $C_{i,l}$, Round-trip logistic cost of component i; d, Distance between the offshore wind farm and onshore maintenance base; $E(t)$, Energy loss during downtime t; $T_{i,downtime}$, Downtime duration of component i; V, Sailing speed of the service vessel; $T_{i,replacement}$, Replacement times of component i; c^T, Transportation cost of crew and components per kilometre; $v(t)$, Average wind speed at unit time t; Δt, Time resolution; p, Power purchase agreement price; v_{ci}, Cut-in wind speeds; v_{co}, Cut-out wind speeds; P_r, Rated power output of offshore wind turbine; $RComp\ i$, Risk of fault component i; $RSys\ s$, Risk of a fault system s; $PSys\ s$, Failure probability of system s; $C_s(t)$, Failure consequence of system s.

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generated to prioritize risk levels of systems/components (Kong et al., 2026). RPN-based risk models and their advancements have been developed for risk analysis, assessment, and management. For instance, the mooring lines were determined as the key component in (He Li et al., 2021) using a weighted RPN-based risk model; the floating foundation was recognized as the most critical component in (Sun et al., 2023) through a correlation RPN-based risk model. However, inconsistent evaluations may arise in RPNs as the subjective expert judgment and un-informative modelling perspective. Consequently, failure probabilities can be a substitution of occurrences, which are assessed by reliability databases (Carroll et al., 2016; Li et al., 2025), logical inference methods such as fault tree (Kang et al., 2019). The failure consequence is qualitatively classified into high, medium, and low severity or is quantitatively assessed through experts' judgment (Xiao and Yuan, 2025; Huang et al., 2025). However, expert-based consequence assessment methods tend to avoid reasoning in abstract terms and linking a failure to a specific consequence, which may lead to over-optimistic or over-pessimistic evaluations due to uncertainty and perceived familiarity (Pasquini et al., 2011). Moreover, the conventional RPN, is defined as the product of severity, occurrence, and detection (i.e., severity × occurrence × detection), suffers from limited interpretability and comparability (Li et al., 2020). This limitation arises from the equal weighting of risk factors, the subjectivity of data input, the use of discrete numerical rating without physical meaning, and the potential for inconsistent or controversial RPN results. Although various improvements have been proposed to mitigate the above issues, RPN-based risk models continue to exhibit shortcomings, including a lack of physical interpretability, poor cross-system comparability, and limited applicability to economical critical systems.

To address these challenges, cost-based models have been proposed to characterize the possible impact of failure items on project benefits by incorporating the failure cost index into risk modelling, see Table 1. These methods generate Cost Priority Number (CPN) and Cost-based Risk Priority Number (CRPN) as a basis to define the risk to be a product of failure probabilities/rates, failure costs, and additional detection probabilities. However, the new methods rely on reliability and maintenance data for failure probability and consequence modelling. For example, the blade was determined as the most critical component in (Shafiee and Dinmohammadi, 2014) with a CPN of €6,771, the gearbox in (Tazi et al., 2017) with a CPN of €49,356 /kWh, and the generator in (Kahrobaee and Asgarpoor, 2011) with a CRPN of €14,110. To ensure trustworthy CPNs, efforts have also been made for detailed failure cost estimation by incorporating factors such as maintenance accessibility (Myhr et al., 2014), logistic constraints (Sarker and Faiz, 2017), and downtime-related revenue losses (Ghigo et al., 2020).

Overall, RPN-based risk models often lack interpretability and comparability as the risk analysis is specially designed according to RPN and expert team, the results of which cannot transfer among wind turbines and wind farms. On the other hand, CPN-based cost models neglect the time-varying nature of risk, overlooking risks evolve dynamically throughout the systems. Additionally, neither approaches accounts for the influence of distance and turbine capacity on risk outcomes, making existing RPN- and CPN-based risk models provide limited support for the operation and maintenance of offshore wind farms, as a result of ignoring of the influence of wind conditions, farm distance, and dynamic nature of system degradation on risk. To address these gaps, this study brings a new methodological contribution by introducing a cost-based dynamic risk model specifically designed for (Offshore Wind Turbines) OWTs. Specifically, the main contributions of this work are as follows:

Table 1
Review of cost-based risk models from existing studies.

Reference	Scope		
	Failure Rate/ Probability	Failure Cost	Detection Probability
(Shafiee and Dinmohammadi, 2014)**	✓	✓	✓
(Tazi et al., 2017)*	✓	✓	—
(Kahrobaee and Asgarpoor, 2011)**	✓	✓	✓
(Cevasco et al., 2018)*	✓	✓	—
(Tao et al., 2025)**	✓	✓	✓
(Peng et al., 2016)*	✓	✓	—
(Wakiru et al., 2019)*	✓	✓	—

* cost priority number.
** cost-based risk priority number
✓: existence; —: non-existence.

(i). Integrate wind farm configuration information into failure analysis, extending the risk analysis from sbjective information-based methods to objective input-based approaches.
(ii). Incorporate dynamic failure probability and wind-speed-dependent failure cost, enabling a dynamic risk analysis concept.
(iii). Develop a cost-based dynamic risk framework that is applicable across a range of offshore wind farms, enabling risk analysis results transferring among wind farms (make the results of risk analysis comparable).

The remainder of this paper is structured as follows. Section 2 presents the proposed cost-based dynamic risk methodology. Section 3 describes the offshore wind turbine and associated input data. Section 4 provides the results, comparative analysis, and discussions. Section 5 concludes the paper.

2. Methodology

A cost-based dynamic risk model is proposed. It incorporates time-varying failure probability and consequence. The steps are as follows, see Fig. 1:

Step 1: System decomposition. Break down OWTs into key systems and components.
Step 2: Data collection. Collect the risk-related data for components, including failure rates, maintenance costs, distance to shore, and turbine capacity.
Step 3: Failure probability calculation. Convert failure rates into failure probabilities by Eqs. (1–2).
Step 4: Failure consequence quantification. Estimate failure costs of components by incorporating distance and wind-speed-dependent downtime costs (see Eqs. (3–8)).
Step 5: Risk analysis. Evaluate and rank the dynamic risks of components by Eqs. (9–10).
Step 6: Recommendation. Propose hazard prevention strategies for components with higher risk levels.

The proposed model is designed for OWTs but it is applicable for all economic-critical-systems. Economically, the evaluated risks quantify the time-varying possible economic losses associated with system/component failures. From the industry's perspective, the proposed method accounts for the impact of offshore wind farm location and turbine capacity on risk, supporting optimal wind farm site selection and maintenance planning. Besides, the use of objective data ensures more convincing risk analysis results, and which can be transferred to a selection of tasks of offshore wind farm O&M.

(1). Failure probability calculation.

Failure probability describes the possibility that a system/component fails to perform the intended function during a given period. The exponential failure model (Li and Soares, 2022) assumes a constant failure rate λ during the useful-life phase of bathtub curve reliability

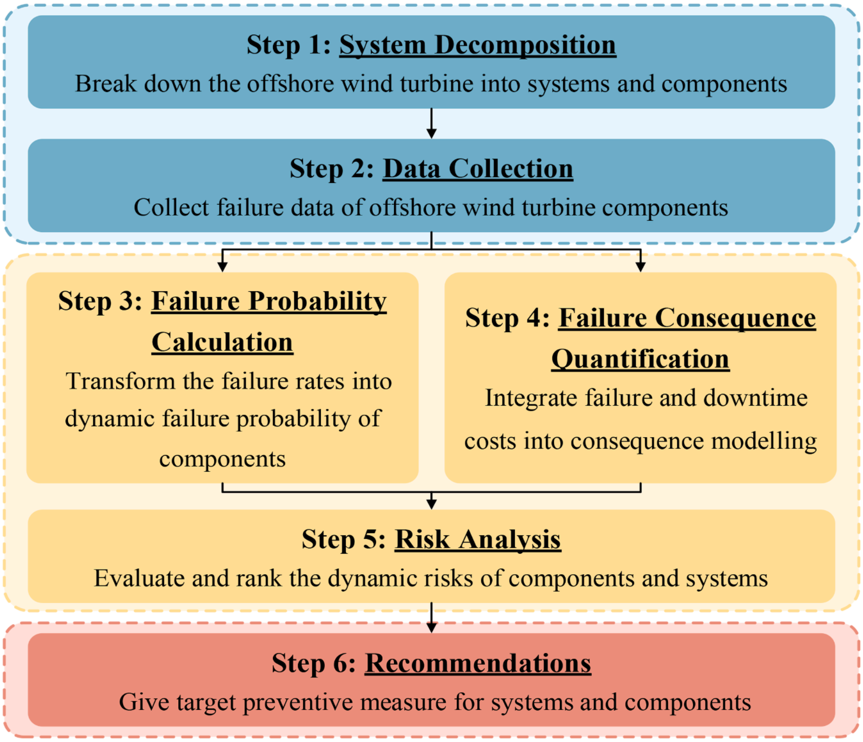


Fig. 1. The framework of the cost-based dynamic risk model for offshore wind turbines.

model, say:

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

Accordingly, the added failure probability of component i ($i = 1, 2, \ldots, m$) during time t and t-1 is given by:

$$P_i^{inst}(t) = P_i(t) - P_i(t-1) = e^{-\lambda_i(t-1)} - e^{-\lambda_i t} \tag{2}$$

where $P_i(t)$ represent the failure probability of component i at time t ($t = 1, 2, \ldots, T$).

(2). Consequence quantification.

Consequences of failures are defined as the negative impact of a fault system/component on the economic performance, human safety, structural integrity, and environment. The failure consequence is quantified in terms of economic losses by integrating failure costs and downtime costs. Specifically:

$$C_i(t) = C_{i,f} + C_{i,d}(t) \tag{3}$$

where C_i, $C_{i,f}$, and $C_{i,d}$ represent the failure consequence, failure costs, and downtime costs of component i, respectively. The failure cost consists of repair and logistic costs, say:

$$C_{i,f} = C_{i,r} + C_{i,l} \tag{4}$$

where $C_{i,r}$ denotes the repair cost of component i, which can be obtained from maintenance records; $C_{i,l}$ is the round-trip logistic cost, as:

$$C_{i,l} = 2 \times d \times c^T \tag{5}$$

where d is the distance between the offshore wind farm and onshore maintenance base, and c^T is the transportation cost of crew and components per kilometre.

The downtime cost is defined as:

$$C_{i,d}(t) = T_{i,downtime} \times E(t) \times p \tag{6}$$

where p is the Power Purchase Agreement (PPA) price, $T_{i,downtime}$ is the downtime duration of component i, which includes both transport and replacement times, as:

$$T_{i,downtime} = \frac{d}{V} + T_{i,replacement} \tag{7}$$

where V is the sailing speed of the service vessel, and $T_{i,replacement}$ denotes the replacement times that can be obtained from maintenance records.

The energy loss during downtime $E(t)$ is calculated based on wind speeds $v(t)$, say:

$$E(t) = \begin{cases} 0, & v(t) < v_{ci} \text{ or } v(t) > v_{co} \\ P_r \times \Delta t, & v_{ci} \leq v(t) \leq v_{co} \end{cases} \tag{8}$$

where P_r is the rated power output; v_{ci}, and v_{co} are the cut-in and cut-out wind speeds, respectively; $v(t)$ is the average wind speed at unit time; Δt is the time resolution.

(3). Risk evaluation.

Risk quantifies the effect of uncertainty on an accident through the combination of failure probability with the severity of associated consequences (van der Werff et al., 2025). The risk of the fault component i, denoted as $R_i^{Comp}(t)$, and the risk of a fault system s, denoted as $R_s^{Sys}(t)$, ($s = 1, 2, \ldots, n$), are calculated by:

$$R_i^{Comp}(t) = P_i^{inst}(t) \times C_i(t) \tag{9}$$

$$R_s^{Sys}(t) = \sum_{i \in s} R_i^{Comp}(t) = P_s^{inst}(t) \times C_s(t) \tag{10}$$

Assume that components' failure in a system is independent, so the system-level failure probability is calculated as:

$$P_s^{Sys}(t) = 1 - \prod_{i \in s} \left(1 - P_i^{inst}(t)\right) \tag{11}$$

Accordingly, the system-level failure consequence is calculated by:

$$C_s(t) = \frac{\sum_{i \in s} P_i^{inst}(t) \times C_i(t)}{P_s^{Sys}(t)} \tag{12}$$

3. System grading and data collection

An OWT is a complex system with numerous interdependent components (He Li et al., 2021; Ye et al., 2025). The OWT is divided into Energy Receiving system (ER), the Energy Producing system (EP), the Energy Transforming system (ET), and the Auxiliary system (AU) (He Li et al., 2021). Specifically, the energy receiving system consists of the blade and hub, which capture wind energy and convert it into mechanical energy, with efficiency heavily dependent on wind speed. The energy producing system comprises the generator and gearbox, which convert the mechanical energy into electrical energy. The energy transforming system includes the converter and transformer, which regulate the variable-frequency and variable-voltage electricity generated by the energy producing system into a stable alternating current output to comply with grid requirements. The auxiliary system consists of the pitch system, yaw system, as well as controller and electrical facilities, which ensure optimal operating conditions for all components, thereby maximizing energy capture, production, and transformation efficiencies.

The failure rate, repair times and replacement costs of components are collected from literatures (Li et al., 2020; Carroll et al., 2016; Li et al., 2025), see Table 2. Wind speeds are collected from three offshore wind farms in Li-Guedes Soares (LGS) database (Li et al., 2025), as shown in Table 3. The full-year wind speed distributions for the three wind farms are presented in Fig. 2. The PPA price is set as €70/MWh (A Franke and Grama). The logistical vessel selected for maintenance intervention is a supply vessel with a transport cost of €500/km (Shafiee and Dinmohammadi, 2014) and a sailing speed of 20 km/h (Adumene et al., 2021). Notably, the 10-min wind speed is used to calculate the average failure probability and failure cost of each component per month.

4. Results, comparisons, and discussions

4.1. Risk analysis at the system level

Fig. 3 presents the time-series risk of OWTs at Wind Farm #1 over a 12-month period. The average risk refers to the mean value of monthly risk during a 12-month period. The auxiliary system shows the highest risk (with an average risk of €2.57k), followed by the energy producing system (€1.67k), energy transforming system (€1.40k), and the energy receiving system (€1.30k). The result differs from those obtained using the cost-based risk models (Li et al., 2020), which identified the energy producing system as the most critical, followed by the energy receiving system, the auxiliary system, and the energy transformer system. This discrepancy is mainly attributed to (i) different data resources, that is, expert judgment is used in (Li et al., 2020; He Li et al., 2021), resulting in subjective results; (ii) different modelling perspectives, that is, the product of failure cost, severity, occurrence, and detection is applied in (Shafiee and Dinmohammadi, 2014; Cevasco et al., 2018; Tao et al., 2025) to measure the risk of systems.

Table 2
Failure rates, replacement costs, and repair times of offshore wind turbine components.

System	Component	Failure Rate /Turbine/Year	Replacement Cost/€#	Repair Time/h**
ER	Blade (BL)	0.0849*	77,000	288
	Hub (HB)	0.0014*	5000	298
EP	Generator (GE)	0.0986*	14,000	81
	Gearbox (GB)	0.1136*	34,000	231
ET	Converter (CV)	0.2341*	39,000	57
	Transformer (TR)	0.001**	13,000	1
AU	Pitch System (PS)	0.2465*	96,000	25
	Yaw System (YS)	0.0342*	51,000	49
	Controller and Electrical Facilities (CE)	0.003**	4000	30

* collected from (Li and Soares, 2022).
** collected from (Carroll et al., 2016).
\# collected from (Li et al., 2020).

Table 3
Characteristics of the three offshore wind farms.

Wind Farm	Distance to Base (km)	Turbine Capacity (MW)	v_{ci} (m/s)	v_{co} (m/s)	v_r (m/s)
Wind Farm #1	23	5	3.5	25	9.6
Wind Farm #2	50	2	3.0	25	9.6
Wind Farm #3	65	5	3.5	25	9.6

From a dynamic development perspective, system risk varies over time, influenced by both external environmental conditions and internal degradation processes. In Fig. 3, the highest risk levels of systems occur during winter, particularly in January. Higher wind speeds, stronger wave conditions, and lower temperatures accelerate system degradation and extend downtime due to lower maintenance accessibility. In contrast, the risk levels of systems tend to be lowest during the summer mainly due to reduced downtime costs. Although lower wind speed in summer leads to lower risks, it also results in decreased energy production. Overall, the implementation of season-specific maintenance strategies is essential for reducing operational risk and improving the profitability of offshore wind projects, such as proactive replacement of critical components and vessel dispatch plans ahead of winter, as well as strategic adjustment of operational priorities.

The auxiliary system shows the highest added failure probability (with an average of 0.0212), followed by the energy transforming system (0.0175), energy producing system (0.0167), and energy receiving system (0.0069), see Fig. 4. Generally, the failure probability is related to the structural complexity and operational frequency of systems. Components such as the pitch and yaw systems operate more frequently than other components, leading to a higher failure probability. On the other hand, failure consequences are influenced by the wind farm location, seasonal accessibility of maintenance, and replacement costs. Fig. 4 indicates that the energy receiving system incurs the most severe failure consequence (with an average failure cost of €224.56k), followed by the auxiliary system (€163.45k), the energy producing system (€137.45k), and the energy transformation system (€121.12k). Overall, maintenance strategies should account for both high-risk systems with higher failure probability and cost, as well as systems with severe failure cost but low failure probability for robust financial and operational safety.

Fig. 5 compares the risk of OWT systems across different wind farms. The system risk increases with the offshore distance. Specifically, as the distance increases from 23 km to 65 km, the system risk increases by approximately 18% for the energy receiving system, 39% for the energy producing system, 51% for the energy transforming system, and 34% for the auxiliary system, respectively. These increases are mainly attributed to higher transport and downtime costs, which may be aggravated under harsh marine conditions. Besides, lower-rated turbines result in reduced system risk but lower economic generation under the same distance conditions.

4.2. Risk analysis at the component level

Fig. 6 presents the risk of OWT components at Wind Farm #1. As shown in Fig. 6(a), the pitch system is determined as the most critical component, with an average risk of €3.07k, followed by the converter

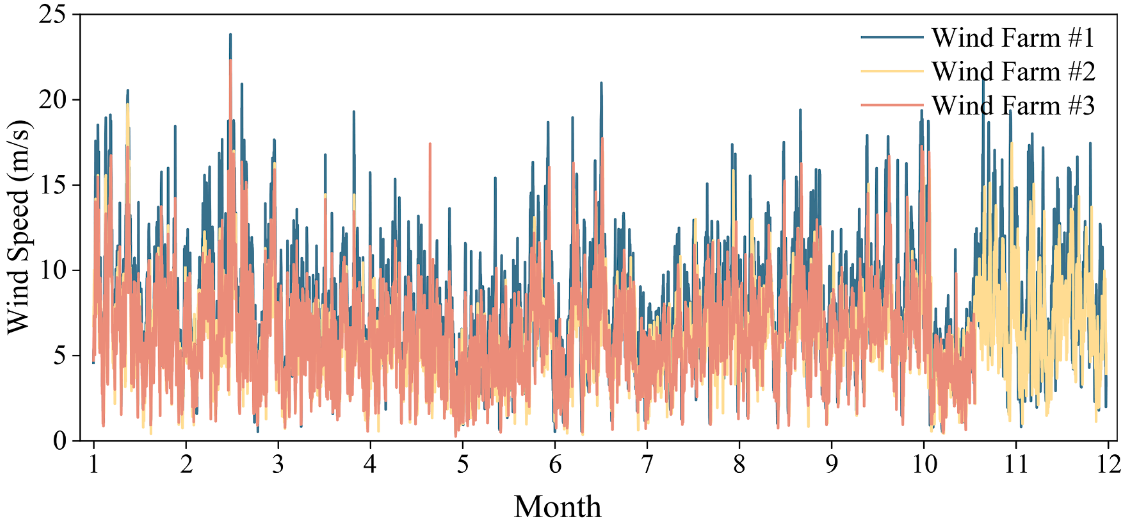


Fig. 2. Monthly wind speed distribution across three offshore wind farms over one year.

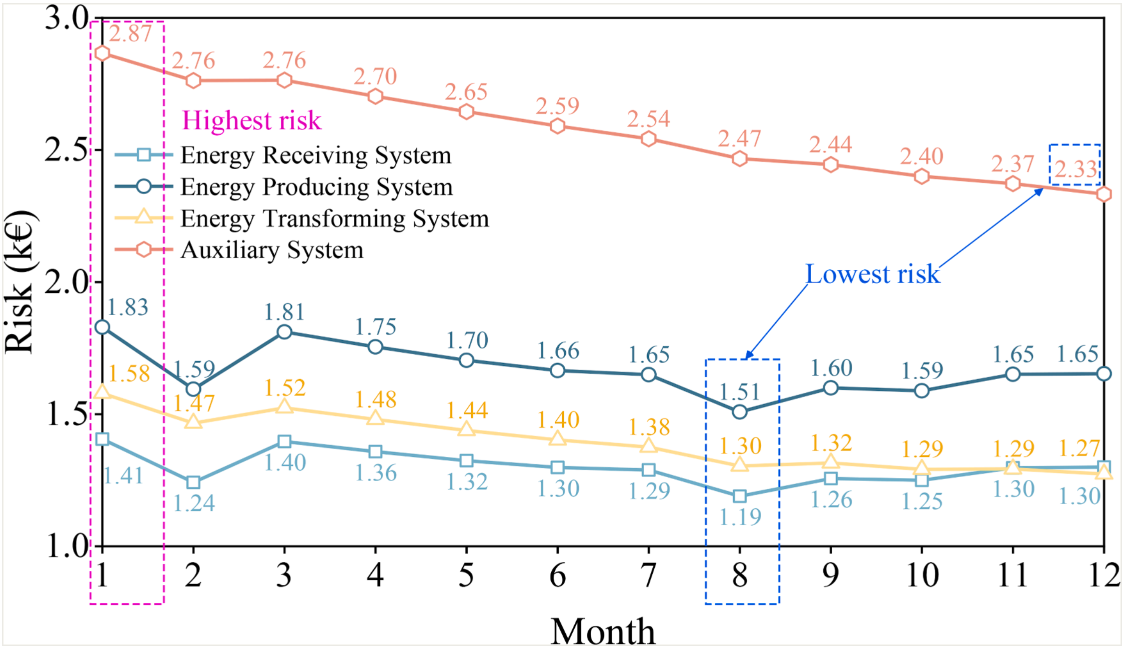


Fig. 3. Time-series risk of offshore wind turbine systems at Wind Farm #1.

(€2.11k), blade (€1.53k), and gearbox (€1.48k) according to the average risk of €1.04k. However, such criticality rank is different from that of the RPN-based risk models (He Li et al., 2021; Sun et al., 2023; He Li et al., 2021) and the cost-based risk models (Li et al., 2020; Tazi et al., 2017; Cevasco et al., 2018; Wakiru et al., 2019) because of the different modelling perspective and data resource, as discussed in Section 4.1.

Within the auxiliary system, the pitch system is the primary contributor to its overall risk. This evaluated risk level is mainly attributed to a higher average failure probability (0.018), which mainly caused by frequent actuation cycles and vulnerability to temperature fluctuations, vibration, and salt-induced corrosion. A failure in the pitch system will reduce the ability to adjust blade angles optimally and therefore decreases the wind energy capture efficiency. Although the yaw system and controller and electrical facilities show lower risk levels, their failures may increase the risk of associated components because of the lack of optimal operating conditions. Therefore, regular inspection and preventive maintenance are necessary for the auxiliary system.

Within the energy transforming system, the converter gives rise to the highest risk level. This is primarily due to its higher failure probability (0.017) and considerable failure consequence (€121.32k). Specifically, high power density and continuous switching operations cause frequent failure of the converter with expensive replacement costs. Moreover, the failure of the converter directly disrupts the energy transformation process between the generator and the grid, leading to considerable economic losses. In contrast, the transformer shows a lower failure probability due to fewer switching operations and robust insulation design. Therefore, it calls for more attention from designers and operators to design robust thermal protection for lower failure probability.

Within the energy receiving system, the blade is determined as the most critical component, with the expensive average failure cost of €225.71k and the low average failure probability of 0.0068. Its expensive replacement cost and downtime cost alter robust design and preventive measures to prevent fatigue and lightning-induced damage.

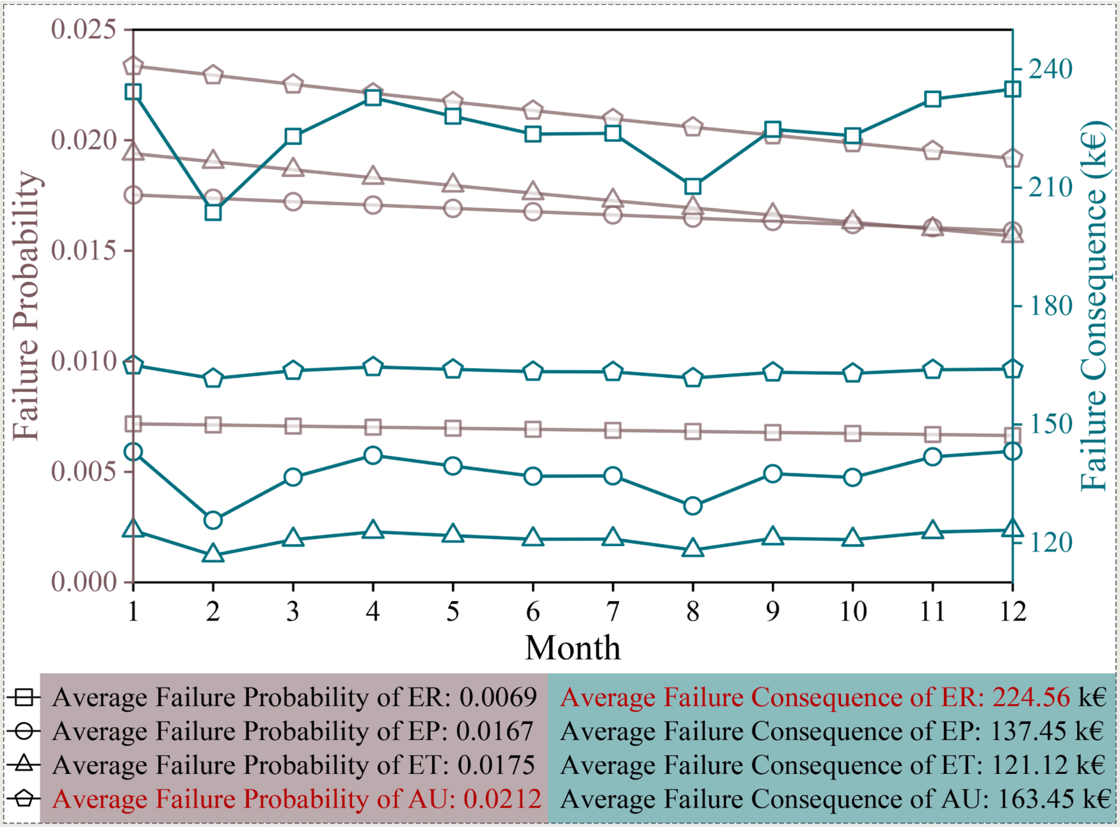


Fig. 4. Addded failure probability and consequence of offshore wind turbine systems.

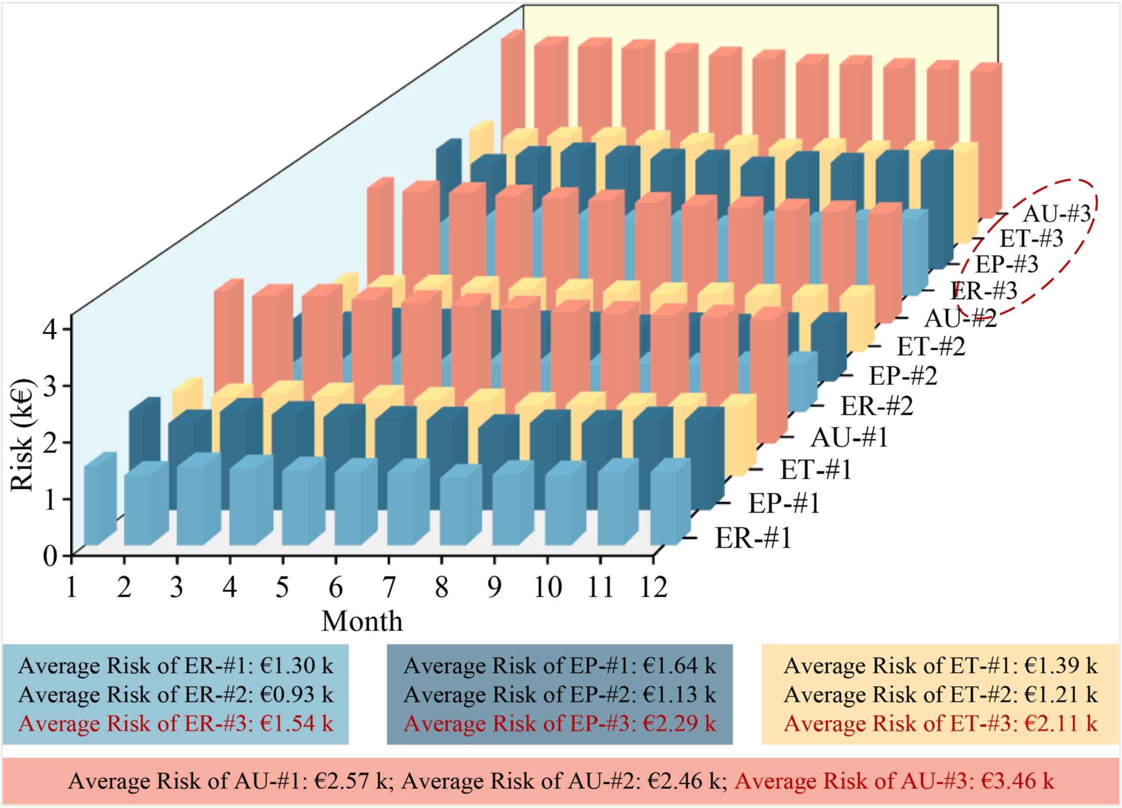
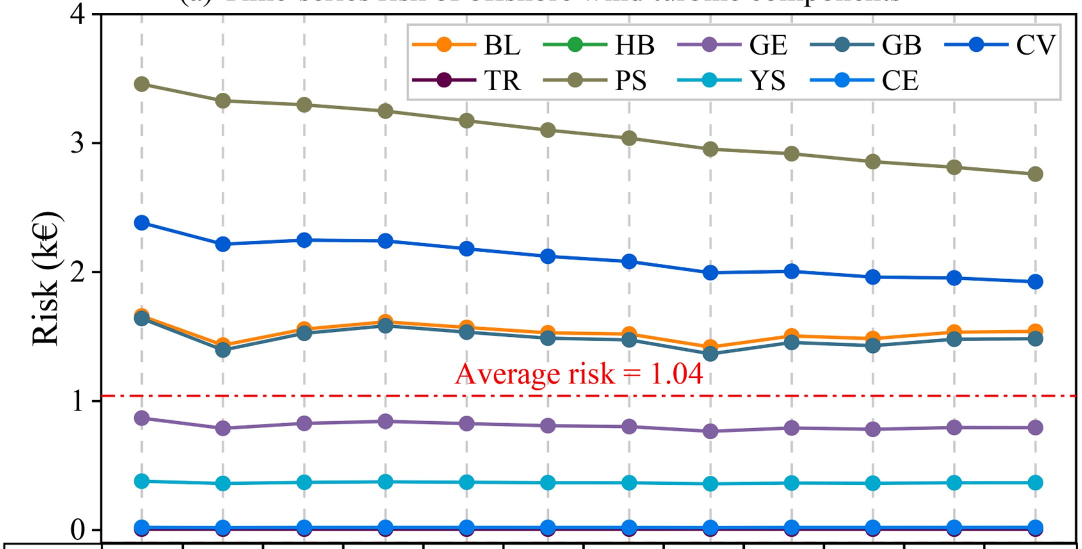


Fig. 5. Comparison of the risk of offshore wind turbine systems across different wind farms/System-#X: the system at Wind Farm #X.

(a) Time-series risk of offshore wind turbine components



System /Month	1 month	2 month	3 month	4 month	5 month	6 month	7 month	8 month	9 month	10 month	11 month	12 month
BL	1.6594	1.4336	1.5578	1.6143	1.5709	1.5289	1.5196	1.4188	1.5051	1.4838	1.5347	1.5402
HB	0.0194	0.0157	0.0181	0.0192	0.0186	0.0181	0.0182	0.0165	0.0182	0.0181	0.0191	0.0195
GE	0.8675	0.7886	0.8271	0.8429	0.8253	0.8082	0.8021	0.7655	0.7913	0.7813	0.7951	0.7941
GB	1.6404	1.3954	1.5258	1.5835	1.5344	1.4872	1.4747	1.3656	1.4543	1.4294	1.4799	1.4834
CV	2.382	2.2165	2.2479	2.2413	2.1807	2.1222	2.0819	1.9949	2.0058	1.9616	1.9546	1.9247
TR	0.0065	0.0065	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066
PS	3.4576	3.3282	3.2971	3.2482	3.1736	3.1011	3.0384	2.9536	2.9178	2.8558	2.8127	2.7595
YS	0.377	0.3611	0.3699	0.3738	0.3704	0.3671	0.3661	0.3583	0.3645	0.3627	0.3663	0.3665
CE	0.0199	0.0190	0.0195	0.0198	0.0197	0.0195	0.0195	0.0191	0.0196	0.0195	0.0198	0.0198

(b) Average failure probability and consequence of offshore wind turbine components

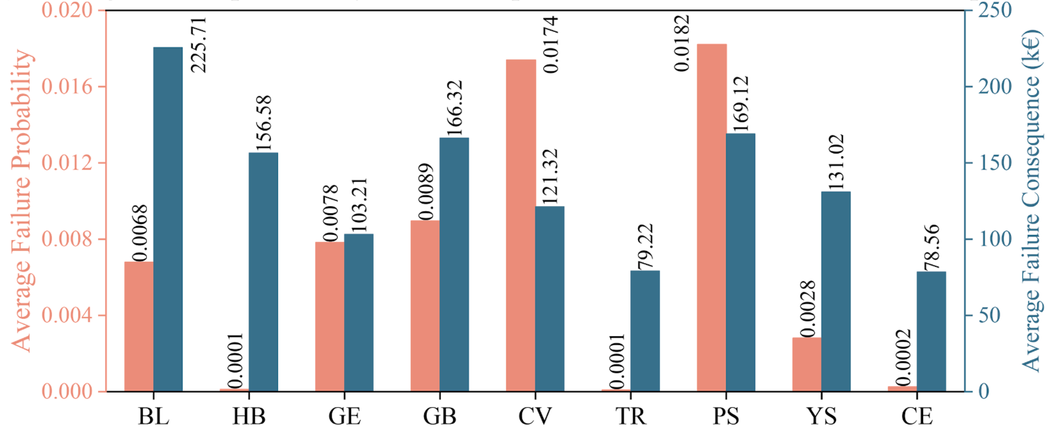


Fig. 6. Risk analysis of offshore wind turbine components: (a) monthly risk; (b) average added failure probability and consequence.

Although the hub exhibits a low risk, its failure can disrupt turbine operations and subsequent failures in other systems, such as rotor imbalance. Therefore, it calls for special attention in risk assessment and design verification for components with a lower risk level but high potential impacts.

Within the energy producing system, the gearbox shows a higher risk than the generator due to its more expensive failure costs. Its complex mechanical structure may cause prolonged repair/replacement time, leading to extended downtime. Opportunity maintenance strategies like resource sharing across maintenance tasks can be employed to reduce logistical and repair expenses. Thermal-electrical stress, cooling inefficiencies, and grid-induced transients are the root causes of generator failure. Although its failure probability is slightly lower (0.0078), the associated consequence (€103.21k) still reflects the critical role it plays in power conversion. Real-time thermal monitoring and insulation protection may be a way to reduce its failure impact. Notably, component risk levels are related to seasonal marine conditions. The harsher marine conditions in winter accelerate the system/component degradation and reduce maintenance accessibility. Climate-aware maintenance planning and risk mitigation strategies may be an alternative to reduce the risk level of offshore wind turbines.

Overall, the proposed cost-based dynamic risk model supports informative and comparative risk analysis of economically critical systems, especially for offshore wind turbines. Specifically, (i) from an engineering perspective, wind farm information is incorporated into risk analysis to assess the impact of the offshore distance and turbine capacity on risk levels, supporting accurate potaintial wind farm sit selection; (ii) from a methodology perspective, the dynamic risk model reflects the seasonal variability across systems. However, the accuracy of the results heavily relies on the data quality, that is, access to more detailed failure rates and cost data from multiple real-world offshore wind farms would contribute to better conclusions.

4.3. Comparisons and discussions

Comparative analysis such as sensitivity analysis are valuable tolls for results validation. For instance, (Liu and Soares, 2023) used sensitivity analysis to determine the effects of various parameters on the mooring and volume of offshore floating equipment. Their findings are of significant importance for ensuring their safety and efficiency. To this end, a comparative analysis is carried out to demonstrate the similarities (for validation) and differences (for the new model's superiority justification) in the component level between the proposed methods and existing methods, see Fig. 7. To ensure consistency and comparability, the component ranks reported in existing studies have been restructured, as some sources include more or fewer components than those analysed in this study, as detailed in Table 4.

Cost-based risk models (CPN/CRPN) agree that the blade, gearbox, converter, and pitch system are more critical than other components. Another agreement is that the risk levels of the transformer and the controller and electrical facilities are low, and several studies even ignore these components in risk/failure analysis because of their lower failure probability. The harmony justifies the model and results to a significant extent.

A disagreement among studies is that the risk contribution (the proportion of each component's risk relative to the total system risk) of components such as the generator, the pitch system, the yaw system, and the controller and electricity facilities, as shown in Fig. 7(a). Specifically, this study identifies a lower risk contribution from the gearbox, yaw system, and controller and electrical facilities compared to previous studies, as discussed in (Shafiee and Dinmohammadi, 2014; Cevasco et al., 2018; Tao et al., 2025; Peng et al., 2016; Wakiru et al., 2019). These discrepancies are mainly attributed to (i) variations in input data, that is, the failure probability derived from various reliability databases or expert experience, and the failure costs derived from different wind farms; (ii) variations in modelling perspective, that is, additional factors consideration, such as the detection probability, are incorporated into risk modelling. It is worth noting that (i) expert experience can compensate for data scarcity but introduces subjectivity into the risk/failure analysis results; (ii) incorporating additional factors can improve

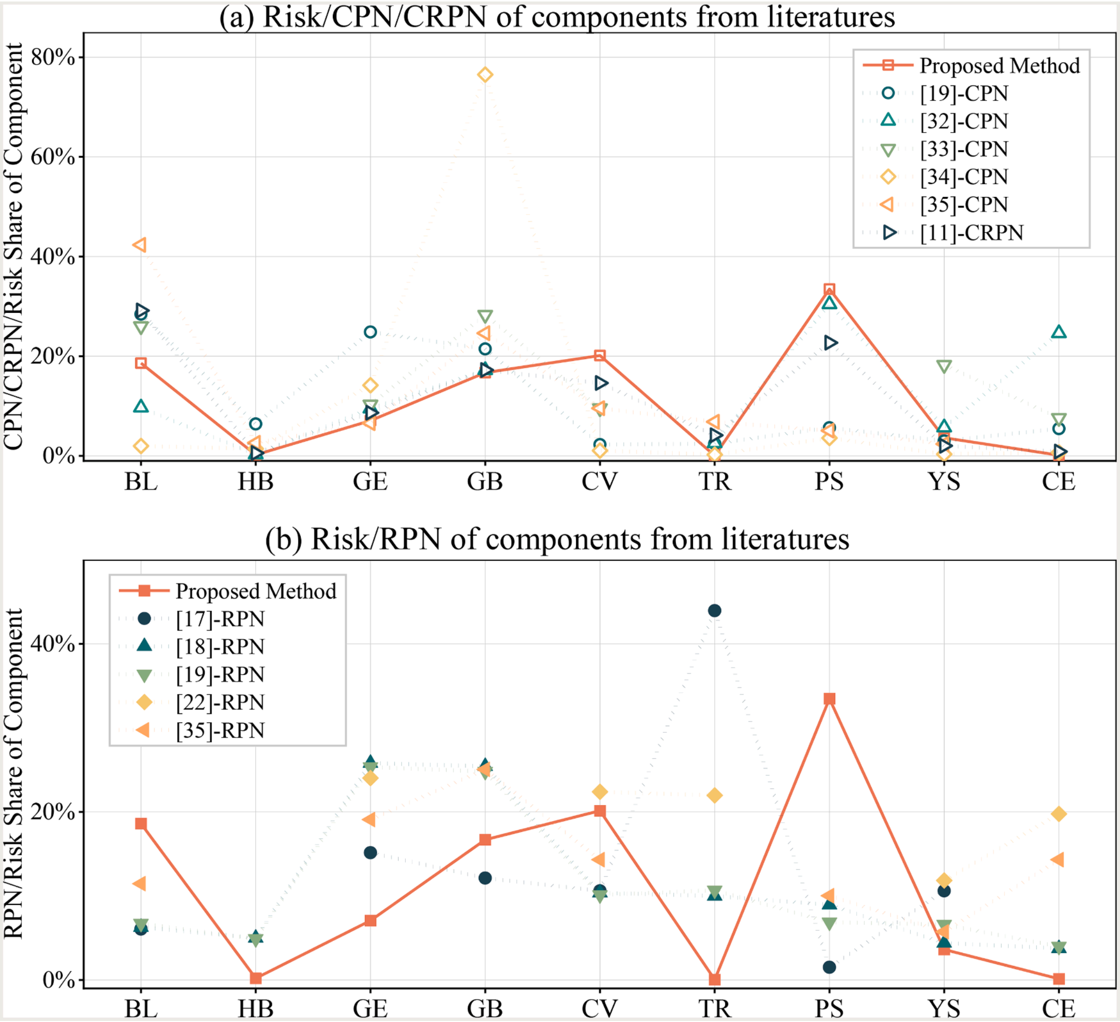


Fig. 7. Comparison of risk analysis results between this study and other existing studies.

Table 4
Comparison of component hazardous ranks in offshore wind turbines based on the proposed method and existing approaches.

Component	*	(Li et al., 2020)	(Du et al., 2017)	(Shafiee and Dinmohammadi, 2014)	(Tazi et al., 2017)	(Cevasco et al., 2018)	(Tao et al., 2025)	(He Li et al., 2021)	(Sun et al., 2023)	(Cevasco et al., 2018)	(Tao et al., 2025)
	**	CRPN	CPN					RPN			
BL	3	1	4	1	2	4	1	6	6	—	5
HB	7	9	8	7	—	5	4	8	7	—	—
GE	5	5	5	5	4	2	2	1	1	1	2
GB	4	3	3	2	1	1	3	2	2	—	3
CV	2	4	—	3	5	6	9	4	3	2	4
TR	9	6	7	4	—	9	8	3	4	3	1
PS	1	2	1	6	—	3	5	5	5	—	6
YS	6	7	6	8	3	8	7	7	8	5	4
CE	8	8	2	—	6	7	6	9	9	4	—

* proposed model.
** cost-based dynamic risk model.

the accuracy of results but increase calculation complexity, particularly the calculation of the detection probability requires practical monitoring data.

Regarding RPN-based risk models, similar risk levels of components are observed in the blade, hub, generator, and gearbox, despite notable discrepancies when compared to the risk results of cost-based methods. This can be traced back to the higher failure probability of these components, which amplifies their CPN/RPN values. This suggests that special attention should be paid to these components during the design and operation stage, although they show fewer hazards in cost-based methods. In contrast, significant disparities in risk contribution are observed in the transformer, pitch system, as well as controller and electrical facilities.

The discrepancy mainly stems from different modelling perspectives, i.e., RPN-based risk models emphasize failure severity, occurrence, and detection, whereas cost-based risk models focus on the failure cost and probability. While the RPN-based method is structurally more comprehensive, it lacks practical engineering meaning, particularly in economically critical offshore wind sectors. Besides, the input parameters for RPN-based risk models typically derive from expert judgment, introducing subjectivity and causing inconsistent risk/failure analysis results. As a result, RPN-based risk models have limited applicability in economically optimized decision-making processes, especially for large-scale offshore wind assets where cost-efficiency and availability are critical.

The comparative analysis demonstrates that the proposed method effectively overcomes critical shortcomings of existing approaches. Specifically, (i) cost-based risk models inadequately represent the dynamic evolution of systems and components risk, and (ii) RPN-based risk models tend to yield subjective, non-informative, and non-comparative outcomes in risk and failure analysis. Therefore, (i) dynamic failure probability and consequences are combined to support climate-aware maintenance planning and (ii) practical failure probability and costs are used for convincing risk analysis results.

Furthermore, the average component risk across different wind farm configurations is compared to evaluating the impact of offshore distance and turbine capacity on risk analysis results, as shown in Fig. 8. The analysis reveals that offshore distance to the onshore maintenance base contributes more to risk than the turbine capacity. Specifically, average risk increases by approximately 56% when the distance increases from 23 km to 65 km and by 28% when turbine capacity increases from 2 MW to 5 MW. These findings suggest that establishing intermediate service hubs for far-offshore wind farms could effectively reduce downtime and associated costs. Moreover, deploying high-capacity turbines in mid-to-far offshore locations may help balance risk reduction with increased energy production efficiency. Notably, only minor effects are observed in the hub, transformer, and controller and electrical facilities due to their lower failure probability or associated consequences, as indicated by the dashed rectangles (1), (2), and (3) in Fig. 8.

The sensitivity analysis is performed to investigate the influence of PPA prices and transport costs on the component hazardous ranks, as shown in Table 5. The results show no noticeable changes in the

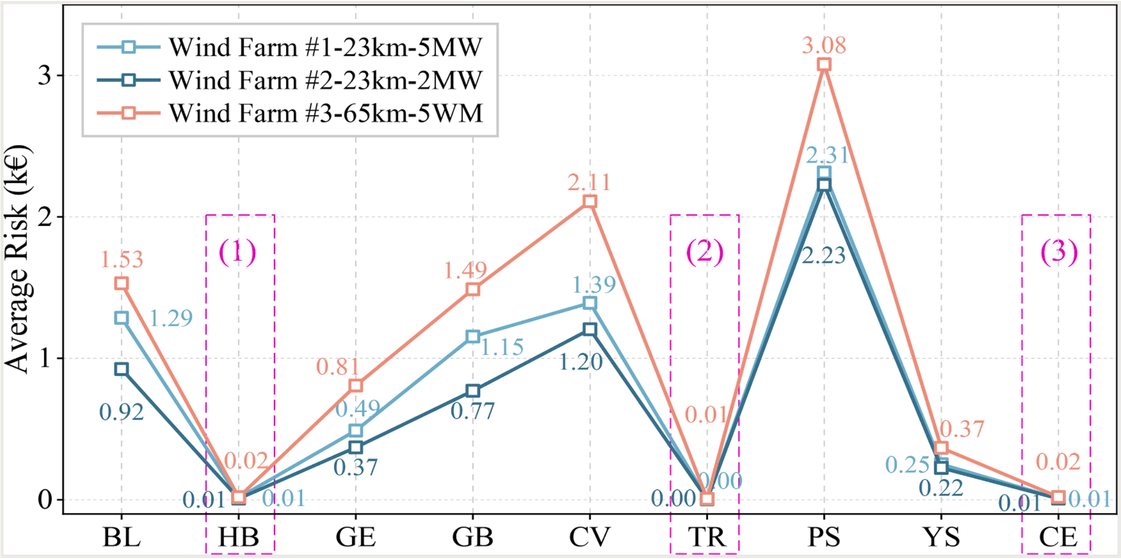


Fig. 8. Comparison of the average risk in components across different wind farms.

Table 5
Sensitivity analysis of component hazardous ranks under different PPA prices and transport costs.

Component	Hazardous Ranks		
	Proposed model	Changed PPA	Changed transport costs
BL	3	3	3
HB	7	7	7
GE	5	5	5
GB	4	4	4
CV	2	2	2
TR	9	9	9
PS	1	1	1
YS	6	6	6
CE	8	8	8

Changed PPA: increase PPA price to 90 €/MWh or decrease to 50 €/MWh; Changed transport costs: increase transport cost to 600 €/km or decrease to 400 €/km.

component hazardous ranks across tested scenarios. The proposed method is robust to variations in PPA prices and transport costs. Notably, the independence assumption of components may underestimate the joint failure probability of components subjected to common failure cause, however, it may overestimate the failure probability of a single component that is positively dependence on other components. Dependent modelling for series and parallel systems will be considered in the future works to address this limitation.

5. Conclusions

This study develops a new cost-based dynamic risk model to enable detailed and quantitatively robust risk analysis of economically critical systems, exemplified by OWTs. By integrating time-dependent failure probabilities with wind-speed-sensitive consequences, the model captures the dynamic evolution of system and component risk profiles and addresses the limitations of traditional cost-based models and RPN-based approaches, which often lack comparability and engineering relevance. The analysis yields several key findings which are currently missing from the existing literature: (1) the auxiliary system presents the highest economic risk, followed by the energy-producing, energy-transforming, and energy-receiving systems; (2) the pitch system, converter, blade, and gearbox are identified as the most critical components in terms of economic impact; (3) winter conditions lead to significantly higher economic risk and reduced energy production compared to other seasons; (4) increasing the distance to the onshore maintenance base has a more pronounced effect on risk escalation than increasing turbine capacity. Overall, these findings provide informative, comparable, and decision-oriented risk assessment results, thereby supporting the development of season-specific maintenance strategies. It is mentioned that the proposed novel risk analysis method extends the risk analysis from objective information-based methods to subjective input-based approaches, enables a new dynamic risk analysis concept, and makes the results of risk analysis comparable. Future research will refine the failure cost modelling by considering its dynamic features and incorporating additional risk factors (e.g. maintenance accessibility) to enhance the model's generalisability and practical applicability across diverse offshore wind farm configurations.

CRediT authorship contribution statement

Ruoxuan Li: Writing – original draft, Methodology. **Xiangyu Kong:** Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis. **He Li:** Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zaili Yang:** Writing – review & editing, Validation, Methodology. **Michaela Gkantou:** Writing – review & editing, Visualization, Validation, Conceptualization. **Hong-Xu Ye:** Writing – original draft, Validation, Formal analysis, Data curation, Conceptualization. **Huanhuan Li:** Writing – review & editing, Visualization, Methodology, Investigation. **Jin Wang:** Writing – review & editing, Supervision, Resources, Project administration.

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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