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**LIFECYCLE-AWARE INTELLIGENT
OPERATION AND MAINTENANCE FOR
FLOATING OFFSHORE WIND ENERGY**

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PhD

The Hong Kong Polytechnic University

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**Lifecycle-Aware Intelligent Operation and Maintenance for Floating
Offshore Wind Energy**

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**A thesis submitted in partial fulfilment of the requirements for the
degree of Doctor of Philosophy**

April 2025

Certificate of Originality

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Abstract

Floating Offshore Wind Turbines (FOWTs) offer a promising solution for accessing deep-sea wind resources, but ensuring 25-year structural reliability under corrosive marine conditions, coupled wind–wave loading, and constrained offshore accessibility remains a significant challenge. High-fidelity aero-hydro-servo-elastic simulators are computationally prohibitive for full life-cycle analysis. Traditional operation and maintenance (O&M) strategies often decouple control actions from offshore logistics, leading to either excessive downtime or deferred interventions. Moreover, current studies seldom bridge long-term structural degradation with real-time control or farm-level aerodynamic interactions. This study aims to elucidate the degradation mechanisms across four critical subsystems, blade, generator, tower, and moorings, under coupled environmental and operational loads; to develop fast yet accurate predictive models; and to establish an opportunistic operation and maintenance (OppOM) strategy that integrates control decisions with offshore maintenance scheduling, from the scale of a single turbine to an entire wind farm.

A high-fidelity OpenFAST simulation framework is first developed to capture the coupled dynamic response of all four subsystems under various wind, wave, and control conditions. The analysis reveals that the generator and tower are highly sensitive to control parameters near rated wind speed, whereas mooring loads are predominantly driven by wave conditions. Moderate derating is shown to effectively compress the fatigue stress envelope across components.

Building upon this, a probabilistic corrosion-fatigue framework is established to evaluate the time-varying reliability of each subsystem, combining site-specific environmental data with dynamic stress histories. The results identify the tower shell and generator components as critical to early-life degradation, and demonstrate that control tuning can significantly postpone reliability decline with minimal impact on energy production.

To address the computational limitations of real-time assessment, a physics-informed machine learning (PIML) surrogate model is developed. By embedding resonance-aware constraints into the learning process, the model accurately reproduces structural responses at second-level speed, thus enabling fast prediction of dynamic states for digital-twin integration.

The surrogate outputs are then fed into a hybrid decision-making framework, where a Dynamic Bayesian Network (DBN) describes subsystem degradation, a Partially Observable Markov Decision Process (POMDP) models uncertainty, and an A3C reinforcement learning agent jointly optimizes control, de-rating, and maintenance actions. Compared with traditional condition-based and opportunistic strategies, this OppOM framework extends offshore maintenance intervals while simultaneously reducing lifetime risk and operational costs.

Finally, the method is scaled to a three-turbine wind farm, incorporating dynamic wake interactions and future climate scenarios. Coordinated de-rating of the upstream turbine mitigates wake effects on downstream units, improves overall energy yield and logistical efficiency, and maintains high reliability even under severe climate-change projections.

By integrating high-fidelity simulation, physics-enhanced surrogate modeling, and reinforcement-learning-based decision-making into a digital-twin framework, this work offers a scalable and intelligent solution for the reliable, economical, and low-carbon operation of deep-sea floating wind turbines. The methodology also lays the groundwork for future advancements in cloud–edge digital twins, large language model integration, and multi-farm, grid-interactive optimization.

Publications Arising from the Thesis

Zhang, J., Heng, J., Dong, Y., Baniotopoulos, C., & Yang, Q. (2024). Coupling multi-physics models to corrosion fatigue prognosis of high-strength bolts in floating offshore wind turbine towers. *Engineering Structures*, 301, 117309.

Zhang, J., Lei, X., Chan, P. W., & Dong, Y. (2024). Integrating physics-informed machine learning with resonance effect for structural dynamic performance modeling. *Journal of Building Engineering*, 84, 108627.

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Fang, L., Zhu, D., **Zhang, J.***, & Dong, Y. (2024). An unsupervised learning framework for health diagnosis by incorporating multiscale data. *Structures* (Vol. 69, p. 107396).

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Guo, H., **Zhang, J.**, Dong, Y., & Frangopol, D. M. (2024). Probability-informed neural network-driven point-evolution kernel density estimation for time-dependent reliability analysis. *Reliability Engineering & System Safety*, 249, 110234.

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List of Abbreviations

FOWT	Floating Offshore Wind Turbine
O&M	Operation and Maintenance
CBM	Condition-Based Maintenance
PM	Preventive Maintenance
CM	Corrective Maintenance
OppM	Opportunistic Maintenance
OppOM	Opportunistic Operation and Maintenance
POF	Probability of Failure
MCS	Monte Carlo Simulation
CF	Corrosion Fatigue
PCF	Probabilistic Corrosion Fatigue
LSF	Limit State Function
DWM	Dynamic Wake Meandering
SCF	Stress Concentration Factor
AI	Artificial Intelligence
PIML	Physics-Informed Machine Learning
PDE	Partial Differential Equation
AC	Actor–Critic
A3C	Asynchronous Advantage Actor–Critic
POMDP	Partially Observable Markov Decision Process
DBN	Dynamic Bayesian Network

CHAPTER 1

Introduction

1.1 Background

As the global energy transition deepens, Floating Offshore Wind Turbines (FOWTs) have emerged as a key technology for harnessing abundant wind resources in deep-water regions, thereby becoming a major direction in renewable energy development (Mathisen et al., 2024). FOWTs offer high energy output and notable environmental benefits, playing an irreplaceable role in the global shift toward zero-carbon energy systems ((IRENA), 2018; Thomas et al., 2024). Unlike traditional fixed-bottom offshore wind turbines, FOWTs can be deployed in water depths exceeding 60 meters, significantly broadening the potential wind resource base, especially for countries and regions with narrow continental shelves and rapidly increasing nearshore depths, thus providing a feasible pathway to tap into rich wind energy resources (Galera-Calero et al., 2021; Li et al., 2024). Many countries worldwide have incorporated FOWTs into their renewable energy strategies and have launched a series of demonstration projects and commercialization plans, underscoring the strategic importance of this technology in future energy architectures (Higgins & Foley, 2014; McCoy et al., 2024).

However, FOWTs face formidable challenges in harsh marine environments, particularly in terms of corrosion fatigue degradation (Shafiee & Sørensen, 2019; Sinha et al., 2013; Walter et al., 2018). The combined effects of high salinity, humidity, and frequent wind-wave loads in the ocean

environment lead to significant corrosion fatigue damage in critical structural components (Chaves & Melchers, 2014; Sinha et al., 2013). Research shows that the high corrosivity of the marine environment can accelerate the fatigue process of metallic structures by up to three times or more, a phenomenon particularly evident in FOWTs (Jacob & Mehmanparast, 2021; Lotsberg et al., 2016). The evolution of corrosion fatigue typically occurs in three stages: pitting corrosion, small crack growth, and long crack propagation, a process that continuously diminishes structural strength (Li et al., 2018). Moreover, compared with fixed-bottom turbines, the floating foundation of FOWTs amplifies the dynamic response of the tower and increases the stress range at critical connection points, further exacerbating the risk of corrosion fatigue degradation (J. Zhang, J. Heng, et al., 2024). Such accelerated deterioration not only compromises the structural integrity of FOWTs but may also lead to abnormal vibrations, unscheduled shutdowns, and, in extreme cases, catastrophic tower collapse (Z. Guo et al., 2020).

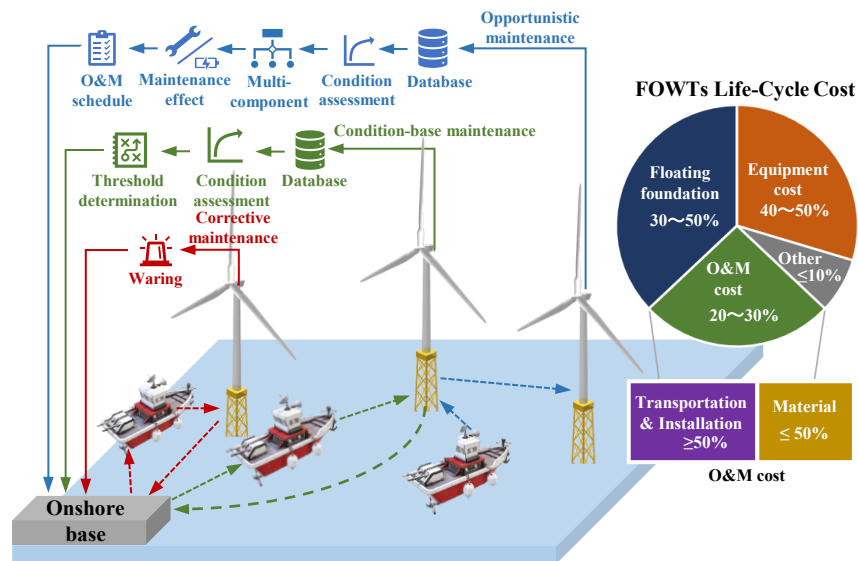


Figure 1-1 Operation and Maintenance strategies and cost distribution of offshore wind energy

Due to these intensified degradation effects, more frequent inspections are required to ensure

turbine performance. According to the 2024 cost analysis report released by the U.S. NREL, accelerated degradation trends in key offshore wind turbine structures have pushed O&M costs to account for as much as 30% of the total investment (McCoy et al., 2024; Stehly et al., 2024). The current passive O&M system exhibits significant efficiency bottlenecks: a corrective maintenance mode driven by detection alarms results in logistical costs exceeding 50% of total O&M expenditures (Njiri & Söffker, 2016), as shown in Figure 1-1. This inefficiency stems from the contradiction between restricted offshore operation windows and the need to address sudden failures. The passive maintenance strategy creates a dual impact: on one hand, unplanned downtime reduces the annual capacity factor of the turbine to a critical level of around 40% (McCoy et al., 2024); on the other hand, the cumulative structural damage significantly shortens the design lifespan (McCoy et al., 2024). In response to these challenges, the latest (International Electrotechnical, 2025) standard emphasizes the importance of intelligent operation, maintenance, and inspection management in wind turbine systems, highlighting the need for risk management. However, the standard currently relies on general operational years to define inspection frequencies, categorizing turbines into early (15%-25% of lifecycle), mid (45%-55% of lifecycle), and late (70%-80% of lifecycle) stages, based on their age. This approach lacks a dynamic framework for real-time risk assessment, continuous updates, and operational management based on actual turbine health data.

To implement such a framework effectively in real-world turbine operation and maintenance environments, three key issues need to be addressed. First, traditional maintenance strategies, including Corrective Maintenance (CM) and Preventive Maintenance (PM), rely heavily on historical data to schedule interventions (Bossanyi, 2003; Walter et al., 2018). CM, being reactive, only initiates maintenance after a failure occurs, leading to unplanned downtime and costly repairs

in offshore environments, where severe sea conditions and limited operational windows exacerbate the problem (Chen et al., 2024). Although PM can reduce unexpected failures, it often fails to accurately reflect the current state of the equipment, resulting in either excessive or insufficient maintenance and, consequently, increased operational costs and inefficient resource utilization (Barlas & van Kuik, 2010; Bossanyi & Wright, 2009). These limitations are even more pronounced in the complex, dynamic environment of Floating Offshore Wind Turbines (FOWTs), where conditions can vary dramatically and unpredictably (Hoghooghi et al., 2020).

Second, while Condition-Based Maintenance (CBM) improves on traditional methods by utilizing real-time monitoring and predictive analytics, it still faces challenges in the accuracy and efficiency of long-term predictions (Dao et al., 2019; Dinwoodie et al., 2013). Current models struggle to provide precise maintenance forecasts over the typical 20-25 year design lifespan of FOWTs due to the uncertainties in multi-physics modeling and the complex nature of material degradation and environmental conditions (Galinos et al., 2016; Qiao et al., 2024). Moreover, although Opportunistic Maintenance (OppM) can optimize maintenance scheduling during favorable operational windows, static scheduling without dynamic adjustment based on real-time data still results in missed opportunities for further cost savings and reduced downtime (Chatterjee & Dethlefs, 2021; Rinaldi et al., 2021).

Finally, the integration of artificial intelligence (AI) is necessary to address these limitations. Traditional multi-physics simulations, while capable of modeling the dynamic behavior of FOWTs, suffer from low computational efficiency and inaccuracies when predicting long-term performance (De Corcuera et al., 2012; Zhang et al., 2016). AI-driven tools can accelerate simulation processes and provide more precise predictions of turbine health, making it possible to implement a more adaptive and data-driven maintenance strategy. This, in turn, allows for more efficient decision-

making and better utilization of resources over the entire lifecycle of the turbine (Kim et al., 2013; Wang & Tomsovic, 2018)

Addressing these challenges will ensure a more data-driven, efficient, and adaptive approach to turbine maintenance. Proactive health assessment systems are being deployed, leveraging integrated sensor networks, including SCADA, acoustic emission monitoring, and corrosion sensors, to quantitatively predict structural degradation trajectories (Lu et al., 2009; Njiri et al., 2015). Besides, opportunity-based multi-objective optimization models are being developed; these models coordinate the maintenance requirements for various components (such as blades, towers, and foundations) under constraints like wake effects and limited weather windows, thereby maximizing the efficiency of each offshore operation (Jiang et al., 2017). Finally, an innovative active control dimension is being introduced by integrating techniques such as variable pitch control and de-rating into the O&M system (Shafiee et al., 2016). This holistic solution, achieved through the deep synergy of intelligent sensing, predictive algorithms, and control strategies, provides a new theoretical framework for addressing the risk–cost–power generation dilemma (Gintautas & Sørensen, 2017; Heng et al., 2024). The concepts align directly with IEC 61400-28 guidance, which emphasizes the shift from passive to intelligent, risk-informed O&M approaches, advocating for periodic re-evaluation of turbine suitability based on health conditions, ambient load profiles, and operational history areas where AI-powered predictive maintenance can contribute decisively to safe life extension and cost efficiency.

This study aims to guide the O&M decisions for FOWTs through pre-emptive analysis and modeling that prevent unnecessary offshore operations or downtime (Dao et al., 2021; Kang & Soares, 2020). By comprehensively considering the multifaceted demands of FOWTs, including safety, economic, environmental, and production capacity aspects, a system-level solution is

developed to address the inherent risk–cost–power generation dilemma (Lu et al., 2009; Zhou & Yin, 2019). Such a holistic solution, realized through the deep integration of intelligent sensing, predictive algorithms, and control strategies, offers a new theoretical framework and practical pathway for the full life cycle management of FOWTs (Lu et al., 2018). In essence, this framework is aligned with the concept of a digital twin (DT), which is more than a static numerical model but a dynamic virtual representation of the physical system that continuously updates with operational data and environmental conditions (Grieves & Vickers, 2016; Yang et al., 2024).

1.2 Objectives

The overarching goal of this thesis is to develop an AI-enhanced predictive framework for intelligent operation and maintenance O&M of FOWTs, aiming to address the challenges posed by harsh marine environments, complex system dynamics, and long-term structural degradation. This work is centered on three primary objectives:

- 1) **To uncover the long-term degradation mechanisms** of FOWTs subjected to the combined influences of external environmental loads and internal control-induced stresses. Understanding these coupled effects is essential for accurate reliability assessment and risk-informed decision-making across the turbine’s lifespan.
- 2) **To develop a physics-informed, AI-driven methodology** capable of achieving both high accuracy and computational efficiency under dynamic, uncertain marine conditions. By integrating domain knowledge into machine learning architectures, the approach will enable real-time prediction of system responses without relying on computationally intensive simulations.
- 3) **To implement a lifecycle-aware coordination strategy** between active control policies (e.g., de-rating) and opportunistic maintenance planning. This includes the co-optimization

of automated control and human interventions, ensuring minimal downtime and extended service life.

To this end, the thesis pursues the following specific research objectives:

- 1) Develop an integrated multi-physics degradation framework that couples aerodynamic, hydrodynamic, structural, and control-related stressors into a unified lifetime modeling approach.
- 2) Propose a physics-informed machine learning (PIML) method that leverages both sensor data and physical constraints to enable real-time prediction of turbine dynamics under stochastic operational scenarios.
- 3) Establish a proactive and opportunistic operation and maintenance (OppOM) strategy, incorporating turbine-level control actions (e.g., de-rating or load shedding) into the maintenance decision-making process.
- 4) Extend the OppOM strategy to the wind farm scale, accounting for inter-turbine wake effects, cooperative control, and the spatial-temporal variability of environmental conditions.
- 5) Bridge the gap between high-fidelity numerical models and practical engineering applications, by developing surrogate models and digital twin platforms that facilitate scalable decision support for real-world offshore wind projects.

Together, these objectives aim to build a comprehensive, AI-augmented digital framework that supports the predictive, prescriptive, and adaptive management of offshore wind energy assets over their full operational lifespan.

1.3 Thesis Organization

This thesis focuses on the dynamic response and long-term degradation behavior of FOWTs, considering the combined influences of realistic wind-wave interactions, corrosive marine environments, and embedded turbine control strategies. The core methodology is built upon PIML, which enables efficient yet accurate analysis under dynamic conditions. The research ultimately proposes a lifecycle-aware OppOM strategy that integrates both automated control and human intervention. The proposed framework is first demonstrated on a single FOWT and subsequently extended to a multi-turbine wind farm with wake interaction effects. The overall structure of this thesis is outlined as follows:

- **Chapter 1** introduces the research motivations and outlines the primary objectives of the study, emphasizing the need for integrated predictive tools for intelligent lifecycle management of FOWTs.
- **Chapter 2** provides a comprehensive review of key enabling technologies for AI-enhanced predictive modeling in OppOM. Topics include multi-physics modeling, control strategies, long-term degradation under coupled wind-wave-corrosion environments, critical performance indicators in offshore wind systems, O&M optimization methods, and AI applications in this context. The chapter identifies key research gaps and outlines the proposed approach to address them.
- **Chapter 3** presents the dynamic response modeling of FOWTs under complex marine conditions using the OpenFAST platform, with various turbine control strategies incorporated. A structural stress analysis workflow is developed to transition from global responses to local stress distributions, enabling detailed degradation assessments. The turbine is decomposed into four critical components—generator, blade, tower, and mooring

for targeted analysis. The impact of de-rating control on both dynamic behavior and stress distribution is assessed using the IEA 15MW reference turbine.

- **Chapter 4** elaborates the corrosion-fatigue degradation mechanisms from a physics-based perspective. It integrates site-specific environmental data, laboratory material test results, and multi-physics simulations into a probabilistic corrosion-fatigue (PCF) framework. A reliability analysis methodology is proposed to assess component- and system-level reliability evolution in harsh marine environments, revealing new insights into C-F-induced lifecycle vulnerability.

- **Chapter 5** introduces a physics-informed machine learning (PIML) model for predicting dynamic turbine behavior. The method embeds resonance sensitivity into the learning process by incorporating physical knowledge directly into the loss function. Resonance characteristics and vibrational modes are carefully considered, resulting in a high-accuracy, high-efficiency surrogate model. The approach is validated on canonical resonance systems and applied to the 15MW FOWT under stochastic wind-wave excitations, laying the foundation for real-time predictive modeling.

- **Chapter 6** proposes a novel OppOM framework that couples de-rating control strategies with maintenance planning. This hybrid scheme leverages every offshore opportunity to perform adaptive scheduling. Structural degradation is embedded within a dynamic Bayesian network (DBN), which is further combined with a POMDP decision process. The overall policy optimization is solved using an A3C deep reinforcement learning framework. The objective function captures safety, energy yield, economic cost, and environmental impact. The proposed strategy is benchmarked against traditional OppM and CBM approaches over a full 25-year service period.

- **Chapter 7** extends the OppOM framework to the wind farm level, incorporating turbine-turbine wake interactions. The effects of wake-induced flow reductions and de-rating coordination are evaluated through coupled simulations. The full OppOM methodology is implemented in a three-turbine wind farm scenario, validating its effectiveness and showcasing its superior adaptability under climate change considerations.

- **Chapter 8** concludes the thesis by summarizing the key findings, highlighting limitations, and providing recommendations for future research directions.

Figure 1-2 illustrates the overall structure of the thesis. The chapters are interlinked as follows:

Chapter 2 establishes the multi-physics modeling of floating offshore wind turbines, which provides the foundation for reliability analysis in Chapter 3. Chapter 4 extends this by incorporating probabilistic degradation models, leading into Chapter 5, where AI-powered surrogate models enable real-time performance prediction. Building upon these predictive tools, Chapter 6 introduces lifecycle-aware O&M strategies, which are further validated at the wind farm scale in Chapter 7. Finally, Chapter 8 synthesizes the findings and presents conclusions. This progressive structure ensures a coherent transition from fundamental modeling, through reliability and prediction, to decision-making and system-level applications. Within this thesis, the PIML surrogate in Chapter 5 serves as the fast simulation core of the DT, the OppOM strategy in Chapter 6 provides the decision-making layer for predictive O&M, and the wind-farm level extension in Chapter 7 illustrates how the DT paradigm can scale under wake interactions and climate scenarios.

The following contributions are made to advance the state of knowledge in the field of FOWT reliability and OM:

- **Integrated multi-physics modeling framework:** A coupled aero–hydro–servo–elastic model is formulated to capture dynamic interactions under realistic marine environments,

enabling consistent propagation of environmental conditions and control settings to component-level responses.

- **Probabilistic corrosion–fatigue modeling:** A reliability framework is established that incorporates the joint action of corrosion and cyclic loading, allowing time-dependent degradation processes to be quantified with consideration of environmental and operational variability.
- **Physics-informed surrogate modeling:** Resonance-sensitive surrogate models are developed that integrate physical laws into machine learning architectures, allowing fast yet physically consistent prediction of dynamic responses and forming the analytical core of a digital twin.
- **Turbine-level opportunistic maintenance strategies:** OppOM policies are designed that combine predictive degradation indicators with adaptive control adjustments, optimizing the balance between reliability, cost, and energy production.
- **Farm-level coordinated OppOM framework:** A system-level decision model is proposed that accounts for wake interactions, heterogeneous turbine conditions, and shared maintenance resources, extending opportunistic maintenance to offshore wind farms.
- **Digital twin architecture for lifecycle O&M:** A unified digital twin is structured by linking multi-physics modeling, degradation assessment, surrogate-based prediction, and decision layers, providing a coherent framework that connects data and physics.

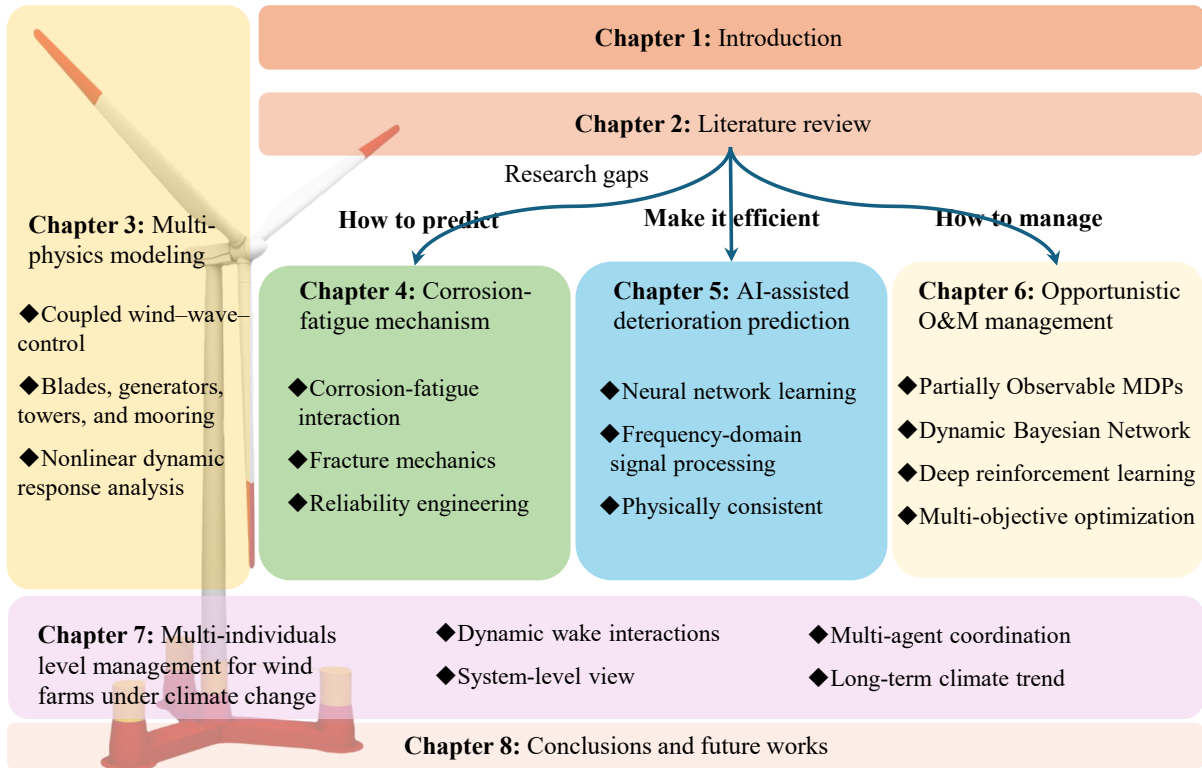


Figure 1-2 Proposed framework of the thesis

CHAPTER 2

Literature review

2.1 Aero-Servo-Elastic modeling of wind turbines

The advancement of wind energy technology has led to the development of increasingly complex wind turbines, particularly those operating in offshore environments. These systems require precise modeling to ensure performance, safety, and reliability. Aero-servo-elastic (ASE) modeling is a comprehensive framework that integrates aerodynamic, structural dynamic, and control system analyses to capture the intricate interactions within wind turbines. This approach is crucial for understanding and optimizing turbine behavior under diverse operational and environmental conditions.

Aerodynamic forces play a fundamental role in dictating the performance of wind turbines by driving power generation and influencing structural loads ([Muller et al., 2024](#); [Yang et al., 2020](#)). Accurate aerodynamic modeling, using methods like blade element momentum theory or computational fluid dynamics (CFD), is essential, particularly under turbulent wind conditions. Meanwhile, the flexibility of turbine blades and tower structures introduces dynamic responses that must be modeled to prevent resonance and fatigue-related failures ([Jessen et al., 2019](#); [Le Guern et al., 2024](#)). Additionally, advanced control systems, including pitch and torque control, are indispensable for regulating power output and stabilizing turbine operations. These systems interact dynamically with aerodynamic and structural components, ensuring optimal performance and reducing operational risks.

The coupling of aerodynamic, structural, and control dynamics is critical for accurately representing the behavior of wind turbines ([Tang et al., 2021](#)). Isolated modeling of these modules often fails to capture the feedback loops and interactions that occur during operation. For example, platform motions in floating offshore wind turbines can induce vibrations in the blades, affecting aerodynamic performance ([Oh et al., 2018](#)). Similarly, blade deformations can alter the flow field, modifying aerodynamic loads and structural responses. Coupled aero-servo-elastic analyses enable designers to predict these interactions, ensuring the integrity and efficiency of wind turbines under complex environmental loads ([Li et al., 2017](#)).

Several methodologies have been developed to address the challenges of ASE modeling. Fully coupled simulation tools, such as FAST and OpenFAST, integrate aerodynamic, structural, and control dynamics within a single simulation environment ([Yang et al., 2020](#)). These tools have been extensively validated against experimental data, demonstrating their ability to predict turbine responses under varying wind and wave conditions ([Jessen et al., 2019](#)). Partitioned frameworks, which couple CFD with multibody dynamics solvers, allow for modular simulation of ASE systems. These approaches reduce computational costs while maintaining accuracy, as evidenced in large-scale turbine studies ([Le Guern et al., 2024](#)). High-fidelity validation techniques, including experiments with scaled models, further ensure the reliability of ASE simulations. For instance, 1:35 scaled tension-leg platform models have shown strong agreement between numerical predictions and experimental results ([Oh et al., 2018](#)). Additionally, combining low- and high-fidelity simulators, such as FAST and BLADED, enhances predictive accuracy while mitigating computational demands ([Abdallah et al., 2015](#)).

Research has demonstrated that ASE modeling provides essential insights into turbine dynamics and performance. Nonlinear effects, such as blade vibrations induced by platform

motions, significantly influence turbine stability and require robust coupling frameworks (Tang et al., 2021). High-fidelity CFD simulations reveal complex flow-structure interactions, enhancing the understanding of rotor wake dynamics and blade deflections (Li et al., 2017). Advanced validation techniques, including experimental tests under misaligned wind and wave conditions, confirm the accuracy of ASE models in predicting real-world turbine behavior (Jessen et al., 2019; Oh et al., 2018). As reviewed above, current efforts mainly are devoted to the global structural behaviour of novel FOWT designs, leaving a gap in detailed insights into the long-term deterioration of FOWT structures.

2.2 Long-term deterioration of marine structure

Offshore wind turbines are increasingly used to harness wind energy in marine environments. However, the harsh conditions in these environments subject the structures to corrosion and fatigue, significantly impacting their durability and reliability. (Shittu et al., 2020) evaluated the reliability of offshore wind turbine structures under pitting CF using a probabilistic model, revealing that the structure becomes unsafe after 18 years, with pit growth accounting for 56% of the total fatigue life. (Esaklul & Ahmed, 2009) explored CF failure modes for high-strength fasteners in offshore applications, emphasizing the importance of CF prediction models for improving structural integrity. (C. Zhang et al., 2019) investigated the effect of corrosion morphology on the fatigue strength of bolted joints, showing that corrosion increased the inverse slope of the S-N curve from 8.29 to 9.05, significantly accelerating fatigue strength degradation in offshore environments.

However, this study was primarily experimental and did not incorporate advanced predictive modeling techniques (Li et al., 2016). Recent advancements in predictive modeling have focused on improving the accuracy and reliability of corrosion fatigue life predictions through enhanced

models and experimental validation . (Liao et al., 2020) conducted corrosion fatigue tests in synthetic seawater using a constant temperature liquid circulating system, providing valuable data for validating physical models and improving their predictive capabilities. Despite this, their study highlighted the challenge of replicating the exact conditions of the marine environment in laboratory settings. (Zampieri et al., 2017) explored the effects of crack growth direction on the corrosion-fatigue behavior of offshore wind turbine steel weldments. Their findings underscore the importance of considering crack orientation in predictive models to better simulate real-world conditions. However, their models did not fully integrate environmental variability and the complex interactions of multi-physics processes. (Jiang et al., 2023) studied the effects of corrosion on the fatigue performance of high-strength bolted friction connections, highlighting the need for detailed modeling of corrosion damage to accurately predict fatigue life. However, their research indicated a gap in the understanding of how environmental factors influence corrosion damage progression over time. (Lan et al., 2018) developed a Weibull model for fatigue life prediction of steel rebar, incorporating corrosion effects. This statistical approach enhances the robustness of predictive models by accounting for variability in material properties and environmental conditions. Yet, their model primarily focused on statistical representation without integrating dynamic environmental factors. (Jacob & Mehmanparast, 2021) proposed a new approach for corrosion-fatigue analysis of offshore steel structures, emphasizing the integration of mechanism models with advanced statistical techniques to improve prediction accuracy. This approach addressed some of the limitations of previous studies but still required extensive validation with long-term operational data. (He et al., 2016; J. Zhang, J. Heng, et al., 2024) discussed the integration of multi-physics models and real site condition to predict corrosion fatigue in high-strength bolts used in floating offshore wind turbine towers. Their research underscored the

importance of considering multiple interacting physical processes to improve prediction accuracy. However, this work mainly targeted high-strength bolts and did not provide an analysis of the overall structure.

FOWTs are highly vulnerable to CF, which can lead to abnormal vibrations and necessitate shutdowns for maintenance (Ryan & Mehmanparast, 2023). In more severe cases, CF progression may result in tower collapse, highlighting the need for quantitative analysis. However, most existing studies focus on individual components, with limited research addressing the structural-level impact of operating strategies on long-term CF performance (He et al., 2016; J. Zhang, J. Heng, et al., 2024). This lack of research limits the ability to provide reliable guidelines for O&M management from the perspective of CF degradation.

2.3 Effects of Control Strategies on Operational Performance

Wind turbines are complex multi-physics systems wherein aerodynamic, hydrodynamic, and control dynamics intricately interact to influence both operational performance and long-term structural behavior. As the demand for offshore wind energy grows, maintaining the structural health and reliability of wind turbines has become increasingly critical. One promising approach that has gained traction in recent years is de-rating, intentionally operating turbines below their rated power output to alleviate mechanical stress and enhance system longevity. Numerous studies have demonstrated that de-rating can effectively reduce fatigue damage and extend turbine lifespan. By lowering the mechanical loads on key components, this strategy mitigates fatigue accumulation and delays structural degradation (Dimitrov & Natarajan, 2021; van der Hoek et al., 2018). As a result, de-rating has been widely incorporated into wind turbine control systems to optimize wind farm performance and reliability (Juangarcia et al., 2018). For instance, (Richards et al., 2014)

observed a 25% reduction in sectional internal forces under de-rated operation, while (De Corcuera et al., 2012) proposed a multivariable control strategy specifically targeting load mitigation.

Recent research has expanded on these foundational insights, exploring multi-objective and optimized control approaches that further improve load reduction. (Galinós et al., 2018) reported fatigue load reductions between 2% and 6% at wind speeds below 8 m/s, and in a follow-up study, achieved up to a 6.5% reduction in tower fatigue loads in the fore-aft direction (Galinós et al., 2019). (Kim et al., 2020) found that de-rating could reduce ultimate loads on blades and towers by 31% and 21.7%, respectively, with fatigue equivalent load reductions ranging from 3% to 8.9%.

Building upon these developments, (Yao et al., 2019) introduced an optimized active power dispatching strategy that achieved fatigue load reductions of up to 57.1% during de-loading operations. (Kipchirchir et al., 2024) further demonstrated that advanced control strategies could reduce dynamic structural loads by 10.7% on rotor blades and 36.2% on towers. Similarly, (Njiri et al., 2019) integrated real-time damage assessment models into de-rating control, showing a 40% decrease in damage accumulation, underscoring the localized fatigue mitigation potential of de-rating strategies.

However, the implications of de-rating for crack formation (CF) and propagation, particularly in offshore wind turbines, remain inadequately understood and warrant further empirical validation. While the benefits of reduced loading are evident, de-rating inherently leads to curtailed energy production (Pan et al., 2023). This necessitates a trade-off approach that judiciously balances energy losses against long-term structural safety and maintenance gains.

In the offshore context, several studies have examined this balance in greater depth. (J. Zhang, J. Heng, et al., 2024) evaluated operational strategies for offshore wind farms, finding that de-rating could effectively mitigate localized damage, particularly on turbine blades. (Y. Cheng et al.,

2023) reinforced the value of de-rating in preventing overload scenarios, which helps preserve structural integrity during periods of maintenance or adverse environmental conditions.

Moreover, the integration of structural health monitoring (SHM) systems with de-rating strategies has emerged as a key enabler for predictive maintenance. (Richards et al., 2014) emphasized the critical role of SHM in early damage detection, facilitating timely interventions that can significantly extend turbine service life. (Odgaard et al., 2015) also supported de-rating strategies by demonstrating their effectiveness in minimizing fatigue loads on turbines, thus enhancing their longevity and reliability. By optimizing power references, they showed that de-rating can effectively balance load management and power generation efficiency. Further, (Griffith et al., 2012) explored the optimization of wind turbine set points through de-rating strategies, focusing on load and power output management.

In summary, de-rating strategies offer a viable solution for enhancing the durability and reliability of wind turbines, especially in offshore environments where maintenance is costly and logistically complex. Nevertheless, realizing their full potential requires robust predictive models, environmental adaptability, and control system integration that considers site-specific operational dynamics. As the offshore wind industry continues to evolve, the refinement of de-rating strategies will remain a key focus in the pursuit of sustainable, resilient energy systems.

2.4 Physics-informed AI techniques in structural analysis

Structural dynamics plays a fundamental role in various branches of engineering, serving as a critical element in understanding and predicting how structures behave under dynamic forces. This knowledge is essential for both the design and maintenance of infrastructure, including buildings, bridges, aircraft, and other systems. Accurate modeling of these structures, coupled with the ability

to anticipate their reactions under different scenarios, is crucial to ensure their stability and performance over time (Bottasso et al., 2014; Dimitrov & Natarajan, 2021; Jensen et al., 2016). Previous trends in structural engineering research encompass a variety of subjects, including the effects of dynamic loads like earthquakes, winds, and vibrations on structures such as buildings, bridges, and offshore platforms (Kwasniewski et al., 2006; Smit et al., 1998; Ying et al., 2009). Moreover, there is a growing focus on understanding the fire effects on structures, the performance of reinforced concrete, steel, and composite structures, as well as masonry and high-rise structures (Kwasniewski et al., 2006; Li et al., 2022). Additionally, the use of computational methods in structural analysis, like Finite Element Method and Boundary Element Method, is being actively explored. Despite these developments, traditional methods for exploring structural dynamics struggle with complex mathematical models, computational inefficiency, and a restricted ability to encapsulate complex nonlinear behaviors (Mendis et al., 2007). Consequently, these limitations often render such methods impractical for large-scale or real-time applications.

In response to these limitations, the emergence of machine learning (ML) in recent years has illuminated new paths for addressing these challenges. Machine learning algorithms have exhibited exceptional capabilities in diverse domains, including image recognition, natural language processing, and predictive analytics. These capabilities emerge from their inherent capacity to process vast datasets in structural engineering, identify complex patterns, and subsequently make accurate predictions (Avci et al., 2021; Lagaros & Papadrakakis, 2012; Xiang, 2006). This synergy between ML and structural dynamics is particularly significant, as with the swift advancements in computer hardware and a more profound comprehension of algorithms, the field of artificial intelligence (AI) has experienced significant breakthroughs, now extending to civil engineering. In this context, a multitude of studies in the realm of academic research have

eagerly sought to refine techniques for forecasting structural responses using AI models. These advancements are critical for improving the safety, efficiency, and sustainability of civil infrastructure, addressing the challenges posed by various external forces, and ensuring the longevity and reliability of structural designs (Flah et al., 2021). (Hosseinzadeh et al., 2023) adopted a method based on support vector machines to predict nonlinear reactions, and (Avci et al., 2021) employed Multi-Layer Perceptron (MLP) networks for deciphering earthquake-induced behaviors. Furthering these innovations, more intricate deep learning networks have been deployed for structural dynamic performance prediction, as demonstrated by (Yinfeng et al., 2008) with deep CNNs for sequence regression and system identification in structural dynamics, and (Lagaros & Papadrakakis, 2012) with a deep LSTM network for seismic loading predictions. These methods validate the applicability and reliability of AI approaches in structural dynamic modeling.

Despite the potency of purely data-driven methods for data-oriented modeling, their application within numerous engineering domains, including structural engineering, continues to pose considerable challenges ((Wu & Jahanshahi, 2019). Firstly, the effectiveness of these data-driven approaches is largely contingent upon the volume and quality of the data. Moreover, such methods often lack physical explicability and the ability to generalize when addressing physical problems (Jiang et al., 2007; Xu et al., 2022; R. Zhang et al., 2019). In response to these challenges, the recent advent of machine learning techniques, in conjunction with the implementation of physics-informed methods, has unveiled new prospects for amplifying the accuracy and efficiency of structural dynamic modeling and the inherent physics of the dynamical system (Katicha et al., 2014; Yang & Peter, 2003). These algorithms have the potential to significantly enhance our ability to model and predict structural dynamics, particularly when they are informed by the physical principles that govern the behavior of these structures. This approach, known as physics-informed

machine learning (PIML), combines the data-driven capabilities of machine learning with the theoretical rigor of physics-based models, potentially leading to more accurate and efficient simulations. The most intuitive approach is to incorporate the physics (including governing equations, value constraints, etc.) as a penalty term in the loss function of machine learning models (Xu et al., 2022). (Zhang et al., 2020b) proposed a physics-guided convolutional neural network (CNN) to predict structural seismic responses, which they subsequently employed for fragility analysis using certain limit state criteria. (Yang & Perdikaris, 2019) proposed a physics-guided ML method that combines a recurrent neural network (RNN) and multilayer perceptron (MLP) for structural dynamics simulation. This method is noted for its enhanced generalization capacity and reduced training cost.

While PIML exhibits considerable potential, it confronts multiple challenges. First, the integration of physical principles with machine learning models is a complex process requiring an in-depth understanding of both domains. Second, the accessibility and quality of data significantly influence the model performance. Furthermore, the interpretation and validation of model predictions, particularly within the context of structural dynamics, are not straightforward and demand careful analysis. Consequently, it is essential to incorporate significant physical phenomena with structural vibration equations for the regulation of neural network structures. Resonance receive significant attention in the analysis of structural engineering reliability, as their occurrence often signifies the emergence of extreme dynamic responses within structures (Yu et al., 2020; Zhang et al., 2020a). Guiding the ML model as a critical physical element, resonance - a phenomenon that occurs when the frequency of external forces coincides with a natural frequency - profoundly impacts its behavior and response. The resonance effect could notably amplify structural vibrations, possibly leading to severe repercussions if not properly understood and

integrated into the modeling process. Purely machine learning methods fail to capture the dynamics related to resonance in dynamic systems.

2.5 Comprehensive assessment of FOWTs in life cycle

In traditional civil engineering, Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) have been widely applied to infrastructures such as bridges, tunnels, and high-rise buildings. These methods quantify environmental, economic, and structural performance throughout the design, construction, service, and decommissioning stages. For instance, (Ji & Zhang) incorporated seismic risk and aging mechanisms into a comprehensive life cycle cost model for bridges, highlighting the profound impact of structural durability on investment efficiency and risk control. Similarly, (Mendis et al., 2007) and (Ghosh & Padgett, 2010) independently developed multi-criteria decision models for the integrated assessment of urban buildings and bridge systems, thereby advancing the quantitative integration of environmental, social, and economic indicators.

Extending this concept to offshore renewable energy systems, FOWTs have emerged as a key technological pathway for future energy systems due to their capability to be deployed in deep-water environments and their potential to harness strong wind resources. The structural system of FOWTs encompasses large-scale turbines (typically 10–20 MW), floating platforms (such as spar, tension-leg platform, or semi-submersible types), mooring systems, cable systems, and multi-source control modules. These systems exhibit highly coupled aerodynamic, hydrodynamic, and structural dynamic behaviors, rendering their life cycle assessment considerably more complex than that of traditional fixed-bottom wind turbines. In a pioneering study, (Asadi et al., 2019) developed a full life cycle assessment model for FOWTs, noting that the manufacturing phase, especially the steel fabrication processes for the floating bodies and towers accounts for the

majority of carbon emissions. (Navarro et al., 2020) reported, through an LCA of 190 Mediterranean 14.7 MW FOWTs, that the average carbon intensity is 31 gCO₂/kWh with an energy payback period of only 3 years, thereby underscoring significant environmental benefits. Furthermore, research by (Weinzettel et al., 2009) and (Brussa et al., 2023) confirms that the manufacturing and operation & maintenance (O&M) stages exert the greatest influence on overall life cycle performance.

It is especially noteworthy that the O&M phase of FOWTs imposes not only a substantial economic burden but also represents a major source of life cycle carbon emissions. Simulations by (Struthers et al., 2023) indicate that OPEX costs range from £16.89 to £19.93 per MWh, with decommissioning costs of £3.47 to £3.65 per MWh, resulting in a total LCOE of £66.73 per MWh. Such high later-stage costs pose significant challenges to economic feasibility. (Lotfizadeh et al., 2025) further highlight that factors such as installation methods, cable deployment, and platform transportation critically affect long-term energy consumption and maintenance expenses (McAuliffe et al., 2024). Cross-disciplinary studies reinforce these findings: (Yildiz et al., 2024) found that, for integrated energy hubs, the O&M phase yields the highest carbon emissions over the life cycle, while (McAuliffe et al., 2024) reported that the O&M carbon footprint of the Beijing–Shanghai high-speed railway reached 31.6%, with associated economic costs of up to USD 900 million. In addition, (D. Wang et al., 2022) observed that maintenance emissions constitute 28% of the life cycle for HVAC systems, far exceeding the share from the decommissioning phase, and (Kaewunruen et al., 2019) noted that road maintenance during traffic management can add an extra 6.4% to carbon emissions.

On the structural reliability side, (Chen & Zhang, 2011) developed a crack propagation model based on fracture mechanics and proposed a life prediction mechanism centered on fatigue

behavior. (Liu et al., 2023) stressed the importance of embedding multi-subsystem coupled responses and condition monitoring systems into comprehensive structural life management. In summary, as a highly interdisciplinary renewable energy facility, FOWTs present complex interdependencies among structural, energy, environmental, and economic indicators. Their full life cycle evaluation has thus evolved from a narrow focus on carbon emissions to an integrated, multidimensional framework that couples structural integrity, energy performance, environmental impact, and economic viability.

2.6 Maintenance strategy for FOWTs

To ensure stable operation of FOWTs during their service life, a substantial amount of maintenance activities are required. However, the logistics of performing operations and maintenance become increasingly complex. Maintenance operations for offshore wind farms constitute as much as 20 to 25% of the life-cycle costs (Moan et al., 2018; Yeter & Brennan, 2024). Early O&M strategies for offshore wind turbines were largely adapted from practices in offshore oil and gas platforms and marine ships, which had already accumulated several decades of development. These systems include reliability-centered maintenance (RCM), condition-based maintenance (CBM), risk-based maintenance (RBM), and predictive maintenance. For example, studies in the oil and gas sector compared preventive, RBM, CBM, RCM, and predictive maintenance using analytic hierarchy process and TOPSIS multi-criteria decision models, and concluded that RCM performed best in terms of cost, efficiency, and reliability (Wang et al., 2025). The same research also reported that RCM, total productive maintenance, predictive maintenance, CBM, and RBM have been widely applied in petrochemical industries, and emphasized that strategy selection should balance cost, safety, and flexibility (Wang et al., 2025). In the shipping industry, maintenance is often classified

into corrective, preventive, and predictive categories. Predictive maintenance incorporates RCM, risk-based inspection, CBM, and computer-based maintenance management systems, aiming to address complex sea conditions and optimize decision-making ([Lazakis et al., 2009](#)). On ships and LPG carriers, condition-based strategies have been shown to save several hundred thousand dollars in costs ([Lazakis et al., 2009](#)). At the same time, digital and intelligent technologies are reshaping O&M practices in these traditional industries. Researchers have proposed frameworks based on the industrial internet and big data, which include multi-source monitoring, adaptive diagnostics, risk prediction, and visualization systems ([Zhang & Wang, 2022](#)). In the shipping sector, digital twin systems synchronize virtual models with real equipment, and achieve error margins of only 3–5 percent when predicting engine and cargo conditions, thereby improving remote monitoring and fault prevention ([K. Wang et al., 2022](#)). Reviews of digital twin applications in the oil and gas industry highlight their potential to provide real-time diagnostics and predictive maintenance, but also note the need for advanced sensors, rapid data transmission, and robust information security ([Meza et al., 2024](#)). Other studies have stressed that failures in complex oil and gas facilities can result in substantial economic and environmental risks, which makes detailed condition-based maintenance plans supported by real-time monitoring essential ([Obinna, 2022](#)). Early research on CBM reported that this strategy can increase production by around 5 percent, improve energy use, and that permanent monitoring devices are required for deep-water facilities where manual inspection is difficult ([Telford et al., 2011](#)). Together, these studies indicate that O&M in traditional industries is shifting toward digital, data-driven, and risk-oriented practices.

However, offshore wind turbines differ fundamentally from oil and gas platforms and ships in both structural features and O&M requirements. Oil and gas platforms and vessels usually adopt low-center-of-gravity and high-buoyancy structures to resist marine environments, and their loads

are dominated by weight, buoyancy, and waves. Offshore wind turbines, in contrast, are designed to capture steady winds at higher altitudes, resulting in tall and slender towers and large rotors ([United States Coast & Security, 2008](#)). For example, a recent U.S. land-based wind report shows that in 2023 the average rotor diameter of new turbines reached 133.8 meters and the average hub height 103.4 meters, representing increases of 178 percent and 83 percent since 1998–1999. The average tip height reached 170 meters, and some projects have proposed tip heights of up to 206 meters ([Wiser et al., 2023](#)). Offshore units are generally even larger, which means that slender towers face higher bending moments and fatigue loads under coupled wind and wave forces. As hub height increases, wind pressure rises sharply, and rotating blades introduce cyclic unbalanced forces, resulting in more complex dynamic loads than those faced by oil and gas or shipping structures ([Mehlan & Nejad, 2023](#)). To balance power generation and structural loads, offshore wind turbines also rely on active control systems. According to NREL guidelines, collective pitch control adjusts all blades simultaneously to match wind speed, while individual pitch control adjusts each blade independently to mitigate fatigue loads, even if this slightly reduces power output ([Stammler et al., 2024](#)).

Another important difference lies in O&M logistics. Offshore wind farms consist of a large number of spatially distributed turbines, which forces operators to rely on real-time condition monitoring, predictive maintenance, and remote fault diagnostics for scheduling and repair ([Alsharif & Ajaj, 2025](#)). In comparison, oil and gas platforms and ships usually have crews on site who can perform scheduled or corrective maintenance as required ([Munoz et al., 2019](#)). In summary, while valuable lessons can be drawn from traditional industries, the unique characteristics of offshore wind turbines, including their tall and flexible structures, complex

coupled dynamic loads, and reliance on unmanned remote O&M, create challenges that require more specialized solutions.

Traditional maintenance strategies for offshore wind turbines primarily include corrective maintenance (CM) and preventive maintenance (PM). Corrective maintenance is a reactive approach where maintenance activities are carried out only after a failure has occurred, leading to significant downtime and high repair costs due to the unexpected nature of failures. Additionally, these actions can be time-consuming and costly due to the need for emergency interventions and the logistics of transporting repair equipment and personnel to offshore sites ([Snyder & Kaiser, 2009](#)). To address the shortcomings of CM, a new preventive method has been proposed. Preventive maintenance (PM) is a proactive approach where maintenance activities are scheduled at regular intervals based on historical data to prevent failures. For instance, scheduled inspections check for blade erosion, gearbox wear, and electrical system integrity ([Costa et al., 2021](#)). While this reduces the likelihood of unexpected failures and extends component lifespan, it can lead to unnecessary maintenance actions, increasing operational costs. Despite their widespread use, traditional maintenance methods have limitations. Corrective maintenance results in prolonged downtime and higher costs due to its reactive nature. Preventive maintenance often involves unnecessary actions, leading to increased costs. These methods do not account for the actual condition of the wind turbines, leading to either over-maintenance or under-maintenance. Additionally, the lack of predictive analytics limits their effectiveness in ensuring optimal turbine performance ([Carroll et al., 2016](#)).

Therefore, the CBM approach based on performance prediction models is applied to wind turbines. CBM leverages real-time monitoring and predictive analytics to assess the actual condition of turbine components, allowing for maintenance actions only when needed. This

optimizes schedules and reduces unnecessary activities. For instance, (Pakenham et al., 2021) and (Scheu et al., 2019) demonstrated neural networks and support vector machines for predictive failure analysis, using historical data and real-time monitoring to predict potential failures and enable timely actions. (Lu et al., 2018) used LSTM networks for CBM, improving reliability by learning from sequential data and identifying failure patterns. (Kang et al., 2020) applied the physics of failure approach to predict when and how components are likely to fail, providing a scientific basis for maintenance decisions. (Sun et al., 2022) discussed integrated CBM modeling and optimization techniques to reduce costs and downtime by considering interdependencies between turbine components. (Gray & Watson, 2010) used SCADA data for condition monitoring, employing normal behavior models to detect anomalies and predict failures. However, the maintenance tasks in CBM are independent of each other and do not ensure the highest maintenance efficiency.

Thus, recent research has proposed an opportunistic maintenance (OppM) method, designed to optimize maintenance activities by leveraging opportunities that arise during the operation of offshore wind turbines. This approach is particularly advantageous in the context of wind farms, where maintenance activities can be aligned with favorable operational conditions, such as periods of low wind, to minimize the impact on energy production and maximize maintenance efficiency. OppM involves scheduling maintenance tasks when specific conditions are met, rather than adhering to a fixed schedule or waiting for failures to occur. This strategy can be integrated with CBM and PM to create a more flexible and efficient maintenance regime. For example, when a wind turbine is scheduled for routine maintenance, other components that are not yet due for maintenance but are accessible and show signs of wear can also be serviced. This reduces the frequency of maintenance interventions and minimizes downtime (Dao et al., 2021). OppM also

allows for the consolidation of maintenance tasks, which can lead to significant cost savings. Sharing resources and maintenance setup costs among multiple tasks reduces the overall maintenance expenditure (Schlechtingen et al., 2013). Additionally, OppM enables better planning and utilization of maintenance resources, such as labor, tools, and spare parts, by aligning maintenance activities with favorable conditions. However, these studies have primarily focused on human intervention as a factor influencing structural safety and operational risk, without adequately addressing the impact of control strategies on the full lifecycle operation and maintenance of FOWTs, as illustrated in Figure 2-1. Current turbine O&M frameworks mainly consider external factors such as environmental conditions and maintenance activities when evaluating turbine safety. However, as shown in Section 2.3, they largely neglect the influence of the turbine control strategies on lifecycle performance. Therefore, it is essential to establish a new O&M paradigm that fully integrates internal control-based operation strategies with external maintenance actions. This coordinated approach is critical for improving O&M efficiency and ensuring the long-term structural integrity and safety of FOWTs.

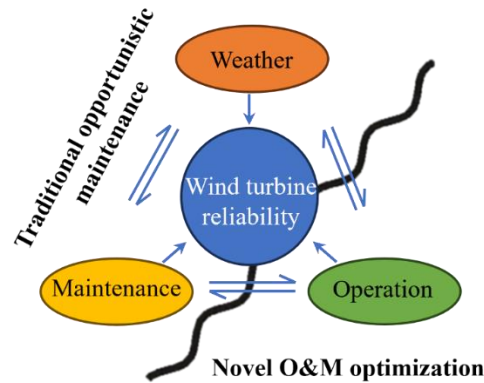


Figure 2-1 Integration of operation into wind turbine O&M

Despite its advantages, the implementation of opportunistic-based O&M presents several challenges. Effective O&M requires sophisticated real-time decision-making algorithms that can identify and exploit opportunities as they arise. This involves integrating real-time monitoring data

and predictive analytics to make informed decisions (Lu et al., 2018). Coordinating multiple maintenance tasks and aligning them with operational conditions adds complexity to maintenance scheduling, necessitating advanced optimization models to ensure optimal scheduling (Tian et al., 2011).

2.7 Reinforcement learning applications in OM optimization

As large-scale infrastructure assets age, ensuring structural safety and extending service life under limited resources have become central issues in optimizing operations and maintenance (O&M). Maintenance of structural systems such as bridges, highways, wind farms, underground pipelines, and railways is characterized by long service intervals, uncertain states, and high repair costs. Although traditional methods such as Markov Decision Processes (MDP) and Genetic Algorithms (GA) have achieved some success, they encounter limitations including high-dimensional state spaces, complex interdependencies between systems, and weak real-time responsiveness (Dao et al., 2021; Schlechtingen & Santos, 2014). For example, in bridge maintenance, existing studies primarily focus on individual bridge components using periodic inspections and life prediction models to formulate repair strategies (Frangopol & Liu, 2007; Liu et al., 1997). However, coordinating resources across a network of bridges and optimizing budget allocation along with safety assessments under multi-objective constraints remain significant challenges in practice (Li et al., 2023; Wang et al., 2023). In recent years, deep learning (DL) methods, such as LSTM and RNN, have demonstrated excellent performance in predicting bridge health (Dong et al., 2014; Liu et al., 2020; Shen et al., 2023); yet, they still face challenges in generalization and real-time decision-making in complex, dynamic, data-scarce environments. These challenges lay the theoretical and practical foundation for introducing Reinforcement Learning (RL) methods.

Reinforcement Learning, with its strong adaptability and self-learning capabilities, has been widely applied to structural systems including bridges, highways, steel structures, underground facilities, and railways. For instance, in bridge O&M, researchers have employed advanced deep RL algorithms such as DQN, BDQN, and DDPG to optimize high-dimensional state representations and large-scale action spaces (A. Guo et al., 2020; Hou et al., 2021; Tavakoli et al., 2018). (Lei et al., 2021) proposed a branch-based action strategy based on BDQN to effectively avoid local optima, while TPGR method employs a tree-structured action selection mechanism to significantly enhance policy efficiency and convergence speed (Dulac-Arnold et al., 2015). (Lai et al., 2024) developed a general-purpose deep RL DRL framework that demonstrated adaptability and cost control in complex structural maintenance tasks on bridges with 7 and 263 components, respectively. (Chen et al., 2019) extended DRL to bridge systems in high flood-risk areas by jointly considering degradation rates, risk costs, and social vulnerability. Furthermore, architectures such as Meta-RL and A3C have reinforced inter-system coordination and parallel optimization capabilities (Taherkhani et al., 2024; Wei et al., 2020).

Similar successes have been observed for highways and underground pipeline systems. (Cheng et al., 2024) developed a long-term road maintenance strategy using 42-dimensional state features, yielding significantly higher investment returns compared to periodic strategies. (Saifullah et al., 2024) introduced a graph convolutional network-based DQN method to achieve geographically coherent maintenance clustering in urban underground networks, and (Yao et al., 2020) employed policy gradient methods to determine optimal maintenance and reconstruction routes in road network clusters. These studies underscore the capability of RL to model “correlated decision-making” across interconnected facility states, offering viable solutions for intelligent maintenance of transportation infrastructure. In railway systems, RL is extensively used in

maintenance planning, scheduling reordering, and resource allocation. (Kerckamp et al., 2022) used PPO to optimize railway maintenance processes, achieving a 48% reduction in carbon emissions and a 68% drop in defect rates. (Sasai et al., 2024) proposed a DDQN-based approach to optimize track renewal and repair decisions in large-scale railway networks, enhancing budget efficiency and overall system reliability. (Sresakoolchai & Kaewunruen, 2023) evaluated A3C and DuDQN on actual track data for optimal ballast maintenance. Meanwhile, (Mohammadi & He, 2022) and (Lee et al., 2024) applied RL to timetabling and train dispatch decision-making, effectively reducing delay costs. (Zhu et al., 2020) utilized DDPG for railway route design optimization in mountainous regions, saving 17.65% in design costs; additionally, (Guo, 2020) employed a POMDP+RL framework to address railway structural degradation under uncertain states, demonstrating the robust modeling capacity of RL even in partially observable environments. (Gao et al., 2022) further applied RL to high-speed rail communication resource allocation, achieving simultaneous improvements in link reliability and throughput.

Particularly in wind power systems, especially offshore wind, maintenance modeling and decision-making are even more challenging due to issues such as inaccessibility, limited weather windows, and scarce maintenance resources. RL is emerging as a breakthrough technology in this field. For instance, (Arcieri et al., 2023) proposed a PPO-based multi-maintenance team scheduling model that significantly improved O&M efficiency in a scenario involving 50 wind turbines; (Zhou & Yu, 2021) developed an RL controller based on load feedback that reduced turbine fatigue loads by 15%; (Pincioli et al., 2021) introduced an RL strategy to implement fault-tolerant control while optimizing power and frequency responses; and (Wu et al., 2024) employed multi-agent DDPG for yaw control, resulting in an 8.7% increase in power generation. In terms of structural control, (X. Zhang et al., 2024) used TRPO to optimize the pitch control of floating

turbines, thereby enhancing system stability; (Deng et al., 2023) combined Petri net modeling with RL to achieve a maximum availability of 99.4%; and (Didier et al., 2023) utilized a multi-agent AGA-DDPG framework to optimize MEC offloading, reducing computational burden by 33% in high-load scenarios. Moreover, (Saleh et al., 2023) demonstrated RL's potential in balancing environmental and economic trade-offs by simultaneously considering carbon emissions and economic benefits. Further research includes the DDPG-based power control framework proposed by (Song et al., 2024), the Helix strategy improvement by (Hendradewa & Yin, 2025) to enhance power production by 6.8%, and Contextual RL for optimizing wind farm market bidding strategies introduced by (Dong et al., 2021). These developments not only advance RL from algorithmic research to practical engineering applications but also provide an integrated perception–decision–control loop for wind energy systems.

In summary, reinforcement learning is rapidly emerging as a key intelligent technology for O&M of structural systems. Its successful application across bridges, highways, underground structures, railways, and wind power systems has not only enhanced operational efficiency and reliability but also established a paradigm for future self-optimizing decision-making in urban infrastructure. Future research should further advance multi-source data fusion, multi-objective trade-offs, system interpretability, and deployability to fully realize RL's potential in intelligent O&M of infrastructure systems.

2.8 *Summary*

Recent advances in the study of floating offshore wind turbines (FOWTs) have yielded meaningful insights across various individual disciplines, including hydrodynamics, aerodynamics, structural mechanics, control systems, and mechanical design. Investigations have been conducted on

dynamic responses under isolated physical fields, localized corrosion and fatigue mechanisms, the effects of transient control strategies, and the optimal design of single turbine units. However, as inherently complex multi-physical coupled systems, FOWTs still lack an integrated theoretical framework that can comprehensively address system-level performance evaluation, full lifecycle management, and large-scale wind farm optimization. Several critical gaps remain unresolved:

- 1) Current research predominantly focuses on individual aspects, including hydrodynamic loads, aerodynamic responses, structural dynamics, or control systems in isolation. While some progress has been made in modeling local responses under specific conditions, existing approaches rarely integrate nonlinear interactions across disciplines. The absence of unified models that concurrently capture fluid–structure interaction, aerodynamic–hydrodynamic coupling, structural nonlinearity, and active control feedback significantly limits the ability to predict system behavior under real-world, multi-factorial operational scenarios.
- 2) Although preliminary studies have explored corrosion and fatigue under extreme marine environments, these efforts largely emphasize localized or short-term degradation phenomena. A holistic and quantitative framework to assess cumulative degradation, considering high salinity, thermal cycles, and fluctuating mechanical loads over the full operational lifespan is still lacking. This deficiency impedes the accurate prediction of long-term reliability and structural durability.
- 3) Existing work has demonstrated the efficacy of various control strategies in regulating instantaneous dynamics and improving energy capture. However, their long-term interaction with progressive structural deterioration, and the compounded effects on system integrity and lifespan, remain poorly understood. In particular, the cooperative impact of

control policies across multiple turbines within a wind farm, especially under complex wind-wave interactions has not been sufficiently investigated.

- 4) High-fidelity numerical models have demonstrated considerable accuracy in capturing local phenomena under complex loading. However, such models are often computationally prohibitive, limiting their application in long-term simulations and engineering-scale optimization. Currently, there is a lack of surrogate or reduced-order models that strike a balance between physical fidelity and computational efficiency, thereby restricting real-time and lifecycle-scale decision-making in practical settings.
- 5) While some progress has been made in linking control strategies to short-term structural response and maintenance logistics, an integrated framework that jointly optimizes control policies, maintenance scheduling, and economic performance throughout the turbine's lifecycle remains elusive. Especially under stochastic environmental conditions and evolving structural health, there is an urgent need to co-optimize operational control and maintenance planning in a dynamically coordinated manner.
- 6) Large-scale deployment of floating turbines demands sophisticated numerical tools and optimization theories to determine optimal layout, spacing, and configuration, accounting for inter-turbine interference and collective dynamics. The absence of scalable, efficient methodologies limits the potential to maximize farm-level energy yield and economic return.

While significant progress has been made in understanding and optimizing the performance of individual FOWT units, substantial gaps remain in modeling multi-physics coupling, lifecycle degradation, long-term control effects, efficient simulation methodologies, and wind farm-level

coordination. These gaps highlight the urgent need for integrated, interdisciplinary, and system-oriented research frameworks to support the next generation of offshore wind power technologies.

CHAPTER 3

Multi-physics modeling of FOWTs

3.1 Introduction

FOWTs operate under highly complex and coupled physical environments, where aerodynamic, hydrodynamic, structural, and control interactions jointly determine their long-term performance. Previous studies, as outlined in Chapter 1, have established reference models and highlighted the challenges of capturing such couplings accurately. Nevertheless, many of these works still analyze single domains in isolation or focus on simplified assumptions, which can limit their applicability for lifecycle decision-making. This chapter develops a fully coupled multi-physics modeling framework tailored for FOWTs. Compared with the broad review, here we emphasize the technical integration of aerodynamic loads, hydrodynamic forces, structural dynamics, and active control feedback. The outcomes not only support reliability assessments in Chapter 4 but also form the computational basis for the predictive modeling approaches in Chapter 5. In this way, Chapter 3 establishes a crucial methodological bridge between fundamental understanding and application-oriented analyses

3.2 Multi-physics modelling with designed control strategy

The integration of the floating IEA 15MW wind turbine with the UMaine VolturnUS-S semi-submersible platform, using the OpenFAST framework, requires an extensive multi-physics modeling approach that covers aerodynamic, hydrodynamic, and structural dynamics ([Huang et al., 2019](#)). To regulate the pitch control of the IEA 15MW turbine, the ROSCO (Reference

OpenSource Controller) is utilized. The interaction between ROSCO and OpenFAST facilitates the continuous optimization of turbine performance and load reduction through real-time feedback and control modifications, as illustrated in Figure 3-1.

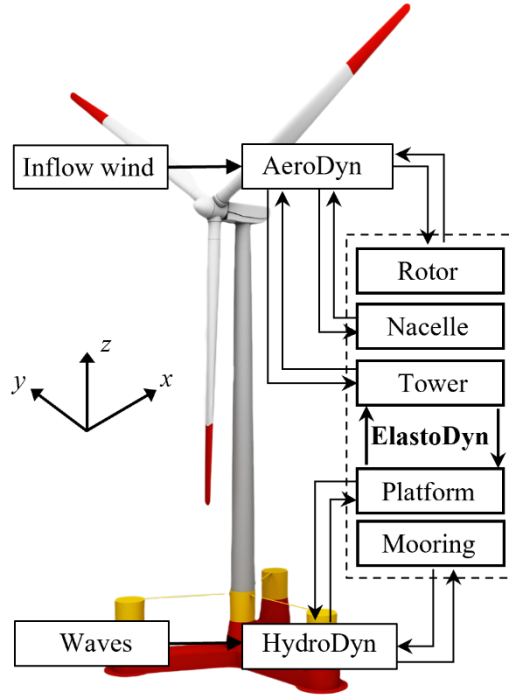


Figure 3-1 OpenFAST framework.

The aerodynamic forces are computed using the Blade Element Momentum (BEM) theory implemented in the AeroDyn module. This theory combines blade element theory and momentum theory to evaluate lift and drag forces along the turbine blades, considering dynamic stall, unsteady aerodynamics, and wake effects. The lift F_l and drag F_d forces on a blade element are given by:

$$\begin{aligned} F_l &= \frac{1}{2} \rho V^2 C_l A \\ F_d &= \frac{1}{2} \rho V^2 C_d A \end{aligned} \quad (3.1)$$

where ρ is the air density, V is the relative wind speed, C_l and C_d are the lift and drag coefficients, and A is the blade element area.

Hydrodynamic modeling, essential for the semi-submersible VoltturnUS-S platform, is performed using the HydroDyn module. This module calculates wave-induced forces through potential flow theory and Morison's equation, incorporating added mass and damping effects. The total hydrodynamic force F_{hydro} acting on the platform is:

$$F_{hydro} = F_{pot} + F_{Mor} \quad (3.2)$$

where F_{pot} represents forces derived from potential flow theory, and F_{Mor} accounts for viscous drag and inertial forces.

Structural dynamics are modeled using the ElastoDyn and SubDyn modules. ElastoDyn simulates the flexible dynamics of the turbine blades, tower, and drivetrain through finite element methods, capturing their elastic behavior. The equations of motion for a flexible structure are given by:

$$M\ddot{x} + C\dot{x} + Kx = F_{aero} + F_{hydro} + F_{control} \quad (3.3)$$

where M is the mass matrix, C is the damping matrix, K is the stiffness matrix, x is the displacement vector, and F_{aero} , F_{hydro} , and $F_{control}$ are the aerodynamic, hydrodynamic, and control forces, respectively.

In OpenFAST, module coupling is achieved through two key techniques: glue code and mesh mapping, which together enable the integration of multiple physical models with varying temporal and spatial discretization schemes (Jonkman & Buhl, 2005). The glue code serves as the core framework that coordinates the interactions among different modules by managing data exchange, advancing simulation time steps, and orchestrating the overall solution process.

Two main solution strategies are employed within the glue code: the explicit loose coupling method and the predictor–corrector approach. In the explicit loose coupling method, each module is executed sequentially using the outputs from other modules at the previous time step as inputs.

While this method offers high computational efficiency, it may suffer from numerical instabilities, particularly in strongly coupled systems (Jonkman & Buhl, 2005). To address this limitation, the predictor–corrector method is implemented. During the prediction phase, the system state at the current time step is estimated based on the previous step, and each module performs computations using these predicted values. In the correction phase, the results from the prediction are used to refine the current state, and the modules recompute accordingly. This iterative strategy enhances numerical stability and is particularly well-suited for simulating complex systems such as floating offshore wind turbines. Complementing the glue code, mesh mapping addresses the discrepancies in spatial discretization across modules. Since different modules may employ distinct meshing strategies and resolutions, mesh mapping ensures the accurate transfer of physical quantities between them. OpenFAST supports various mapping techniques, including point-to-point, projection-based, nearest-point, and interpolation methods.

The ROSCO (Reference OpenSource Controller) is used to regulate the pitch control of the IEA 15MW turbine (Laboratory; Nielsen et al., 2006). The interaction between ROSCO and OpenFAST ensures that the turbine operates at peak efficiency and experiences reduced load through ongoing feedback and control adjustments (Lenfest et al., 2020). The control strategy primarily aims to adjust the blade pitch angle θ to maintain the rotor speed within optimal limits and to minimize structural loads (Abbas et al., 2020). A Proportional-Integral-Derivative (PID) controller is utilized to implement pitch control, with the pitch angle θ being modified according to the error $e(t)$, which represents the difference between the desired and actual rotor speed.

$$\theta(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (3.4)$$

where, K_p , K_i , and K_d are the proportional, integral, and derivative gains, respectively.

The coupling of ROSCO with OpenFAST involves initializing the models with configuration files specifying the turbine parameters, control settings, and environmental conditions. During the simulation, OpenFAST continuously provides updated simulated data on rotor speed, blade pitch angles, and platform motions to ROSCO, which processes this data and computes the necessary control actions. These control commands are then sent back to OpenFAST to adjust the blade pitch angles, updating the aerodynamic, structural, and hydrodynamic states.

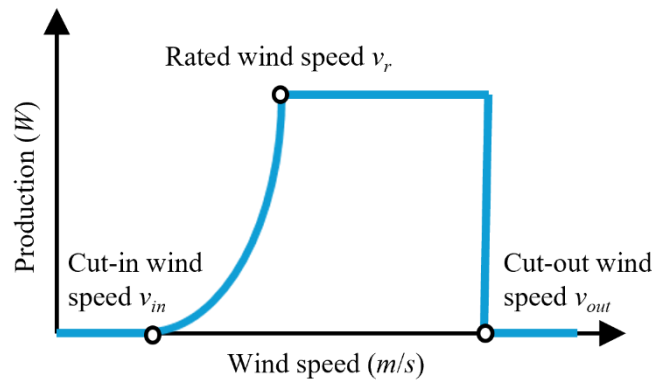


Figure 3-2 Power production and wind speed.

This study selects different de-rating operational strategies. By lowering the rated wind speed, the wind turbine enters the rated operating state earlier. The corresponding rated power is calculated using a cubic function (NREL, 2024) according to Equation 3.5.

$$p(v) = \begin{cases} 0 & v < v_{in}, v_{out} \leq v \\ \frac{1}{2} A \rho_a v^3 & v_{in} \leq v < v_r \\ p^r & v_r \leq v < v_{out} \end{cases} \quad (3.5)$$

where $p(v)$ denotes the power in watts associated with a wind velocity v in m/s, A represents the rotor area in m^2 , and ρ_a , typically 1.225 kg/m^3 , is the air density. The rated power is given as p_r , with v_{in} and v_{out} indicating the cut-in and cut-out wind speeds in m/s, respectively, and v_r as the rated wind speed in m/s. Refer to Table 3-1 for the corresponding power curve illustration.

Table 3-1 Different controlling strategies and parameters.

Strategy	Wind velocity (m/s)			Rated rotor speed (rpm)	Rated power (MW)
	Cut-in	Rated	Cut-off		
CS 1	3	10.59	25	7.6	15
CS 2	3	7	25	6.5	7.8
CS 3	3	9	25	7.1	12.1

A reference controlling strategy (CS1) and two different de-rating strategies are applied in the subsequent analysis. The specific parameters are shown in Table 3-1. The pitching control methods corresponding to the different strategies are illustrated in Figure 3-3.

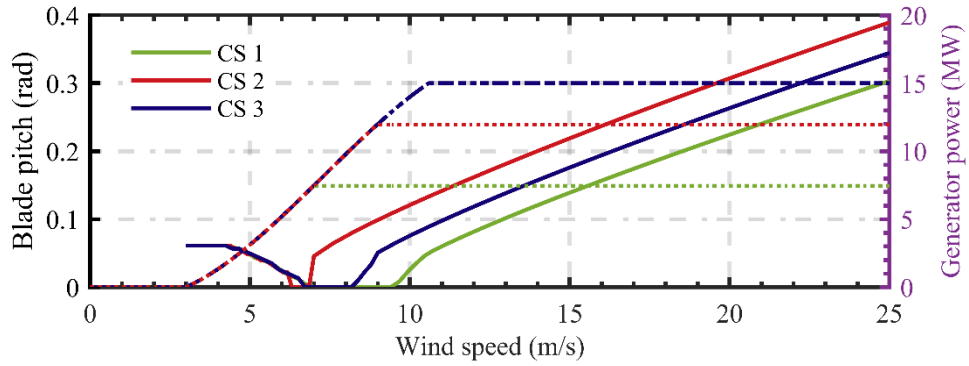


Figure 3-3 Different types of controlling strategies

This study aims to model the structural dynamic response using OpenFAST, further analyse long-term degradation, and assess the impact of control strategy modifications on its long-term performance. Thus, a comprehensive analysis under different control strategies with separate modelling is required. In the reference control schemes, when the wind speed reaches the rated value V_{rated} , the wind turbine adopts a pitch control strategy, wherein the pitch angle is adjusted to β_0 to regulate power output. This reduction in pitch effectively lowers the angle of attack and forces the overall aerodynamic load coefficient to drop (Abbas et al., 2022; Carrillo et al., 2013).

$$C_{F,0} = C_F(\beta_0) \quad (3.6)$$

Typically, the relationship between $C_F(\beta)$ and the pitch angle β is nonlinear. In the vicinity of a pitch adjustment, a first-order Taylor expansion yields

$$C_F(\beta) \approx C_F(\beta_{\text{ref}}) + \left. \frac{\partial C_F}{\partial \beta} \right|_{\beta_{\text{ref}}} (\beta - \beta_{\text{ref}}) \quad (3.7)$$

where β_{ref} is a reference pitch angle. Under reference pitch control, one can take $\beta_{\text{ref}} = \beta_0$ and the large change in β leads to a rapid decline in C_F .

To mitigate transient structural responses, a de-rating strategy that advances the rated condition to a lower wind speed is proposed.

$$V'_{\text{rated}} = \kappa V_{\text{rated}}, \quad 0 < \kappa < 1 \quad (3.8)$$

The method allows the turbine to enter the power-limited region at a lower wind speed. In this de-rated operation mode, the control system simultaneously reduces the rated power output by a de-rating factor κ_p (where $0 < \kappa_p < 1$). This enables a smooth pitch adjustment, wherein the pitch angle is only adjusted to β_{dr} (with $\beta_{\text{dr}} < \beta_0$). As a result, the aerodynamic load coefficient is modified:

$$C'_F = C_F(\beta_{\text{dr}}) \approx C_F(\beta_0) + \left. \frac{\partial C_F}{\partial \beta} \right|_{\beta_0} (\beta_{\text{dr}} - \beta_0) \quad (3.9)$$

The pitch control scaling factor is defined as

$$\kappa_p = \frac{C_F(\beta_{\text{dr}})}{C_F(\beta_0)} \quad (3.10)$$

which reflects the nonlinear correction resulting from the gentler pitch control. When the pitch angle variation $\Delta\beta = \beta_{\text{dr}} - \beta_0$ is relatively large, both the value and the rate of change of $C_F(\beta_{\text{dr}})$ decrease, leading to a significantly lower de-rating factor κ_p , which may be substantially less than 1.

On the other hand, the de-rating strategy also leads to a reduction in rotor speed r , effectively serving as a frequency reduction.

$$\omega' = \eta \omega, \quad 0 < \eta < 1 \quad (3.11)$$

which directly lowers the local relative wind speed experienced by the blade. The local relative wind speed is expressed as:

$$v_{\text{rel}} = \sqrt{V^2 + (\omega r)^2} \quad (3.12)$$

and, after applying the de-rating, it becomes

$$v'_{\text{rel}} = \sqrt{V^2 + (\eta \omega r)^2} \quad (3.13)$$

The scaling factor for the local relative wind speed can be defined as

$$\xi(r) = \frac{v'_{\text{rel}}(r)}{v_{\text{rel}}(r)} = \frac{\sqrt{V^2 + (\eta \omega r)^2}}{\sqrt{V^2 + (\omega r)^2}} \quad (3.14)$$

which satisfies $\xi(r) < 1$ since $\eta < 1$.

Thus, the aerodynamic load per unit chord length under the combined control strategy becomes

$$F'_{\text{aero}} = \frac{1}{2} \rho [v'_{\text{rel}}(r)]^2 c C_F(\beta_{\text{dr}}) = \frac{1}{2} \rho [\xi(r)]^2 [v_{\text{rel}}(r)]^2 c \kappa_p C_F(\beta_0) \quad (3.15)$$

In comparison, the aerodynamic load under reference control is given by

$$F_{\text{aero}} = \frac{1}{2} \rho [v_{\text{rel}}(r)]^2 c C_F(\beta_0) \quad (3.16)$$

The resulting scaling relation is therefore

$$\frac{F'_{\text{aero}}}{F_{\text{aero}}} = \kappa_p \xi(r)^2 \quad (3.17)$$

Since both κ_p and $\xi(r)$ are scaling factors less than 1, the aerodynamic load F'_{aero} under de-rating control is reduced compared to that in the reference control scheme. The specific load reduction effects will be analysed through simulations in [Section 3.5](#).

3.3 Reference turbine and site condition

The investigated FOWT is an IEA reference 15MW turbine with a UMaine VoltturnUS-S semi-submersible platform. Figure 3-4 shows the overall layout of the wind turbine and floating structure, as well as the detailed design of the tower ring flange (RF). The tower has a total length of 135 meters and is installed on a floating column centered among three 12.5-meter diameter pontoons. The diameter of the tower shells varies from 11.4 meters at the bottom to 5.4 meters at the hub, with thicknesses ranging from 75 mm to 29 mm. Three tower flanges are equally spaced 50 meters apart from the hub downward. The flange design increases in strength from top to bottom, with thicknesses of 140 mm, 150 mm, and 160 mm, connected by high-strength bolts with diameters of 56 mm, 64 mm, and 72 mm, respectively. The key parameters of the investigated FOWT are summarized in Table 3-2.

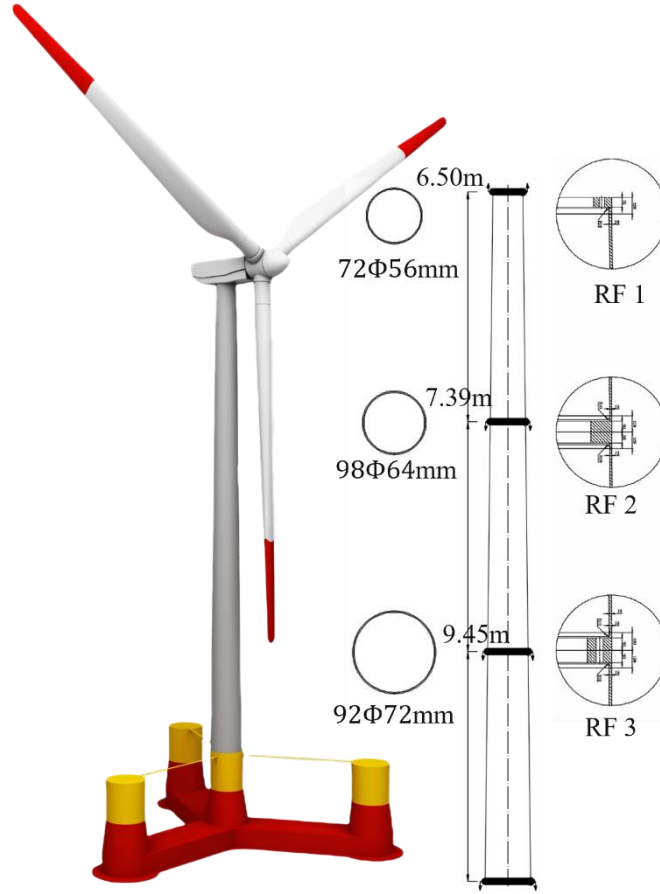


Figure 3-4 Investigated turbine and detailed configuration

The IEA 15MW reference turbine is chosen for this study (Abbas et al., 2022; NREL, 2024) and is mounted on a 135-meter-high tower positioned on the UMaine VolturnUS-S floating platform (Papi & Bianchini, 2022). The tower features a diameter that decreases from 10 meters at the base to 6.5 meters at the hub, with the thickness ranging from 82.95 mm at the pile to 21.21 mm at the transition piece. This design is tailored to withstand dynamic marine conditions, providing the necessary support for the large size and forces associated with the 15MW turbine, thereby ensuring stability and optimal performance in offshore environments.

Table 3-2 Key parameters for the reference turbine and platform

Parameter	Value	Parameter	Value
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Rotor diameter (m)	240	1st fore-aft natural frequency of tower	0.496
Hub diameter (m)	7.94	2nd side-side natural frequency of tower	0.483
Hub overhang (m)	11.35	Location of fairleads above MSL (m)	15
Shaft tilt angle (deg)	6	Line breaking strength (kN)	22,286
Rotor pre-cone angle (deg)	-4.0	Anchor depth (m)	200
Cut-in wind speed (m/s)	3	Fairlead depth (m)	14
Cut-out wind speed (m/s)	25	Nominal chain diameter (mm)	185
Tower density (kg/m ³)	1.85×10 ⁵	Dry line linear density (kg/m)	685
Tower modulus (N/m ²)	2.0×10 ¹³	Extensional stiffness (MN)	3,270
Tower shear modulus (N/m ²)	7.93×10 ¹²	Fairlead pretension (kN)	2,437

The selected site for this study is Station Cape Elizabeth, located approximately 83.34 kilometers northwest of Aberdeen, Washington, with a water depth of approximately 131 meters ((NDBC), 2019). Key annual data on wind speed, wind direction, and wave height were collected. Figure 3-5a presents the wind rose diagram for this location, depicting the distribution of wind speed and direction. The diagram shows that the wind direction predominantly follows the SW-NE axis, with the highest wind speeds generally occurring from the NE direction, while winds from the perpendicular direction are less frequent. Figure 3-5b illustrates the relationship between wind speed and wave height at the selected station. The data suggest a trend where wave height increases with wind speed, reflecting the transfer of energy from the wind to the water surface. However, the spread of the data points indicates variability, with some higher wind speeds not leading to proportionally higher waves, likely due to the intricate dynamics of local meteorological conditions. Understanding this correlation is essential for assessing environmental loads on offshore structures, such as wind turbines, where both wind and wave forces are critical to their design and operation. Therefore, this study incorporates this correlation by generating wind speed and wave height samples based on their actual distribution and relationship. Additionally, the relevant corrosion environment parameters are summarized in Table 3-1 ((NDBC), 2019; AccuWeather, 2019; Agency, 2019)).

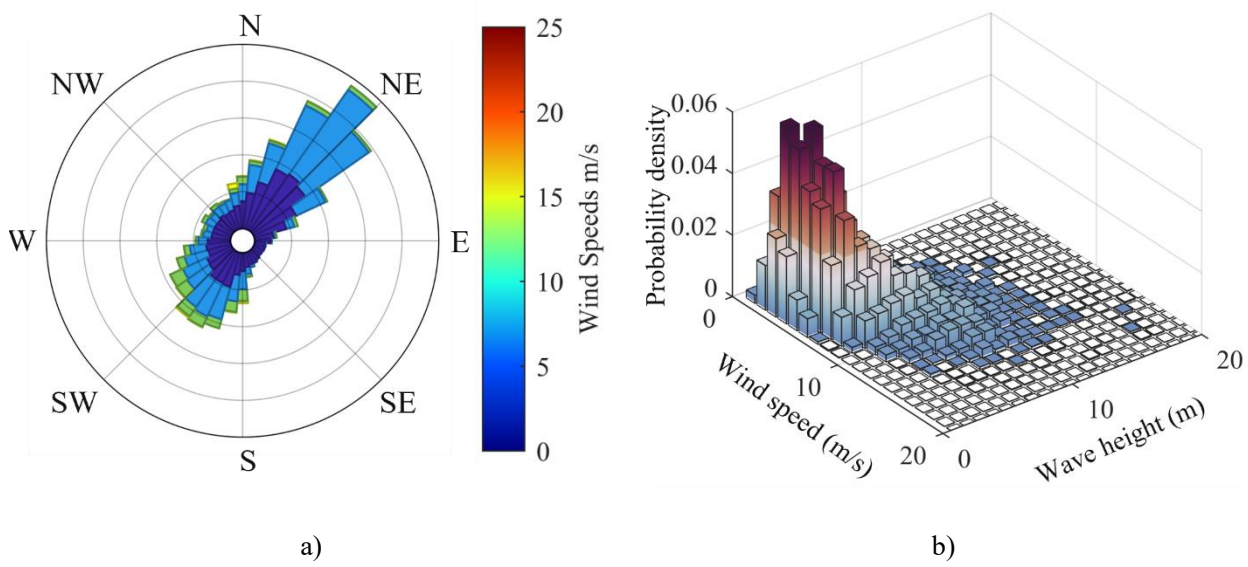


Figure 3-5 Wind speed distribution and correlation between wave and wind. a) Wind rose; b) Correlation between wind speed and wave height.

Table 3-3 Key parameters of the site ambient condition.

Parameter	Sym	Unit	Value
Annual average temperature	T	$^{\circ}\text{C}$	14.1
Annual average relative humidity	RH	%	70.0
Annual average SO_2 deposition	P_d	mmd	1.0
Annual average Cl^- deposition	S_d	mmd	483.2

3.4 Stress extraction of multi-components

In this study, we present an integrated methodology to compute the stress time histories of key components (blades, generator, tower, and mooring lines) based on the dynamic responses derived from these simulations. This procedure not only supports robust structural safety assessments but also aids in fatigue life prediction, thereby informing design optimization and maintenance planning.

The process begins with the dynamic simulation using OpenFAST, which generates a wide range of load parameters such as axial forces, bending moments, torsional moments, and shear

forces. These outputs are subsequently processed to extract critical load data. Simultaneously, the geometric and material properties of each component are determined either from design documentation, specialized section analysis tools (e.g., BECAS) (Blasques & Bitsche, 2012; Cesnik & Hodges, 1997). The cross-sectional properties include parameters such as the cross-sectional area A , moments of inertia I_{xx} and I_{yy} , polar moment of inertia J , shape factors, and material properties such as the elastic modulus E and the shear modulus G . The combination of load data and sectional properties forms the basis for computing the stress time histories of each component via established conversion formulas.

For the purpose of tractable analysis, several simplifying assumptions are introduced. The blade material is treated as an equivalent isotropic continuum, so that stresses can be represented through conventional conversion formulas, even though the actual composite layup exhibits orthotropic behavior. The tower is modeled as a uniform tubular structure with isotropic steel properties, while mooring lines are idealized as tension-dominated elements. Generator components are simplified using lumped parameter representations. These assumptions allow consistent stress histories to be extracted across heterogeneous components, facilitating a comparative analysis of degradation trends. It is acknowledged that such simplifications do not fully capture the anisotropic strength behavior of composite blades or the nonlinearities of mooring line dynamics. Nevertheless, the present treatment is considered adequate for trend analysis and relative fatigue assessment. Future extensions should include composite-specific criteria and progressive damage models for blades, as well as more detailed nonlinear hydrodynamic–structural coupling for mooring systems, to refine the accuracy of reliability evaluations.

3.4.1 Generator

The methodology for the generator follows a similar procedure. Dynamic parameters such as

generator torque, high-speed and low-speed shaft torques, and bearing loads are extracted from the ElastoDyn and ServoDyn modules. For example, the torsional stress in a circular shaft is calculated by

$$\tau(t) = \frac{T(t) r}{J} = \frac{16 T(t)}{\pi d^3} \quad (3.18)$$

where $T(t)$ is the instantaneous torque, $r = d/2$ is half the shaft diameter d , and $J = \pi d^4/32$ is the polar moment of inertia. Similarly, the bending stress is determined by

$$\sigma_{\text{bending}}(t) = \frac{M(t) y}{I} = \frac{32 M(t)}{\pi d^3} \quad (3.19)$$

with $M(t)$ representing the bending moment at time t , $y = d/2$ the distance from the neutral axis, and $I = \pi d^4/64$ the moment of inertia. The overall stress state can then be evaluated using either the maximum shear stress theory or the von Mises criterion.

$$\tau_{\text{max}}(t) = \sqrt{\left(\frac{\sigma_{\text{bending}}(t)}{2}\right)^2 + \tau(t)^2} \quad (3.20)$$

3.4.2 Blade

In this study, the von Mises equivalent stress was applied as a simplifying assumption to represent the structural response of the blade. This approach treats the fiber-reinforced composite material as an equivalent isotropic medium, which allows the degradation trend and the relative distribution of stresses to be evaluated in a consistent framework. (Elsherif et al., 2019) It is acknowledged that this criterion does not strictly represent the failure behavior of composite materials. The present use is intended for comparative analysis of stress evolution and for identifying critical regions rather than for absolute strength prediction. For the analysis of blade stresses, the axial

stress is computed as

$$\sigma_{\text{axial}}(t) = \frac{F_z(t)}{A} \quad (3.21)$$

where σ_{axial} denotes the axial stress at time t , F_z is the axial force at time t , and A is the cross-sectional area of the blade. The bending stresses in the x - and y -directions are calculated by

$$\sigma_{\text{bending}_x}(t) = \frac{M_y(t) \cdot z}{I_{yy}}, \quad \sigma_{\text{bending}_y}(t) = \frac{M_x(t) \cdot y}{I_{xx}} \quad (3.22)$$

where M_x and M_y represent the bending moments at time t in the x and y directions, respectively; y and z denote the distances from the neutral axis to the point of stress evaluation; and I_{xx} and I_{yy} are the corresponding moments of inertia. When dealing with composite blades, it is necessary to incorporate material anisotropy via the stiffness matrix (Kim et al., 2013):

$$\begin{bmatrix} \sigma_x \\ \sigma_y \\ \tau_{xy} \end{bmatrix} = [Q] \begin{bmatrix} \varepsilon_x \\ \varepsilon_y \\ \gamma_{xy} \end{bmatrix} \quad (3.23)$$

where $[Q]$ is the stiffness matrix, ε_x and ε_y are the normal strains, and γ_{xy} is the shear strain.

The shear stresses can be determined by either a refined formulation for heterogeneous cross-sections:

$$\tau(s, t) = \frac{V(t) Q(s)}{I b(s)} \quad (3.24)$$

where $V(t)$ denotes the resultant shear force at time t ; $Q(s)$ is the first moment of area at location s ; I is the moment of inertia; and $b(s)$ represents the width at point s . The torsional stress is given by

$$\tau_{\text{torsion}}(t) = \frac{M_z(t) r}{J} \quad (3.25)$$

where M_z is the torsional moment at time t , r is the distance from the torsion center, and J is the polar moment of inertia. For non-circular cross-sections, a thin-walled approximation is applied (Gholami Bazehhour & Rezaeepazhand, 2011):

$$\tau_{\text{torsion}}(t) = \frac{M_z(t) t}{2A_m} \quad (3.26)$$

where t is the wall thickness and A_m is the area enclosed by the midline of the cross-section. The overall normal stress is then obtained by superimposing the axial and bending components:

$$\sigma(t) = \sigma_{\text{axial}}(t) + \sigma_{\text{bending}_x}(t) + \sigma_{\text{bending}_y}(t) \quad (3.27)$$

and the combined shear stress is expressed as

$$\tau(t) = \sqrt{\tau_{\text{shear}_x}^2(t) + \tau_{\text{shear}_y}^2(t) + \tau_{\text{torsion}}^2(t)} \quad (3.28)$$

These stresses are further synthesized via the von Mises criterion to yield an equivalent stress:

$$\sigma_{\text{vm}}(t) = \sqrt{\sigma(t)^2 + 3 [\tau(t)]^2} \quad (3.29)$$

where σ_{vm} is used to assess potential yield or failure under dynamic loading conditions.

3.4.3 FOWT tower

The bolt force can be determined through sectional analysis and load transfer functions (LTF), such as the Schmidt and Neuper approach (Gaertner et al., 2020), based on the structural response.

As illustrated in Figure 3-6, the process for analyzing stress amplitude using the LTF involves several steps. First, the dynamic response of the section in question is extracted. Next, the normal stresses within the section are calculated based on this dynamic response. Following this, shell forces, which are influenced by both the applied loads and the section's inherent characteristics, are determined. Finally, the LTF, specifically the tri-linear function proposed by Schmidt/Neuper (Allen et al., 2020), is applied to understand how these shell forces are transferred to the bolts.

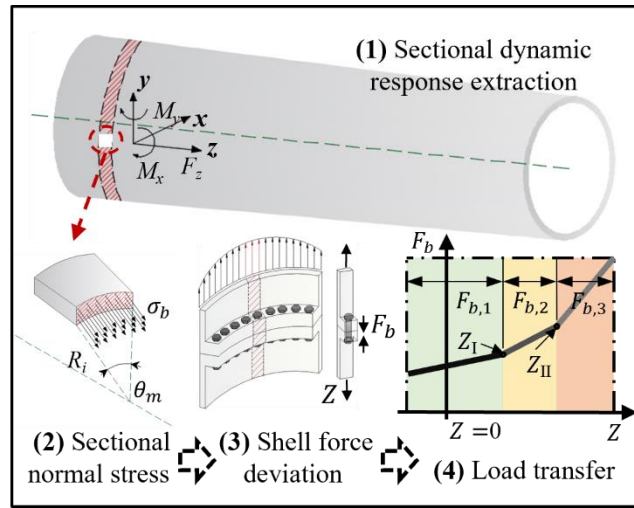


Figure 3-6 Flowchart of stress extraction by using LTF method.

Geometric imperfections play a significant role in influencing bolt behavior. The associated LTF has been validated using a combination of monitoring data and the finite element method, ensuring a conservative approach (Schmidt & Neuper, 1997). Specifically, the Schmidt/Neuper approximation within the LTF inherently accounts for the effects of geometric imperfections (Schmidt & Neuper, 1997). Given the high computational demands of probabilistic simulations, utilizing the LTF-based simplification is essential as opposed to conducting detailed finite element (FE) simulations. The LTF effectively captures the global stress range on the bolts, though additional refinements are needed to determine the stress spectra for Modes 1, 2, and 3. Subsequently, Stress Concentration Factors (SCF), derived from detailed stress analysis, are used

to estimate the stress spectra under specific failure modes.

It is important to note that the M46 bolt is used for towers with fixed-bottom foundations, while the M72 bolt is preferred for towers with a floating design, as the latter design experiences significantly reduced forces on the tower shells. The rain-flow cycle counting method (Heng et al., 2019; Kwon & Frangopol, 2010) is then applied to convert the stress history into stress spectra.

Figure 3-7 provides a detailed summary of the above derivation process.

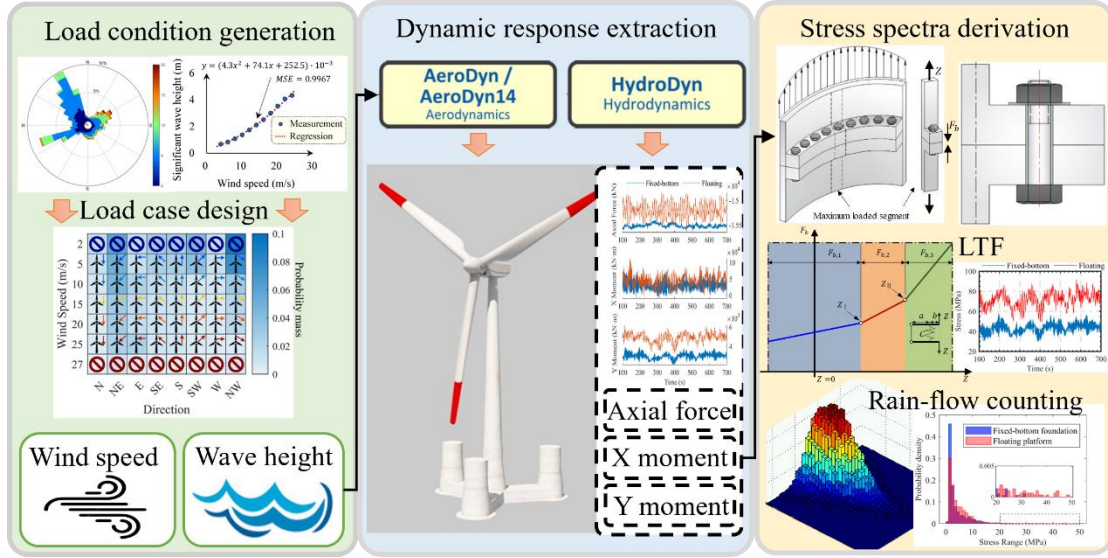


Figure 3-7 Procedures to derive fatigue stress spectra in bolts.

3.4.4 Mooring lines

The mooring lines are analyzed using load data from MoorDyn. With the line diameter d establishing the cross-sectional area via

$$A = \frac{\pi d^2}{4} \quad (3.30)$$

the axial stress is calculated from

$$\sigma_{\text{axial}}(t) = \frac{T(t)}{A} = \frac{4 T(t)}{\pi d^2} \quad (3.31)$$

where $T(t)$ is the line tension at time t . In cases where bending effects are significant, the bending stress is determined by

$$\sigma_{\text{bending}}(t) = \frac{E d}{2 R(t)} \quad (3.32)$$

where E is the elastic modulus and $R(t)$ is the local bending radius at time t , which is estimated from the positions of successive nodes via geometric relations. The total stress is obtained by summing the axial and bending contributions, yielding

$$\sigma_{\text{total}}(t) = \sigma_{\text{axial}}(t) + \sigma_{\text{bending}}(t) \quad (3.33)$$

Overall, the integrated methodology comprises several phases: data acquisition via OpenFAST simulations, extraction and transformation of load data, and finally the application of stress conversion formulas at each time step. Advanced post-processing, including statistical analysis, spectral analysis, and rainflow counting methods ([Amzallag et al., 1994](#)), further refines the understanding of fatigue damage and critical load conditions.

3.5 *Dynamic response of FOWTs*

The multi-physics model discussed in [Section 3.2](#) has been developed specifically for the prototype floating wind energy structure using OpenFAST. The load case design is based on the actual distribution of environmental parameters as shown in [Figure 3-5](#) to ensure accurate simulation of dynamic responses under real-world conditions. In the simulations, wind speeds ranging from 3

m/s to 27 m/s are incorporated, with intervals of 2 m/s, to ensure both uniformity of the test design and a conservative approach. Wind directions are divided into eight directions, and wave heights range from 0 to 25 meters, with intervals of 2 meters. Based on uniform design, a total of 576 conditions are considered in the analysis. The probability of each condition is analyzed according to the joint probability distribution of the environmental parameters, as shown in Figure 3-8.

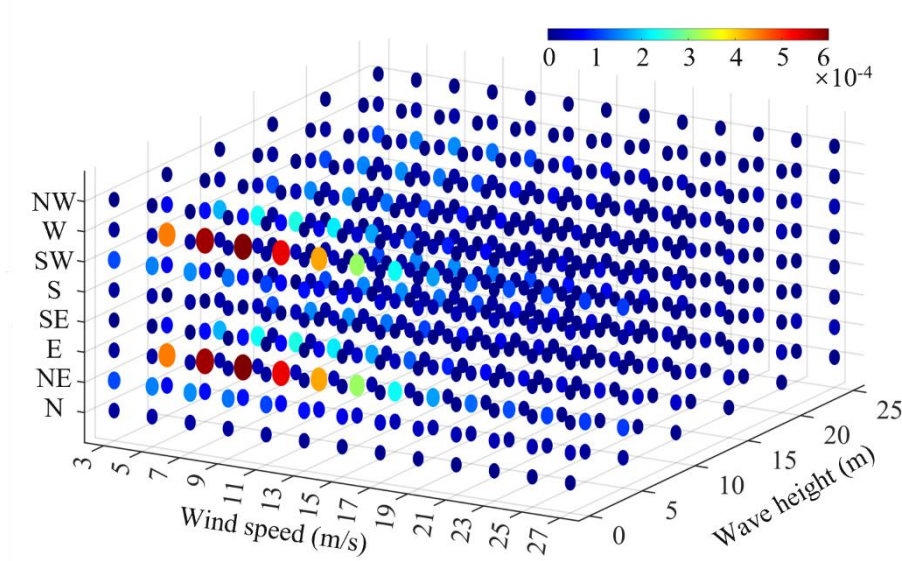


Figure 3-8 Load case design of wind-wave coupling conditions.

Structural forces (i.e., the moments M_x and M_y , and the axial force F_z) at the flange position of the wind turbine under a typical operating condition of 15 m/s are obtained, as shown in Figure 3-9. These forces were analyzed in accordance with the lateral displacement (marked as D_{tot}) at the nacelle. It can be observed that by altering the wind turbine control strategy, the dynamic response of the turbine is significantly reduced. When the rated speed is reduced to 9 m/s (CS 3), the turbine forces are 0.8 times that of the reference controller (CS 1). Further reduction of the rated speed to 7 m/s (CS 2) results that is only 0.5 times the value in CS1. The ratio of forces from the bottom to the top flange (RF1, RF2, RF3) is approximately 4:3:1.

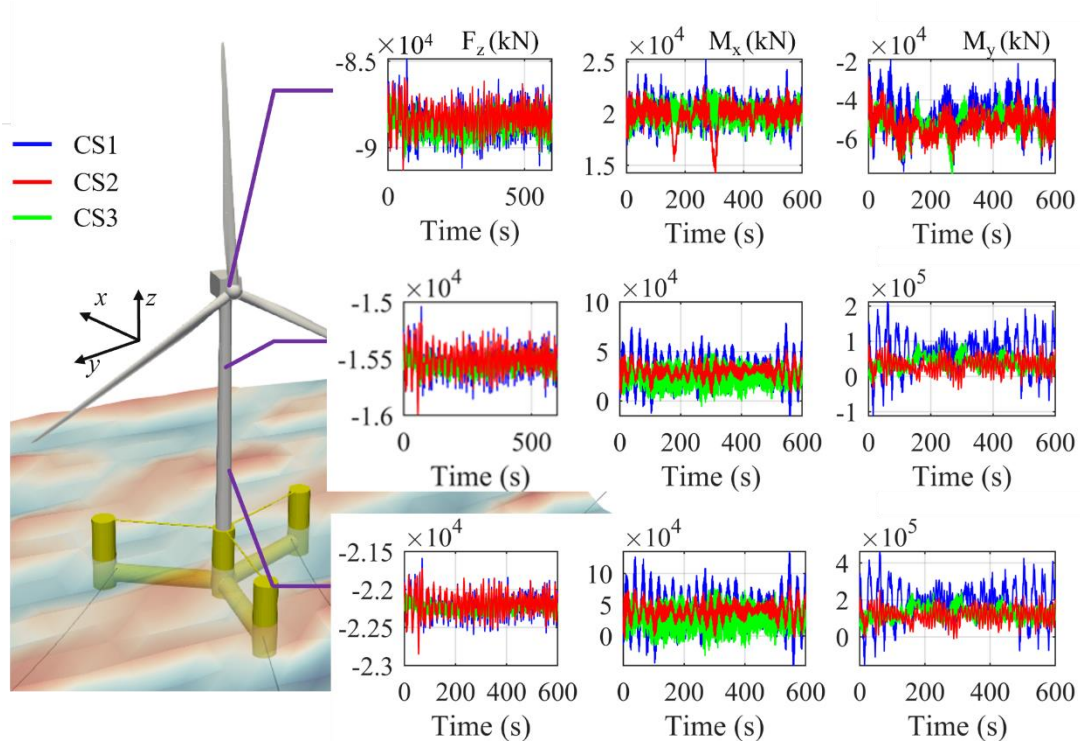


Figure 3-9 Structural response force under wind speed of 15m/s.

Based on the structural response, the bolt force can be determined using sectional analysis and load transfer functions (LTF), such as the Schmidt and Neuper approach ([Cosenza et al., 2011](#)). The process begins with the extraction of the dynamic response of the specific section, as illustrated in [Figure 3-10](#). Subsequently, the normal stresses within the section are calculated from this dynamic response. Following this, shell forces, which are affected by the applied loads and the section's intrinsic properties, are derived. The LTF, particularly the tri-linear function proposed by Schmidt and Neuper ([Ypma, 1995](#)), is then applied to transfer shell forces to the bolts. Geometric imperfections, which are inherently considered in the Schmidt/Neuper approximation within the proposed LTF, critically affect bolt behavior and have been validated through monitoring data and finite element methods to ensure safety margins ([Schmidt & Neuper, 1997](#)).

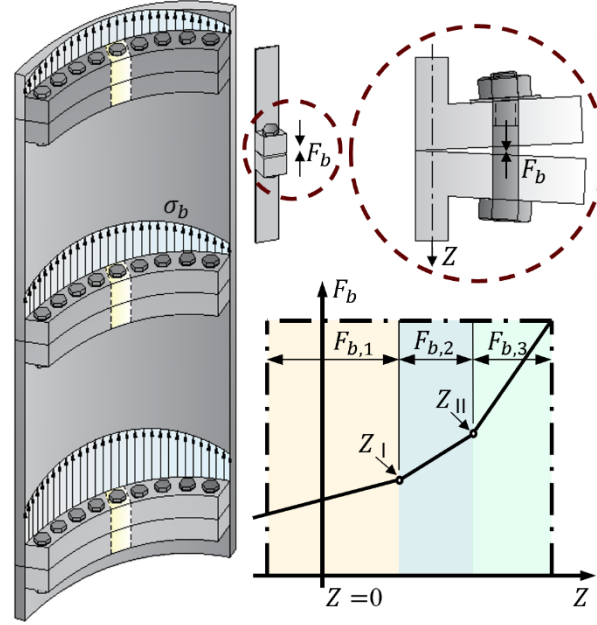


Figure 3-10 Procedures to derive fatigue stress spectra of the tower.

Both CF and pretension loosening pose considerable challenges in the operational performance of wind turbines, though they affect the system in different ways. CF, especially in environments with high levels of corrosive elements, can undermine the material strength of bolts, accelerating their deterioration (Weijtjens et al., 2021). In contrast, loosening of the pretension alters the load distribution and transfer behavior of the bolts, potentially compromising the integrity of the joint (Schaumann & Eichstädt, 2015). This study, which focuses on the probabilistic progression of CF deterioration, addresses the issue of long-term pretension loosening by applying a reduction factor of 0.9 to the bolt preloads (Adasooriya et al., 2017). Due to the nonlinear nature of LTFs, variations in the mean shell force result in significant changes in the range of bolt forces (Kumar et al., 2009).

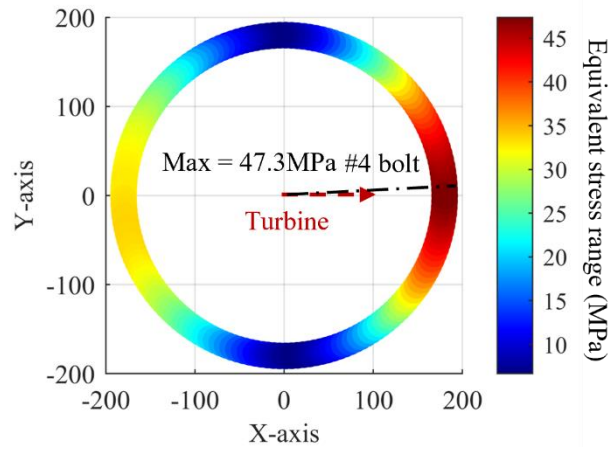


Figure 3-11 The equivalent stress range for all the bolts.

The fatigue stress spectra for each bolt are converted into an equivalent stress range in order to identify the critical bolt most susceptible to CF deterioration (Adasooriya et al., 2017; Weijtjens et al., 2021). Figure 3-11 shows the equivalent stress range for all 170 bolts on the flange of interest. The analysis reveals that bolt #4, positioned at a 6° angle to the turbine orientation, experiences the highest equivalent stress range of 47.3 MPa. As a result, bolt #4 is designated as the critical bolt and will undergo further examination in the reliability assessment. Figure 3-12 illustrates the stress history for this critical bolt under two typical loading conditions (LCs), comparing the results for both floating and fixed-bottom foundation scenarios.

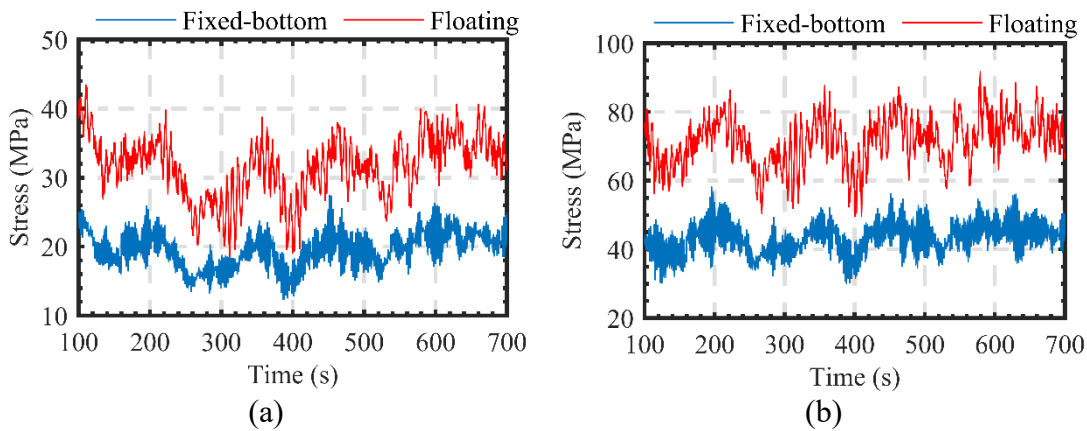


Figure 3-12 Stress history of the critical bolt in two typical LCs: (a) 10 m/s; (b) 20m/s.

Due to the high residual stress by preloading, the mean stress has a minor effect on bolt fatigue (Amzallag et al., 1994). Thus, the 3-dimension (3D) fatigue stress histogram is simplified into a 2D spectra by ignoring the mean stress, as shown in Figure 3-13. The result indicates a notable difference in the distribution of bolt stress ranges between the floating and fixed-bottom foundation. Especially, the proportion of high-level ranges is much higher in floating foundation than that in fixed-bottom foundation.

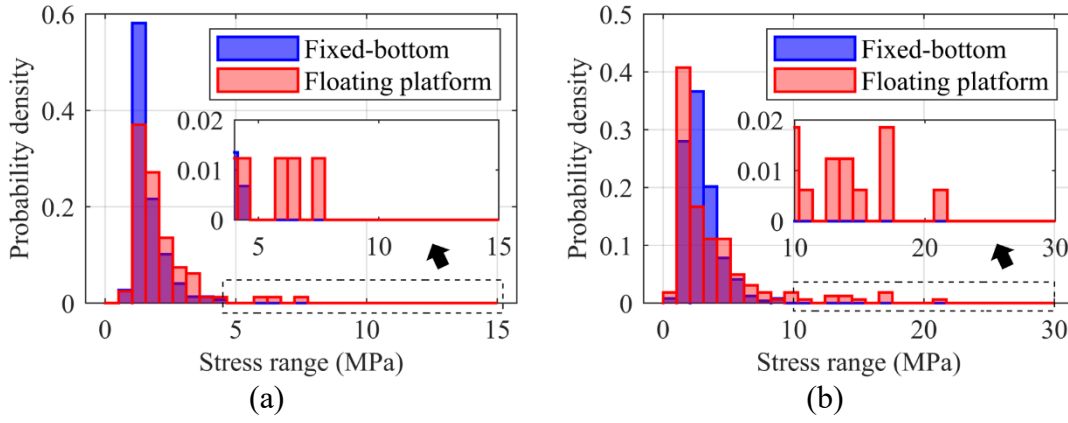


Figure 3-13 Fatigue stress spectra of the critical bolt in two LCs: (a) 10 m/s; (b) 20m/s.

In this study, the total history of wind-wave is synthesized by sampling according to the probability of occurrence for various LCs. An essential target in synthesizing the loading history is its robustness and effectiveness in representing the lifetime loading. To this end, the probability proportional to size sampling (ASTM, 2017) is used for sensitive analysis against the length of loading history, as shown in Figure 3-14.

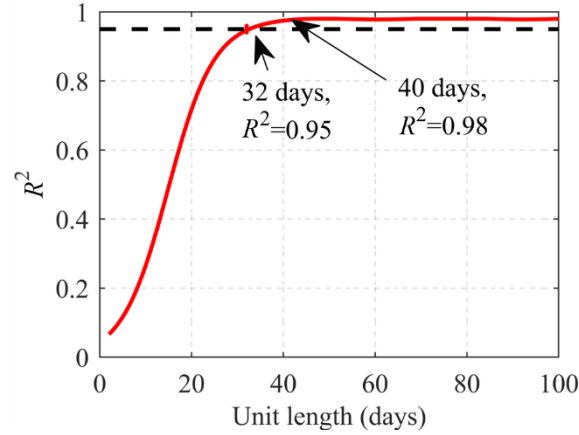


Figure 3-14 Sensitive analysis of sampling length.

The unit length is defined as one day (i.e., 24 hours), and convergence is assessed based on the coefficient of determination R^2 (Eichstädt, 2019). Convergence is considered to be achieved when R^2 reaches a threshold of 0.95 (Skinner, 2014), which occurs at a length of 32 days. When the length is further extended to 40 days, R^2 increases to 0.98. Therefore, a length of 40 days is adopted, and the total spectra are presented in Figure 3-15. Similar to Figure 3-13, the spectra for the floating foundation exhibit a higher proportion of high-level stress ranges compared to those for the fixed-bottom foundation, suggesting a potential variation in the C-F behavior between the two foundation types.

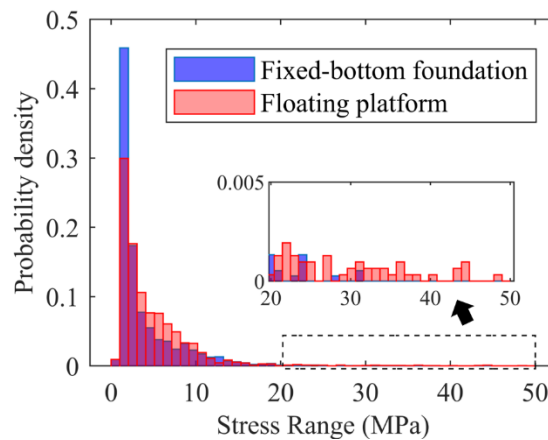


Figure 3-15 Synthesized fatigue stress spectra of the critical bolt.

The equivalent stress of the wind turbine under different strategies is illustrated in Figure 3-16. It can be observed that there is a significant correlation between the equivalent stress of the circumferential flange bolts and the high wind speed distribution in the region, with the most critical bolt positions occurring in the high wind speed direction. The distribution of internal forces within the structure, as shown in Figure 3-16, exhibits significant differences. There is no noticeable distinction in equivalent stress among the various flanges, highlighting the coherence between flange design and structural loading. Under the de-rating strategy, the equivalent stress of the wind turbine is significantly reduced. The maximum equivalent stress under the original Controller Strategy (CS1) at RF1 is 79.8 MPa. Under the same site conditions, the stress decreases to 59.1 MPa, a reduction of approximately 25.9%, with CS2, and decreases to 68.3 MPa, a reduction of approximately 14.4%, with CS3.

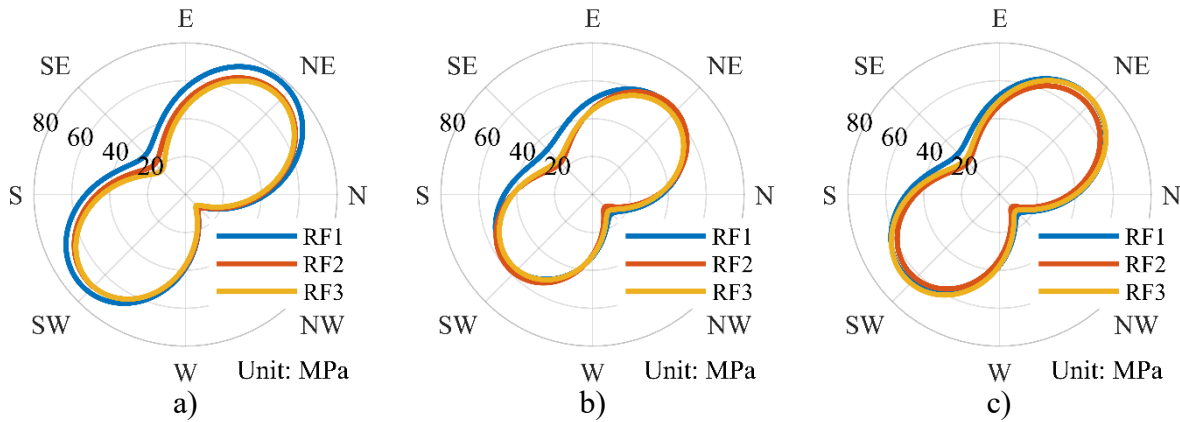


Figure 3-16 The equivalent stress of the wind turbine under different strategies. a) CS1; b) CS2; c) CS3

Based on the most critical bolt positions shown in Figure 3-16, a stress spectrum distribution for the full lifecycle of the bolts is plotted in Figure 3-17. It can be observed that the stress spectrum distribution forms of each flange are similar, and the ratio of the upper and lower bounds of the intervals is close to the ratio of the equivalent stresses. Different control strategies significantly

affect the stress distribution, influencing not only the mean values but also the upper and lower limits. The lower limit of the stress interval does not show significant changes under different control strategies, while the upper limit of the stress amplitude under CS2 is much smaller than that of the other two strategies, approximately half. The upper limits of the distributions under CS1 and CS3 are similar, but there are more high-level stress areas in CS1. This indicates that different control strategies not only alter the mean values but also affect the stress distribution intervals, thereby impacting corrosion fatigue performance.

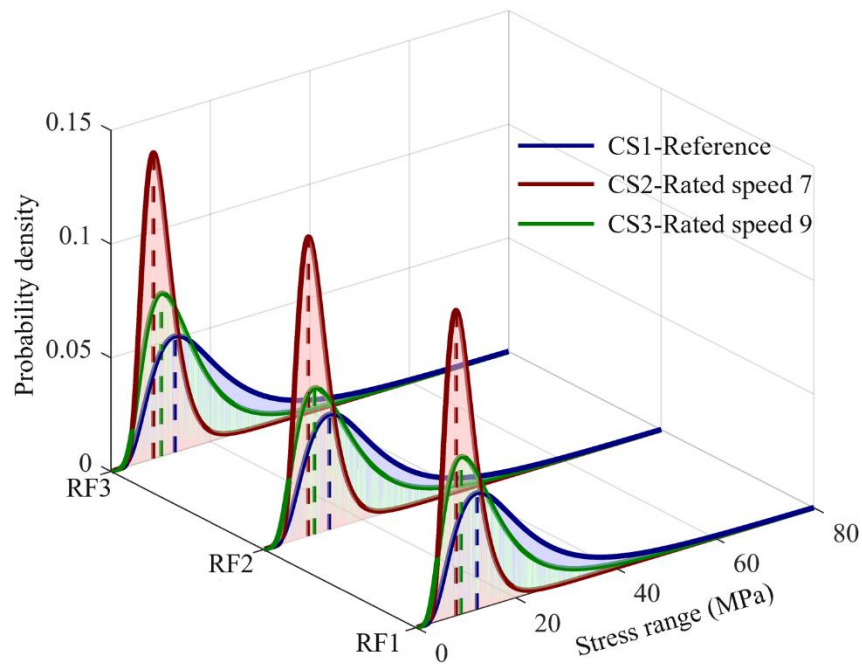


Figure 3-17 Integrated fatigue stress spectra under different strategies.

Key response distributions at different wind speeds are extracted, as shown in Figure 3-18. It is evident that the response distributions of different turbine components vary in form. For the blade structure (Figure 3-18a), due to the presence of the yaw system, the blades are oriented upwind, resulting in a strong positive correlation between wind speed and response extreme values. For the turbine tower (Figure 3-18b), the tower response initially increases and then decreases with

wind speed, reaching a peak near the rated wind speed (as shown in Table 3-2). This conclusion is consistent with findings in the literature (Rinker et al., 2020). For the generator (Figure 3-18c), the overall response trend is similar to that of the tower. However, as a key connection between the blade and tower, it also exhibits some response characteristics similar to the blade. Specifically, the response distribution is more concentrated at lower wind speeds but diverges as wind speed increases. The mooring line, being submerged underwater, is influenced both by the motion of the upper platform and by its strong correlation with wave impacts (Zhong et al., 2024). Therefore, the dynamic response exhibits high dispersion.

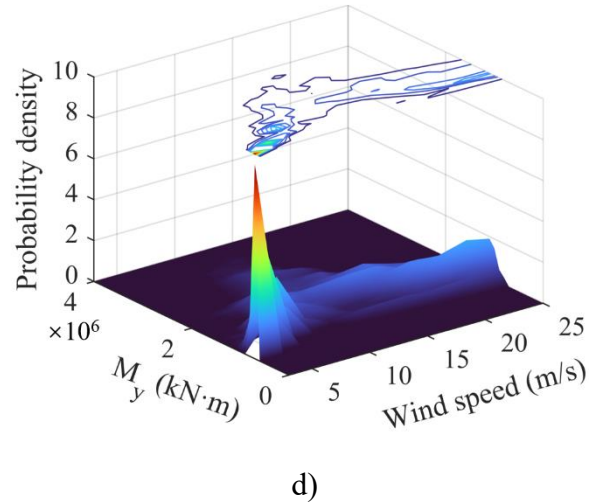
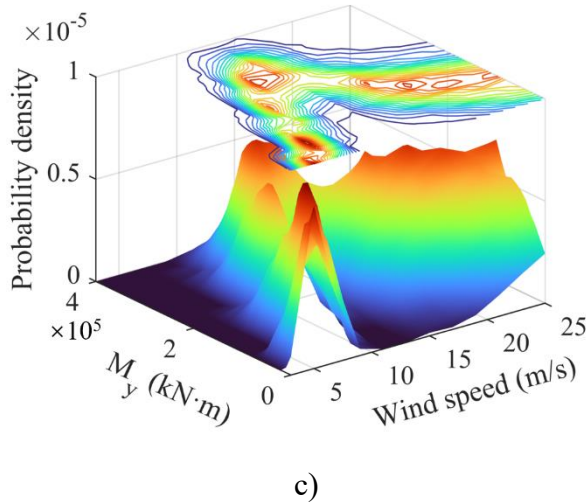
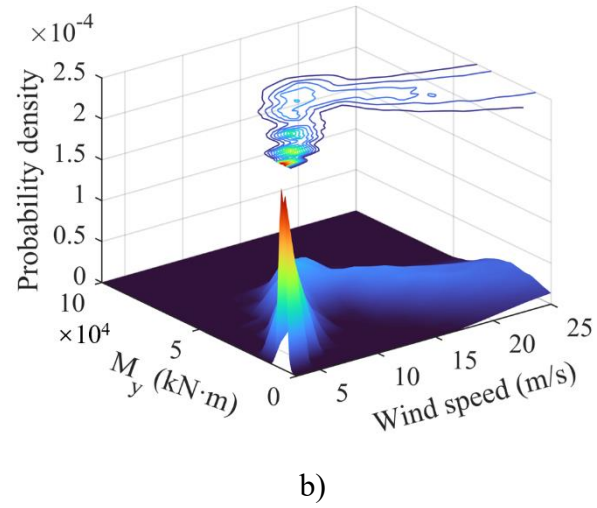
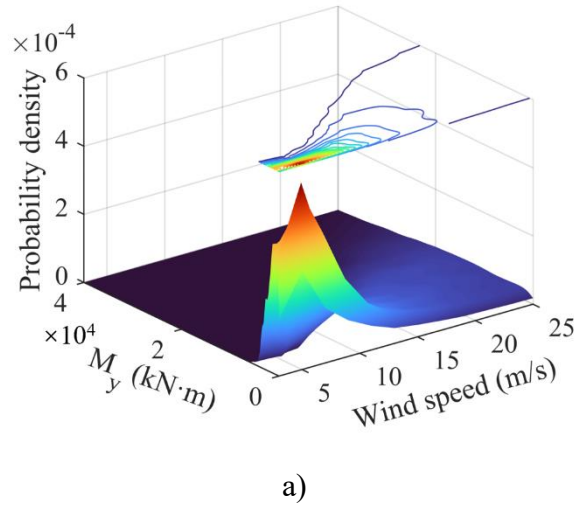


Figure 3-18 Stress distribution under different wind speed of multi-component. a) Blade; b) Generator; c) Tower; d) Mooring.

3.6 Summary

This chapter presents an effective simulation of offshore floating wind turbines using OpenFAST, which can be coupled with actual wind speed distributions for long-term simulations. However, OpenFAST primarily outputs component-level results, focusing on dynamic time series of operational modes and internal forces within the turbine cross-sections, and does not directly calculate the long-term performance degradation of the structure. Therefore, this chapter further establishes a stress calculation method to bridge dynamic responses with localized structural stress analysis, providing support for subsequent corrosion-fatigue degradation evaluations over the turbine's lifecycle. Additionally, to further explore the impact of control strategies on long-term structural performance, the ROSCO controller was modified to drive the turbine into a pre-rated power generation state. The effect of such de-rating strategies on long-term performance was then investigated. The findings are as follows:

- (1) The turbine control strategy significantly influences the dynamic performance of the structure, but the extent of the impact varies across components. For FOWTs, the generator and tower are most affected by the control strategy, with response increases near the rated wind speed and relatively smaller changes at other wind speeds. The blade response, due to the yaw system, tracks the maximum wind speed, exhibiting a monotonically increasing trend with increasing wind speed. The mooring system, on the other hand, is primarily influenced by wave action.

- (2) The de-rating strategy effectively reduces the turbine's dynamic response, thereby lowering the stress distribution across the components. This results in a significant alleviation of long-term degradation characteristics.

CHAPTER 4

Corrosion-fatigue development in coupled environment

4.1 Introduction

One of the most critical degradation mechanisms for offshore wind turbines is corrosion-fatigue, which arises from the combined action of a corrosive marine environment and cyclic mechanical loading. As discussed in Chapter 1, both corrosion and fatigue have been studied extensively in isolation, but their interaction in offshore conditions remains far less understood. This gap leads to underestimation of risks and uncertainties in structural reliability assessments.

Building directly on the multi-physics loading framework developed in Chapter 3, this chapter focuses on the synergistic effects of corrosion and fatigue. By incorporating site-specific environmental parameters, material properties, and loading histories, we establish a probabilistic framework that captures the time-dependent deterioration of key structural components. The models and findings here provide essential input for the predictive performance modeling in Chapter 5, ensuring that degradation mechanisms are realistically represented.

4.2 Probabilistic modeling for corrosion-fatigue degradation

4.2.1 Conceptual framework and foundational assumptions

Building on previous studies ([Adedipe et al., 2016](#); [Ryan & Mehmanparast, 2023](#)), the corrosion-

fatigue (C-F) evolution in carbon steels can be categorized into three distinct phases, as illustrated in Figure 4-1. These phases including corrosion-driven, competition, and fatigue-driven are defined by variations in crack size, crack growth rate (CGR), and the driving forces involved (Zhang et al., 2021). As widely recognized, corrosion-fatigue cracking typically begins at stress concentrators at the micro-meter scale, such as those caused by surface roughness. During this initial phase, fatigue plays a secondary role in crack growth due to the small crack size, with corrosion being the dominant factor driving crack formation. Therefore, this stage is referred to as the corrosion-driven phase.

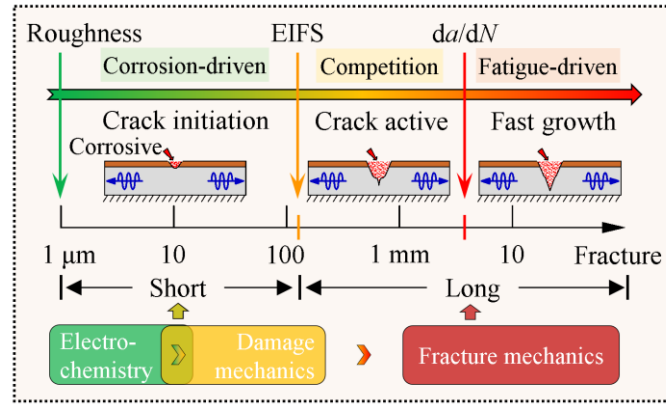


Figure 4-1 Three-phase evolution of corrosion fatigue cracks

Simultaneously, the interaction between corrosion and fatigue remains significant, facilitating the growth of fatigue cracks (Y. Zhang et al., 2019). In this context, as proposed by (Wang, 2011), a superposition of fatigue- and corrosion-induced damage is employed to provide a more conservative estimate of crack growth rates.

$$\frac{da_{s1}}{dt} = \left(\frac{da_{s1}}{dt} \right)_{cor} + \left(\frac{da_{s1}}{dt} \right)_{fat} \quad (4.1)$$

where a_{s1} stands for the crack size in the Stage 1; t is the service time reflecting the number of loading cycles; and the two subscripts “ cor ” and “ fat ” denote the driven forces of corrosion and

fatigue, respectively.

As suggested by ISO 9224 (Maeng et al., 1999), the loss in thickness by corrosion can be estimated using the empirical formula,

$$D_{cor}(t) = r_{cor} \cdot t^\beta \quad (4.2)$$

where $D_{cor}(t)$ stands for the time-variant loss in thickness by corrosion; r_{cor} is the first-year thickness-loss of carbon steels by corrosion, which indicates the environmental corrosivity; and β is a material-controlled constant.

Numerous studies (Hahin, 1994; Jia et al., 2011; Liao et al., 2022; Standardization, 2012b) have shown that uneven pitting corrosion is more harmful to crack growth than uniform thickness loss. As a result, the ratio of pitting depth to general corrosion is used to estimate corrosion-induced crack growth.

$$a_{pit}(t) = \omega_{pit} \cdot D_{cor}(t) \quad (4.3)$$

where $a_{pit}(t)$ stands for the crack growth by corrosion; and ω_{pit} is the ratio of pitting depth to general corrosion.

In the initial stage, due to the small crack size, the estimation of fatigue-related crack growth rates (CGR) falls outside the scope of classical fracture mechanics (FM), which does not adequately address small crack growth. Despite efforts to modify the models, FM remains impractical for engineering applications (Hahin, 1994). As an alternative, an equivalent CGR is estimated using linear damage accumulation methods (G. Chen et al., 2020).

$$\left(\frac{da_{S1}}{dt}\right)_{fat} = \frac{d}{dt} \left(\frac{1}{f} \cdot \sum_i \frac{n_i}{[N_i]} \right) \quad (4.4)$$

where f is the loading frequency; n_i and $[N_i]$ are respectively the number of applied cycles and allowance at a given stress range $\Delta\sigma_i$.

With further crack growth, the classic FM comes into effective once the crack size exceeds a certain limit. In this study, the effective initial flaw size (EIFS) proposed by (Zerbst et al., 2019) is applied as the limit for the transition,

$$a_{EIFS} = \left(\frac{[dK_{th}]}{Y_{fcg} \cdot [\Delta\sigma_L]} \right)^2 / \pi \quad (4.5)$$

where a_{EIFS} is the EIFS; $[dK_{th}]$ stands for the fatigue crack growth threshold, below which the crack arrest occurs; $[\Delta\sigma_L]$ is the cut-off limit, below which the stress range has no contribution to damage; and Y_{fcg} is the crack size-related correction factor.

Once the crack grows beyond the EIFS, the fatigue-related CGR can be estimated using the classic FM. Consequently, the C-F crack enters the second phase of evolution, i.e., the C-F competition. As proposed by (Standard, 2005), the CGR will be determined after the dominant effect between corrosion and fatigue,

$$\frac{da_{s2}}{dt} = \max \left[\left(\frac{da_{s2}}{dt} \right)_{cor}, \left(\frac{da_{s2}}{dt} \right)_{fat} \right] \quad (4.6)$$

where a_{s2} stands for the crack size in the Stage 2.

With the service time increasing, when the same loading scenario is assumed, corrosion-related CGR decreases while fatigue-related CGR increases. Finally, fatigue overtakes corrosion as the dominant cracking-driven force until the failure fracture, which is defined as Phase 3 (i.e., the fatigue-driven growth). In this phase, the same formula can be employed in estimating the CGR.

4.2.2 Computational fracture modeling framework

Fatigue cracks in bolts typically initiate at three locations, as shown in Figure 4-2: the head-to-shank transition, the root of the first engaged thread, and the root of the thread run-out (Liu &

Mahadevan, 2009). Consequently, three failure modes are considered to co-exist within the bolt, referred to as Mode 1, Mode 2, and Mode 3. According to (Syrotyuk et al., 2021), for in-air fatigue deterioration of bolts, Mode-3 accounts for 65% of the total, followed by Mode-2 at 20% and Mode-1 at 15%. Furthermore, an elliptical crack shape is assumed for all three failure modes, with two degrees of freedom (DOF): crack depth, denoted as “ a ”, and crack length, denoted as “ c ”. The diameter of the effective section of the bolt is denoted as D_0 .

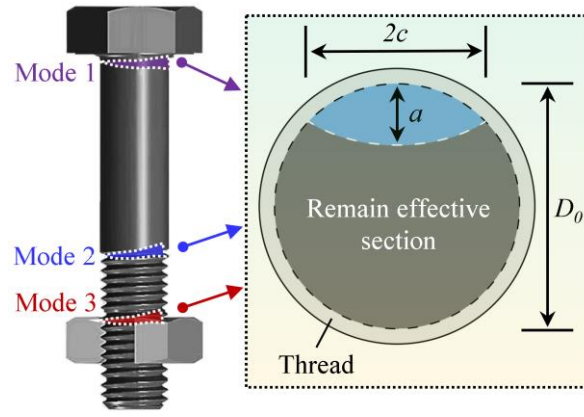


Figure 4-2. Fatigue crack modelling of high-strength bolts.

Fatigue-related crack growth rate (CGR) is determined by assuming linear damage accumulation during Phase 1 of corrosion-fatigue (C-F) deterioration. Unlike other engineering structures, the wind turbine tower is subjected to sustained fatigue spectra, where the lower-level stress ranges make up the majority of the stress distribution (Eccles, 2023). To model this, the trilinear probability-stress-life (P-S-N) curve (Fu et al., 2020; Haselibozechaloe et al., 2022) is utilized, with the P-S-N curve extended beyond the cut-off limit $[\Delta\sigma_L]$ by a power index of $m = 22$. In this study, the cut-off limit is treated as a random variable (RV). Typically, more than 90% of the fatigue life is consumed during crack initiation in smooth specimens (Hobbacher, 2016). Consequently, the design fatigue strength of smooth specimens, under a survival rate of 97.7% (i.e., FAT 160 ((Standard, 2005))), is considered, with a coefficient of variation (COV) of 0.1439, as reproduced by (Ibrahim & Miller, 1979). Using lognormal distributions, the original probability

density function (PDF) of material-level crack initiation is derived. The PDF of the cut-off limit for each failure mode in the bolts is then constructed by dividing this by the local stress concentration factor (SCF). According to , the SCF values are 4.0 and 4.37 for Mode 2 and Mode 3, respectively, while the SCF for Mode 1 is determined as 4.21 based on the local stress gradient of bolts (Guo et al., 2012). Additionally, a general SCF value of 2.85 (Chen, 2018) is applied to the remaining parts of the bolts.

Another critical factor in the fracture model is the fatigue crack growth threshold, $[dK_{th}]$. The design value for $[dK_{th}] = 63 \text{ N/mm}^{3/2}$ (at a survival rate of 97.7%) provided by BSI is used, with a COV of 0.15 as suggested by (Eccles, 2023). The distribution of dK_{th} is assumed to follow a lognormal distribution. As the C-F crack progresses into Phase 2, after the attainment of the end of initiation and formation stage (EIFS), the Paris law (Eccles, 2023) is applied to estimate the fatigue-related CGR.

$$\left(\frac{da_{s2}}{dt}\right)_{fat} = A_{fcg} \cdot (\Delta K_i - [dK_{th}])^{m_{fcg}} \quad (4.7)$$

where A_{fcg} and m_{fcg} are material-related factors of fatigue-related CGR; and ΔK_i is the variation in stress intensity factors (SIFs), corresponding to the stress range $\Delta\sigma_i$.

In quantifying growth-associated uncertainties, the power factor m_{fcg} is taken as a deterministic value of 3.0, while the linear factor A_{fcg} is modelled as a RV (Walbridge, 2005). Based on the design value in (Anderson, 2017) and the standard deviation in (Slatcher, 1987), the distribution of A_{fcg} can be constructed. As discussed in Section 2.1, the influence of corrosion should also be incorporated in predicting fatigue-related CGR. For instance, IIW (Institution, 2019) suggests a conservative method to multiply the linear factor by an environment assistance factor

(EAF) of 3.0 in marine conditions, regardless of corrosivity. Similarly, an adaptive EAF is proposed conditional on corrosivity,

$$C_{EAF} = 1 + 2 \cdot \frac{r_{cor}}{r_{cor}^0} \quad (4.8)$$

where r_{cor} is the first-year corrosion-loss of carbon steels; r_{cor}^0 is the benchmark value of r_{cor} in the environment category C5 (very high corrosion), which is set as 200 $\mu\text{m}/\text{yr}$ after the upper limit.

The variation in SIFs can be determined based on the crack configuration and stress ranges,

$$\Delta K_i = Y_{fcg}(a, c) \cdot \Delta \sigma_i \sqrt{\pi a_j} \quad (4.9)$$

where a_j denote the crack depth of an arbitrary failure mode, *e.g.*, $j = 1, 2 \text{ or } 3$; $Y_{fcg}(a, c)$ is the correction factor conditional on the crack shape.

Due to the exhaustive solution effort associated with the probabilistic simulation in this work, the analytic solution offered in Section M.10.4.2 of BS 7910 (Veritas, 1984) is leveraged. According to the hired solution, the correction factor is mainly controlled by the crack depth, while the crack length only shows a minor influence and can be neglected with enough conservativeness. In this regard, the problem can be further down-scaled into the issue with one DOF at the crack depth. Besides, it is noteworthy that the four SCFs stated before are used to account for the difference in the SIF between the three failure modes. Based on the above method, the C-F crack growth can be predicted until the final fracture, which is marked by the achievement of the critical crack depth. As suggested by (Hobbacher, 2016), the ratio of critical crack depth to effective diameter is determined as $\delta_{cr} = 0.65$ in this work. In other words, the failure of the bolt is assumed in case any of the three cracks reach the depth equivalent to 58% of the effective diameter D_0 . Table 3-1 summarizes the key parameter used in the PCF model.

Table 4-1 Key parameters of the PCF model.

Variable	Sym ¹	Unit	Type	Mean	Std ⁴	Source
Cut-off limit	Mode 1	$\Delta\sigma_{L,1}$	MPa	20.71	2.98	(Institution, 2019; James & Mills, 1988)
	Mode 2	$\Delta\sigma_{L,2}$	MPa	21.80	3.14	(Chen, 2018; Standard, 2005)
	Mode 3	$\Delta\sigma_{L,3}$	MPa	19.95	2.87	(Chen, 2018; Standard, 2005)
Fatigue crack growth threshold	$[dK_{th}]$	N/mm ^{3/2}		85.85	12.88	(Standard, 2005)
Linear factor for CGR	A_{fcg}	/		$3.30 \cdot 10^{-13}$	$1.60 \cdot 10^{-13}$	(Chen, 2018)
Power factor for CGR	m_{fcg}	/	Det ³	3.0	-	(Walbridge, 2005)

¹: Symbol; ²: Lognormal; ³: Deterministic; ⁴: Standard deviation.

4.2.3 Structural integrity evaluation using FAD and LSF

As aforementioned, the bolt fracture is assumed by the achievement of critical crack depth at any of the three modes. The limit state function (LSF) can be at first established for arbitrary failure modes,

$$G_i(t) = \delta_{cr} \cdot D_0 - a_i(t) \quad (4.10)$$

where $G_i(t)$ is the time-variant LSF for failure mode i ; D_0 is the effective diameter of bolts; and $\delta_{cr} = 0.58$ denotes the ratio of critical crack depth to effective diameter.

The bolt failure can be idealized into a linking system, as shown by the failure assessment diagram (FAD) in Figure 4-3. The probability of failure (POF) of the bolt can be estimated,

$$P_{f,bolt}(t) = P\left[\bigcup_{i=1}^3 G_i(t) < 0\right] = 1 - \bigcap_i (1 - P_{f,i}(t)) \quad (4.11)$$

where $P_{f,blt}(t)$ the time-variant POF of the bolt under investigation; $P_{f,i}(t)$ stands for the time-variant POF of an arbitrary failure mode i .

Using the Load Stress Function (LSF) and Fracture Assessment Diagram (FAD) discussed earlier, Monte Carlo simulations (MCS) can be employed to predict the evolution of the C-F state in FOWTs, as depicted in Figure 4-2, with the uncertainty quantified. In each MCS run, parameter sampling is initially performed based on the probabilistic models. It is important to note that the two Paris law-related RVs, A_{fcg} and $[dK_{th}]$, are shared across the three failure modes, as they are material-level constants. In contrast, the three fatigue cut-off limits are modeled independently, as they serve as general statistics at the component level. Using the sampled values, the lifetime evolution is simulated by applying the C-F prediction model.

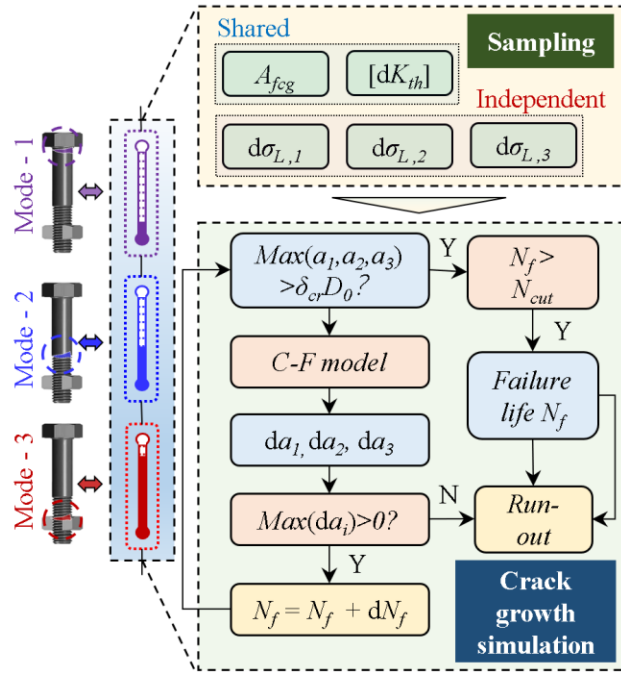


Figure 4-3 Failure assessment diagram (FAD) and computational procedures.

4.2.4 System level reliability and risk analysis framework

As highlighted in the introduction, current research lacks quantified indices and criteria for systematically evaluating CF degradation characteristics at the system level. Given the comprehensive attributes of FOWTs, which include structural health, energy production requirements, and the complexities of maintenance such as offshore operations and repair costs. It is crucial to develop a robust system-level reliability and risk (R&R) model. The overall R&R assessment framework is illustrated in [Figure 4-4](#). The CF progression for bolts at the same position on a given flange is calculated using these statistical results, leading to the determination of individual bolt reliability. Each simulation iteration provides the number of failures for each flange. Different bolt failure thresholds are set for two types of consequences, and the failure rate for each scenario is derived from the sample distribution. This process forms the bolt-to-flange reliability analysis framework. Ultimately, multiple flanges on the same tower are treated as a series system, where the failure of a single flange results in the failure of the entire tower, allowing for the calculation of overall tower reliability. An analysis of the economic losses associated with the tower under different consequences, combined with the failure probability, provides the risk analysis results.

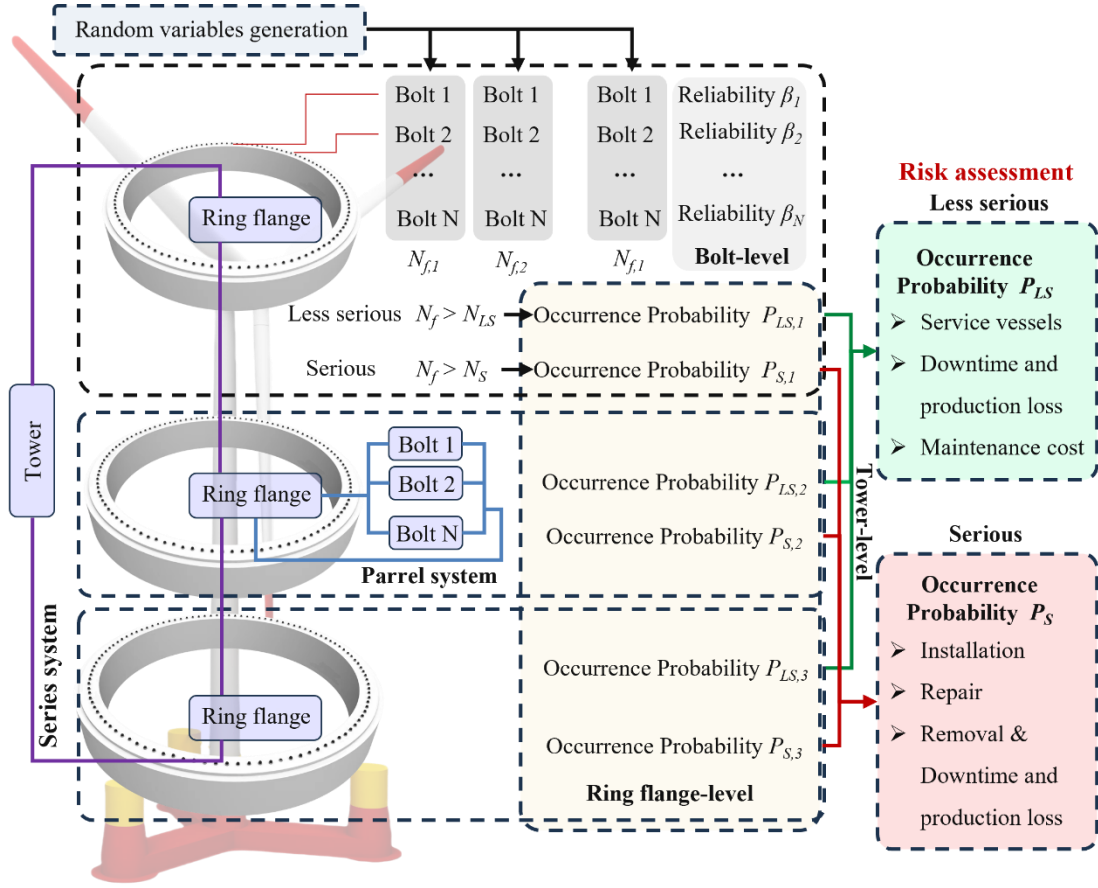


Figure 4-4 Reliability and Risk assessment framework.

The inherent material uncertainties significantly impact CF performance, necessitating robust reliability estimation methods. This study employs the importance sampling technique (Bastidas-Arteaga et al., 2009; Tabandeh et al., 2022) to evaluate the CF reliability of the FOWTs.

The first step involves calculating the individual bolt reliability. Given the complexities associated with directly sampling from the target distribution $p(x)$ of material properties. A proposal distribution $q(x)$ that is computationally convenient and adequately spans the range of interest is chosen. The sampling process for importance sampling is illustrated in Figure 4-5.

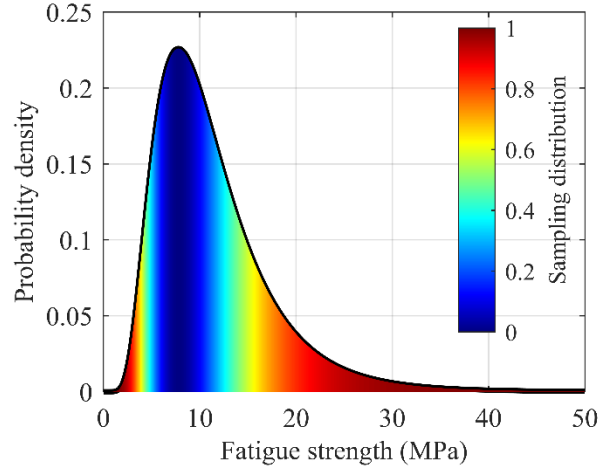


Figure 4-5 Importance sampling method for random variables generation.

Samples $x_1, x_2, \dots, x_N$ are generated from the proposal distribution $q(x)$. For each sample x_i , the importance weight is computed as:

$$w_i = \frac{p(x_i)}{q(x_i)} \quad (4.12)$$

where $p(x_i)$ represents the probability density of the target distribution at x_i , and $q(x_i)$ represents the probability density of the proposal distribution at x_i .

The failure probability P_f in CF reliability analysis is defined as the probability that the limit state function $g(X)$ is less than or equal to zero:

$$P_f = P(g(X) \leq 0) \quad (4.13)$$

where $g(X)$ represents the limit state function (LSF), defined as:

$$g(X) = f(x_i) \leq f_0 \quad (4.14)$$

The failure probability can be expressed as an integral over the failure domain $g(x) \leq 0$ using the probability density function $f(x)$ of the random variables X :

$$P_f = \int_{\Omega_f} f(x) dx = \int_{R^n} I(g(x) \leq 0) f(x) dx \quad (4.15)$$

Importance sampling involves selecting an alternative probability density function $h(x)$, known as the importance density, to efficiently sample in the regions where $g(x) \leq 0$. The failure probability P_f can then be reformulated as:

$$P_f = \int_{R^n} I(g(x) \leq 0) \frac{f(x)}{h(x)} h(x) dx \quad (4.16)$$

The failure probability can be estimated by drawing N samples X_i from the importance distribution $h(X_i)$ and using the following unbiased estimator:

$$\hat{P}_f = \frac{1}{N} \sum_{i=1}^N I(g(X_i) \leq 0) \frac{f(X_i)}{h(X_i)} \quad (4.17)$$

The reliability index of a single unit can further be calculated from the failure probability, as shown in [Equation 4.18](#).

$$\beta_{bolt} = -\Phi^{-1}(\hat{P}_f) \quad (4.18)$$

Each substructure can be considered as a system composed of multiple unit. The system is deemed to fail when the number of failed bolts exceeds a certain threshold. To generalize, consider a system consisting of m independent components, where the system is defined as failed if at least k components fail. The system failure probability, denoted as $\widehat{P}_{sys}$, can be expressed as follows:

$$\widehat{P}_{sys} = P \left(\sum_{i=1}^m I(g(X_i) \leq 0) \geq k \right) \quad (4.19)$$

where $I(g(X_i) \leq 0)$ represents the failure indicator function for the i -th component. The function outputs a value of 1 if the failure condition $g(X_i) \leq 0$ is satisfied; otherwise, it outputs 0. The term $\sum_{i=1}^m I(g(X_i) \leq 0)$ represents the total number of failed components within the system.

Assuming that the system failure probability follows the joint distribution $f(x)$ of m random variables, the system failure probability $\widehat{P}_{\text{sys}}$ can be expressed as:

$$\widehat{P}_{\text{sys}} = \int_{\Omega_{\text{sys}}} f(x) dx \quad (4.20)$$

Here, Ω_{sys} denotes the failure domain of the system, which can be expressed as:

$$\Omega_{\text{sys}} = \left\{ x \in R^n: \sum_{i=1}^m I(g(X_i) \leq 0) \geq k \right\} \quad (4.21)$$

By incorporating Equation 4.19, the system failure probability can be estimated using the following estimator, based on N samples drawn from an importance distribution $h(x)$:

$$\widehat{P}_{\text{sys}} = \frac{1}{N} \sum_{j=1}^N I \left(\sum_{i=1}^m I(g(X_{i,j}) \leq 0) \geq k \right) \frac{f(X_j)}{h(X_j)} \quad (4.22)$$

where N represents the total number of samples; $X_{i,j}$ denotes the random variable corresponding to the i -th component under the j -th sample; $f(X_j)$ and $h(X_j)$ are the joint PDF of the system and the importance sampling distribution, respectively.

Risk assessment is widely recognised as the cornerstone for formulating precise maintenance strategies (Zheng & Wang, 2020). By quantitatively analyzing the potential failure risks and fatigue degradation of equipment, researchers can establish risk-driven inspection and maintenance frameworks that accurately predict system behavior under complex operational conditions and facilitate effective risk management (Javid, 2025; Tabandeh et al., 2022). The risk assessment for FOWT is based on a set of probabilistic wind and wave scenarios. The risk is considered as the aggregation of all CF degradation-related events associated with the investigated FOWT. Two consequences are considered: strong vibration and tower collapse. A small number of bolt failures in the flanges, leading to significant impact on the tower vibration characteristics (Yu et al., 2025),

is considered a serious consequence. A failure proportion of 5% is considered the threshold for this consequence (Dui et al., 2025). The failure of the flange connection, leading to tower collapse, is identified as a serious consequence risk. For a flange system comprising N bolts subjected to a total applied load Q , the equal load sharing assumption implies that each bolt initially carries a nominal load of $\frac{Q}{N}$ (He et al., 2016). When a fraction f of the bolts fails, the effective load per surviving bolt becomes:

$$Q_{\text{eff}} = \frac{Q}{N(1-f)} \quad (4.23)$$

To account for uncertainties and load redistribution due to local failures, a partial safety factor γ is introduced such that the design condition for each bolt becomes $\frac{\gamma Q}{N}$. This leads to a design condition for each bolt of $\frac{\gamma Q}{N}$. Equating the effective load per surviving bolt to the design load per bolt, the critical bolt failure fraction f is directly related to the partial safety factor γ by:

$$f = 1 - \frac{1}{\gamma} \quad (4.24)$$

In IEC 61400-6 ((ASME), 2022), a partial safety factor $\gamma = 1.4$ is introduced, corresponds to a bolt failure ratio of approximately 0.29. In the present study, this value is rounded to 30%, reflecting the critical state at which the redistributed loads exceed the residual capacity of the connection, thereby precipitating a catastrophic collapse of the tower. This type of failure involves the compromise of the flange structural integrity, which can precipitate the tower collapse. The risk in terms of CF loss can be computed (Lawlor et al., 2005).

$$L_{CF}^i(t) = p^i(t) \times C \quad (4.25)$$

where $L_{CF}^i(t)$ is the risk of consequence i at time t ; $p^i(t)$ is the probability of the event occurring at time t ; C is the loss corresponding to the consequence.

Table 4-2 Parameter values for losses due to FOWTs maintenance and replacement.

Description	Sym	Value	Units	ref
Cost of maintenance vessel	c_v	400	€/h	(Commission, 2020)
Fixed vessel cost per day	c_{fv}	3400	€	(Guo et al., 2025)
Cost of maintenance task	c_{mt}	1500	€/h	(Bocewicz et al., 2024)
Cost due to production loss when the system stops	C_{lt}	0.83	€/MWh	(Bocewicz et al., 2024)
Installation cost of the turbine	c_{ins}	127.5	€/MWh	(Gonzalo et al., 2022)
Semi-submersible crane vessel for installation per day	c_{cr}	28,840	€	(Gonzalo et al., 2022)
Downtime caused by flange bolt maintenance	t^{dt}	7	h	(Roggenburg et al., 2020)

Figure 4-6 illustrates the losses associated with different consequences. In particular, the costs for a single vessel operation, maintenance, and production as illustrated in Equation 4.26 and Table 4-2, respectively. The cost of a new turbine (C_{NT}) is defined by Equation 4.26:

$$C_{NT} = (c_{ins} \times E_{WT}) + (c_{cr} \times t_{cr}) \quad (4.26)$$

where E_{WT} is the turbine capacity output (MWh); t_{cr} is the duration of crane usage (days).

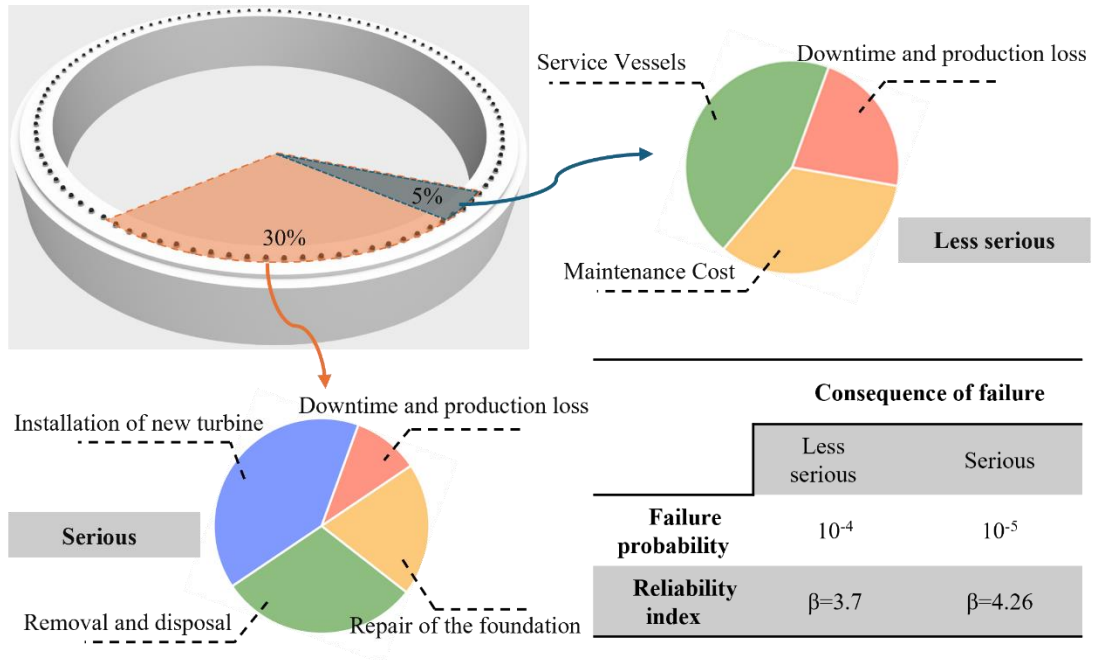


Figure 4-7 Two-level failure consequences of the flanged ring

4.3 Illustrative cases

4.3.1 Single bolt level

Given the prognosis result in the probabilistic form, the reliability index (Jiang, 2021) is hired to investigate the failure rate of bolts from a general perspective. As discussed before, Monte Carlo (MC) runs (Stork, 2024) are used for the probabilistic simulation. In facing the high computational cost and very small failure rate in this solution, the importance sampling method (Heng et al., 2019; Raychaudhuri, 2008) is applied. For a delicate balance between solution efficiency and accuracy, sensitivity analysis is conducted to find the optimal sample size, as shown in Figure 4-8. The result delineates the reliability of the critical bolt at three key time points of 5, 15 and 25 years. Overall, the convergence point varies with the reliability level. Specifically, the 25-year curve converges first at a sample size of 1,000. Then, the 15-year curve attains convergence at the sample size of 2,000 before the 5-year curve converged at the size of 3,000. Therefore, a slightly large sample size of 5,000 is chosen after the available computational resource.

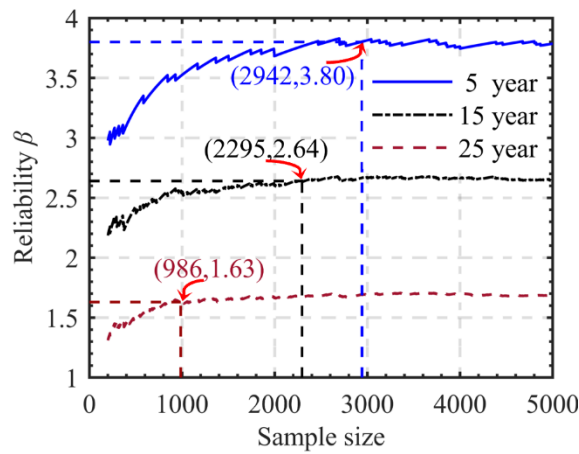


Figure 4-8 Statistical convergence of reliability metrics across sample sizes.

The time-variant reliability evolution is calculated for all three failure modes at the

component level, as illustrated for the critical bolt in Figure 4-8. A safety boundary of $\beta = 2$ is assumed, corresponding to a survival rate of 97.7%, in line with Eurocode 3 (Grooteman, 2008). In general, both Mode 1 and Mode 2 demonstrate positive reliability values, remaining well above the safety boundary after 25 years. In contrast, Mode 3 starts with a lower reliability and falls below the safety boundary earlier than the other two modes. At the component level, where the three modes are coupled, reliability decreases further, resulting in a characteristic life of 20.4 years. Overall, the critical bolt maintains a satisfactory but limited reliability over its design life of 20 years. However, if the service life is extended to 25 years, which is common in the offshore wind industry, there is a significant risk of premature bolt failure due to accelerated deterioration. Additionally, the differences in reliability across the three failure modes highlight their varying contributions to corrosion-fatigue (C-F) deterioration, with Mode 3 having the greatest impact, followed by Mode 1 and Mode 2.

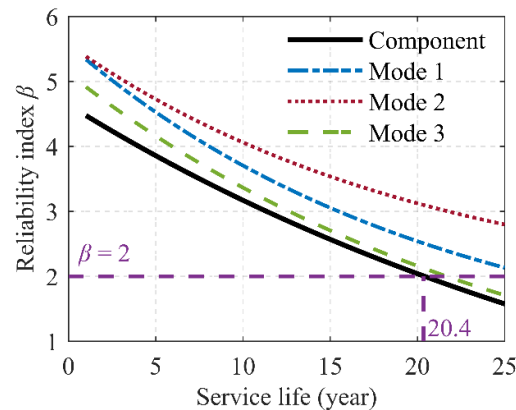


Figure 4-9 Corrosion fatigue reliability evolution

The investigation is further carried out on the correlation between the C-F damage and the location of bolts relative to the wind-wave distribution, as shown in Figure 4-9. The reliability reveals a strong correlation with bolt locations. Especially, the critical region aligns with high-speed winds, which is also the direction of high waves.

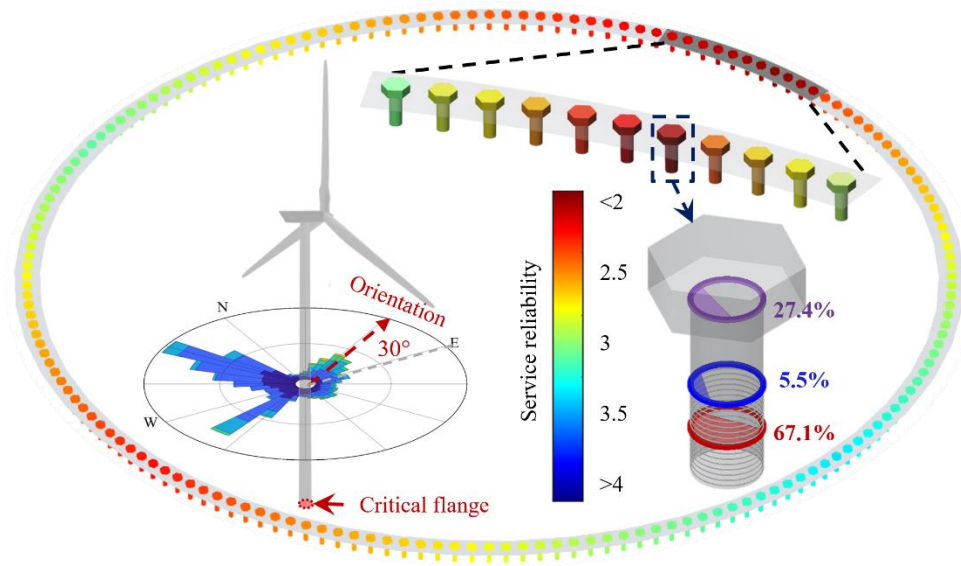


Figure 4-10 Corrosion fatigue reliability of bolts after 25 years

A detailed examination is carried out on a total of 11 bolts in the critical region, as shown in the detailed view. The most critical bolt is identified at an angle of 6° to the turbine orientation, which aligns with the findings in Section 3.2. Additionally, the distribution of failure modes is analyzed, with Mode 1, Mode 2, and Mode 3 contributing 27.4%, 5.5%, and 67.1%, respectively. In comparison with the in-air fatigue test results of bolts (Cai et al., 2019), a slight difference is noted in the proportions of Mode 1 and Mode 2 (i.e., 15% and 20% under in-air conditions), the reasons for which will be discussed in further detail later.

Further insight is provided into the corrosion-fatigue (C-F) crack growth within the stochastic space, as shown in Figure 4-11a) and b). Generally, the crack exhibits exponential growth, with increasing variability. Since the 97.7% characteristic value (CV) of the crack depth exceeds the critical crack size within the first 25 years, a more refined inspection is conducted on the distribution of crack depths during this period, as illustrated in Figure 4-11b).

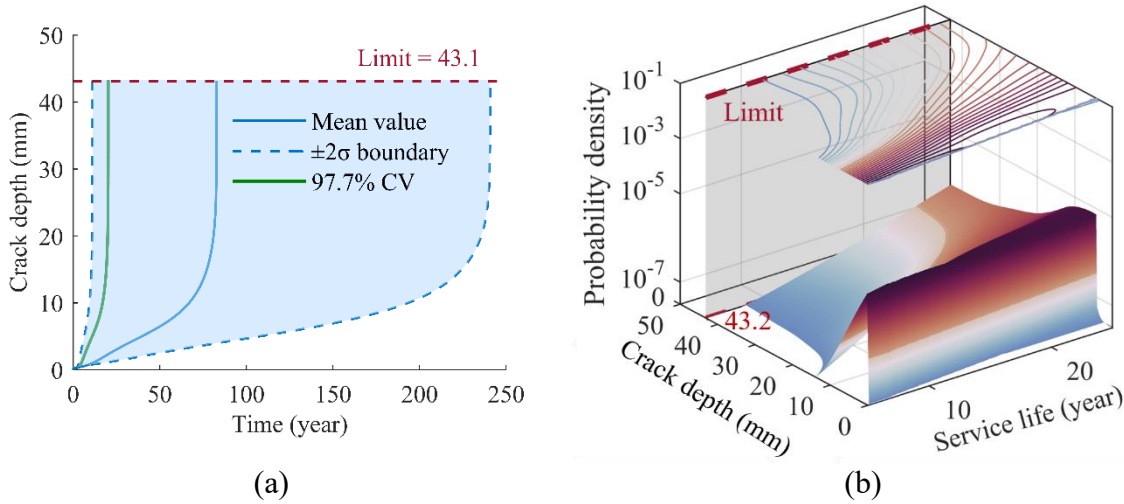


Figure 4-11 Probabilistic crack growth evolution in the critical bolt: (a) Mean and variance; (b) Probability density function after 25 years.

During the first decade, the probability density is predominantly concentrated in the region of small cracks (i.e., less than 5 mm deep), indicating a low likelihood of bolt fracture. However, as time progresses, a small but noticeable proportion of samples display rapid crack growth, approaching the critical limit. With the increasing service life, the probability density shifts from the initial region below 5 mm to a more scattered range closer to 10 mm. As a result, both the variability in crack depths and the failure probability increase nonlinearly over time, which aligns with the trends observed in [Figure 4-11a](#).

The PCF model highlights corrosivity as a key factor influencing the C-F evolution. In this context, an analysis is performed on the C-F crack growth of the critical bolt under five typical corrosivity levels, denoted as C1 to C5 ([Standard, 2005](#)), as shown in [Figure 4-12](#). Corrosivity is defined based on the first-year corrosion rate in carbon steel, as illustrated in the bar chart of [Figure 4-12](#). For conservativeness, this study adopts the upper limit of each category as suggested by ([Haselibozechaloe et al., 2022](#)). In general, the crack grows exponentially, with two distinct inflection points at 10 and 20 years. Additionally, the crack growth rate significantly increases with

the level of corrosivity.

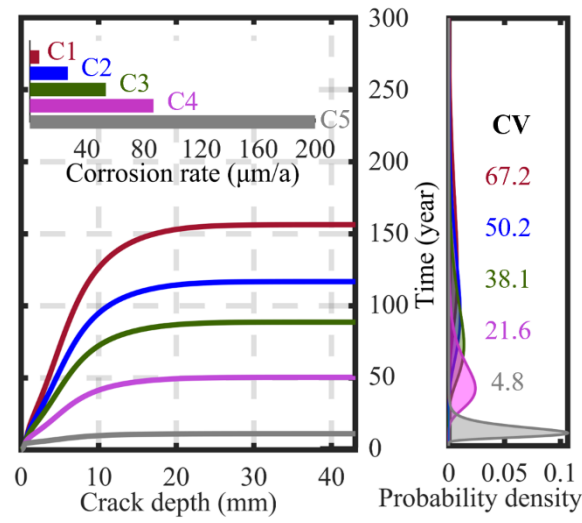


Figure 4-12 Crack depth evolution under various corrosivity

The right section of [Figure 4-12](#) presents the predicted distribution of service life across different corrosivity categories, with the coefficient of variation (CV) calculated under a survival rate of 97.7%. As corrosivity increases, the distribution shifts to the right and becomes more concentrated. For example, in the case of C1 (representing very low corrosivity, such as onshore sites), the critical bolt demonstrates a service life of 67.2 years, which is 2.33 times longer than the predicted service life of 20.4 years under the conditions of the investigated site. Therefore, in deep-water regions where floating offshore wind turbines (FOWTs) are deployed, increased corrosivity (such as C4 and C5) poses a significant risk of premature bolt fracture. In the extreme case of C5, the service life CV of the critical bolt decreases to just 4.8 years, which is only 19.2% of the design life.

Given the substantial difference in fatigue stress spectra between bolts in fixed-bottom and floating towers, additional comparisons are made to assess the impact of foundation types, as shown in [Figure 4-13](#). Fixed-bottom towers experience reduced stress, and thus, two bolt dimensions, M48 and M46, are considered for these towers. [Figure 4-13a](#) shows the proportion of

failure modes across three cases, revealing notable differences between floating and fixed-bottom towers. The proportion of Mode 1 remains relatively constant, at 27.4% for floating towers and 30%–31% for fixed-bottom towers. In contrast, the proportion of Mode 2 increases significantly, shifting from 5% to 20%–21% as the foundation type transitions from floating to fixed-bottom. Additionally, the contribution from Mode 3 slightly decreases from 67.1% to 50%–51%.

As shown in Figure 4-13b, fixed-bottom towers exhibit reduced C-F issues in bolts. Despite having the same structural configuration, M46 bolts in fixed-bottom towers demonstrate C-F life comparable to that of M72 bolts in floating towers. When the bolt size increases slightly from M46 to M48, the design life of 25 years can be ensured with high reliability. Specifically, the characteristic life of the critical bolt increases from 20.4 to 38.1 years (an improvement of 86.8%). Therefore, special attention should be given to high-strength bolts used in ring-flange connections during the development of FOWTs.

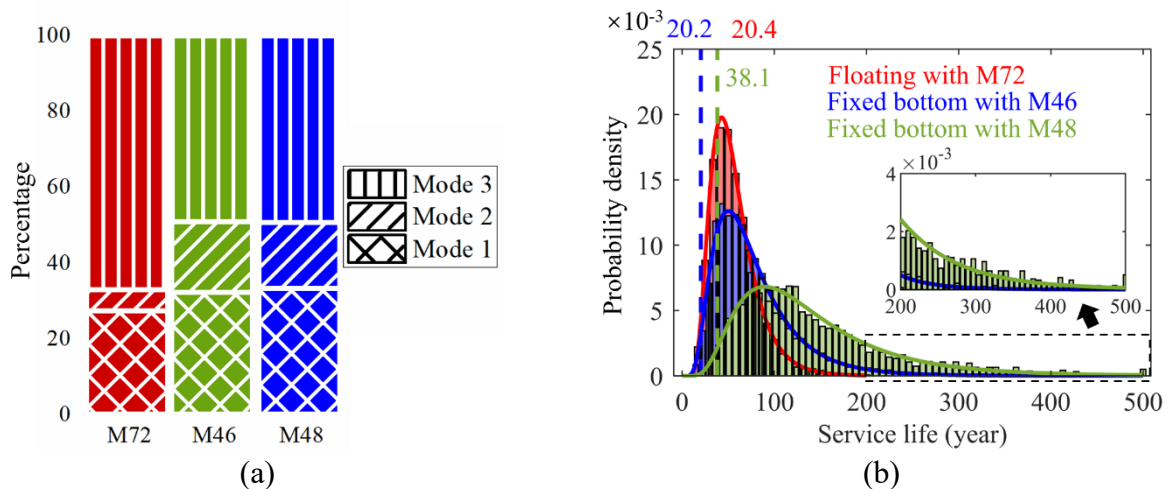


Figure 4-13 Comparison between floating or fixed-bottom foundations: (a) Percentage of failure modes; (b) Service life distribution.

Figure 4-14 provides further insights into the C-F crack growth in bolts of fixed-bottom towers. As indicated in Figure 4-14a, the bolt M46 of fixed-bottom towers exhibits a crack growth

pattern similar to that in the bolt M72 of the floating tower. By contrast, as illustrated in [Figure 4-14b](#), the bolt M48 of fixed-bottom towers shows a reshaped crack growth pattern, indicating an enhanced C-F performance.

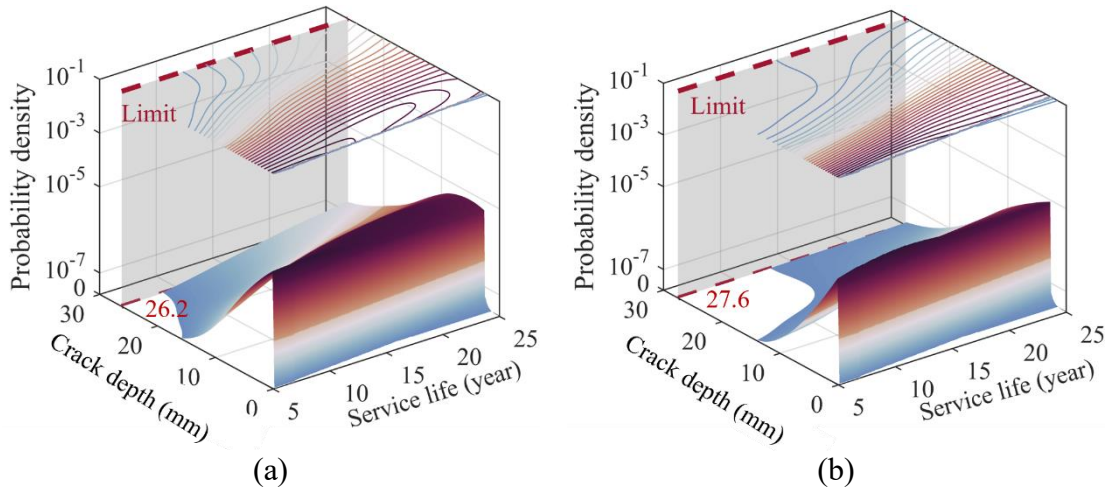


Figure 4-14 Crack growth in different bolts of fixed-bottom towers: (a) M46; (b) M48.

Initially, the concentration of probability mass near the critical crack depth is delayed from 10 to 18 years. Furthermore, even after 25 years, the probability mass remains concentrated around the region of small-to-medium cracks (i.e., less than 10 mm). In light of this, the use of larger-sized bolts is strongly recommended for FOWT towers to enhance their C-F performance.

4.3.2 FOWT tower level

The reliability analysis was conducted on the top 20 most disadvantageous bolts. Under various maintenance strategies, the distribution of the bolts corrosion-fatigue (CF) reliability index is shown in [Figure 4-15](#).

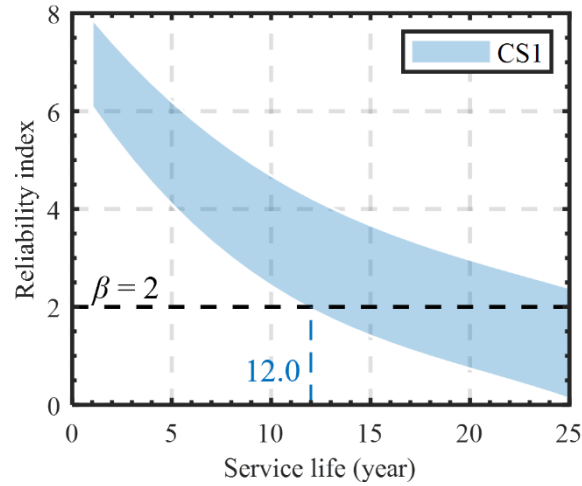


Figure 4-15 The corrosion fatigue reliability of the 20 most critical bolts in the bottom flange.

Figure 4-15 illustrates the reliability progression of the 20 most critical bolts in the RF3 (the lowest flange) under the reference controller. The reliability of the bolts each year follows a log-normal distribution. The safety boundary of $\beta = 2$ is assumed to account for a survival rate of 97.7%, according to Eurocode 3 (Standardization, 2012a). It can be observed that the most critical bolt reaches the safety boundary at 12 years, with the remaining bolts reaching the threshold annually thereafter. All of the first 16 bolts reach the safety boundary within the 25-year service life of the wind turbine. Furthermore, the flange reliability can be determined based on the number of failed bolts and the failure proportion limits under different consequences.

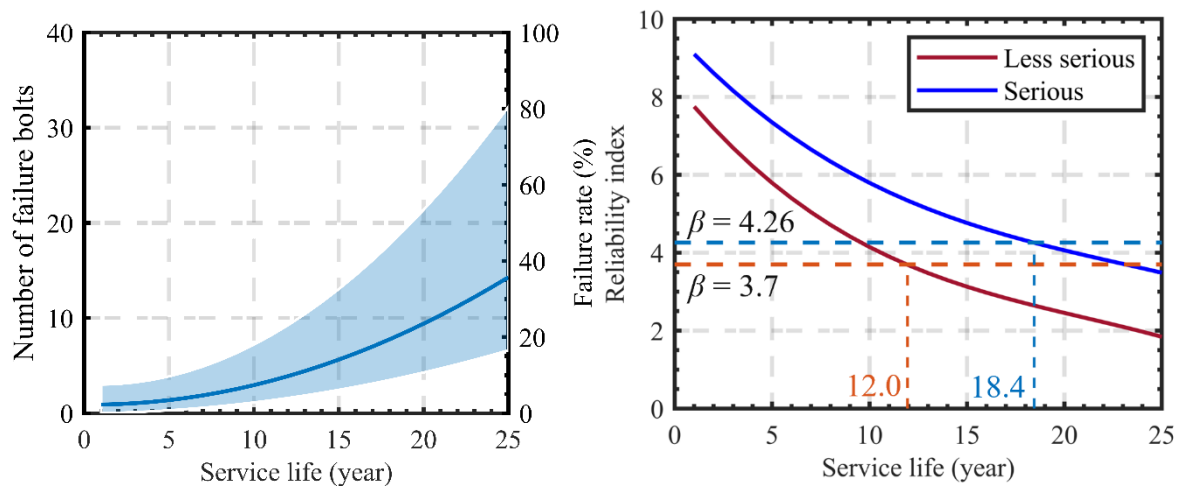


Figure 4-16 Time-variant reliability of the flanged ring. a) Distribution of numbers of failure bolts. b) Reliability of the flanged ring

Figure 4-16a) shows the distribution of bolt failures in the RF3. It can be observed that the mean and lower bound of the number of bolt failures slowly increase with service years, while the growth rate of the upper bound increases annually. This demonstrates that as the service life increases, more bolts are prone to corrosion fatigue failure. Furthermore, Figure 4-16b) compares the reliability index β of the ring flange (RF) under different consequences, with thresholds set at 3.7 and 4.26, respectively. For less serious consequences, the RF reaches the threshold at 12 years, which coincides with the time the most critical bolt enters the danger zone. This indicates that when bolts start to experience fatigue fractures, the flange also enters a critical phase. The RF reaches the serious stage relatively later, at around 18.4 years. This suggests that in the mid to late service life of the FOWT, attention should be paid to tower collapse accidents caused by bolt corrosion fatigue fractures. Additionally, after bolts begin to experience corrosion fatigue fractures, greater attention should be given to the serious consequence of tower collapse.

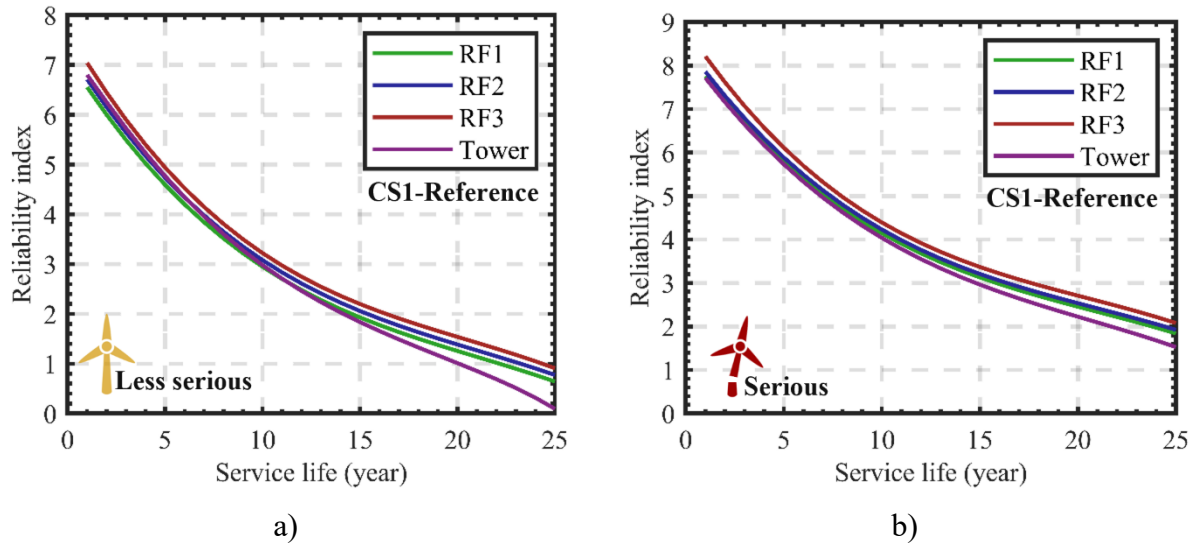
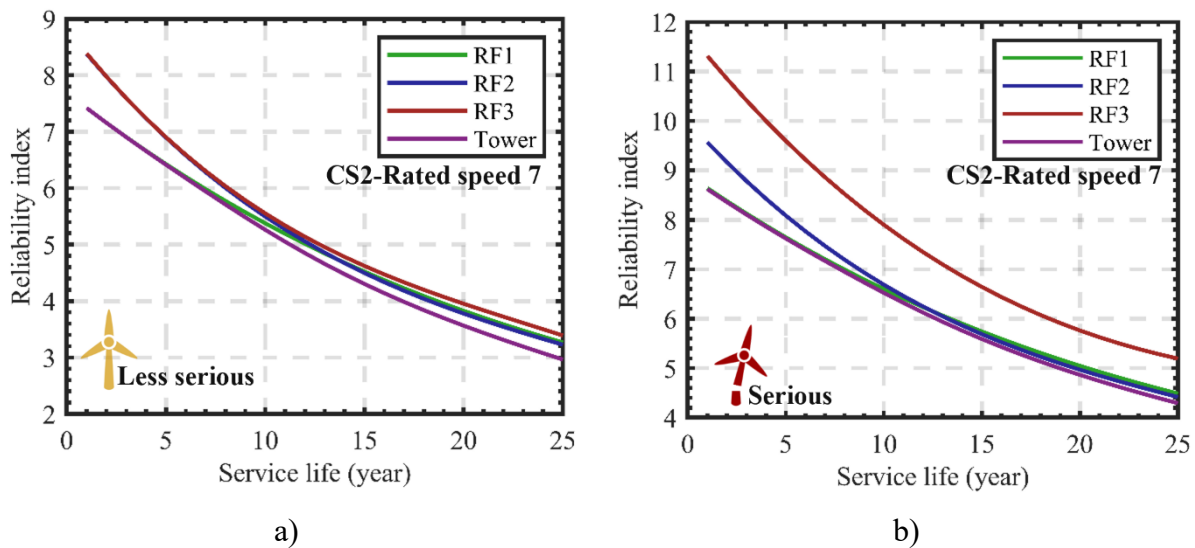


Figure 4-17 Time-variant reliability of the 15MW FOWT tower. a) Less serious; b) Serious

Figure 4-17 shows the reliability of each flange under two different consequences, as well as the overall CF reliability of the wind tower summarized according to Eq 4.15. It can be observed that the CF degradation rates of the three flanges on the same tower are similar, all exhibiting a concave function development trend. However, for less serious consequences, the tower-level CF degradation accelerates towards the end of the service life, indicating that such stages should be avoided in wind turbine CF maintenance. The CF reliability for serious consequences is similar to that for less serious consequences. Notably, the reliability index of the top flange (RF1) is relatively smaller than that of the other two flanges, indicating a higher likelihood of failure.

Discuss how various control strategies influence the structural integrity and fatigue life of wind turbine components.



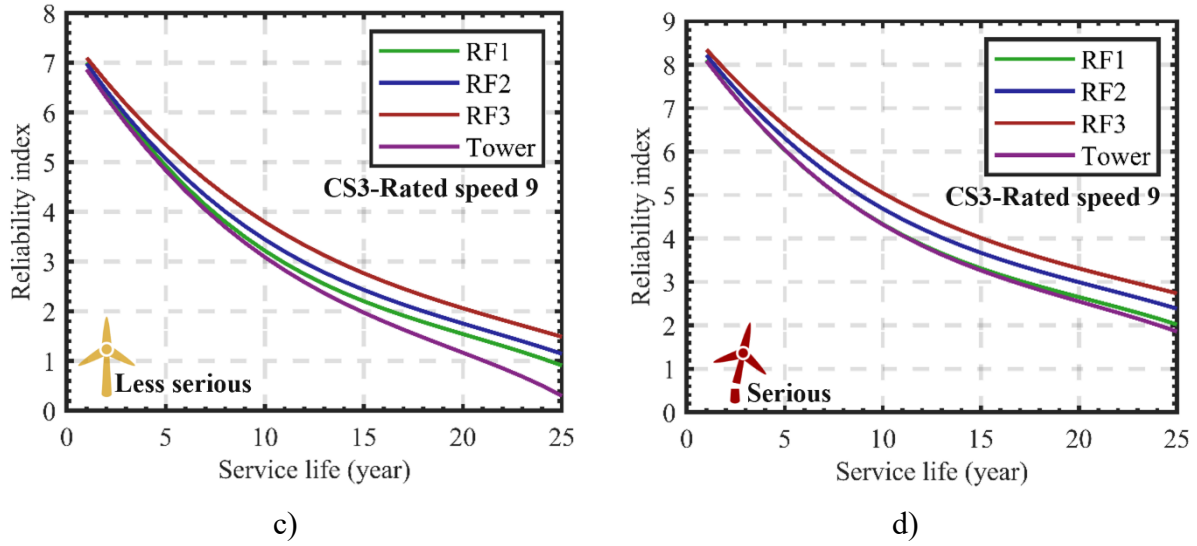


Figure 4-18 Influence of different strategies on the reliability evolution

Figure 4-18 illustrates the CF development under different consequences with de-rating. Compared to Figure 4-17, it can be seen that CF performance significantly improves over the life cycle of the FOWT. For CS2, as shown in Figure 4-18a,b), RF3 exhibits greater reliability than the other ring flanges in the initial years, especially under serious consequences. This is due to the smaller dynamic response of the wind turbine under the CS2 strategy, which is less conducive to CF crack initiation. RF3, as the lowest flange, has a design strength matched to the CS1 operating state, thus having higher strength and being less prone to CF cracking under low-stress levels. In contrast, under the CS3 operating state, the stress levels are slightly lower than under CS1, resulting in a smaller improvement in the reliability of the three flanges compared to CS1, and no significant differences between the flanges are observed, as shown in Figure 4-18c,d).

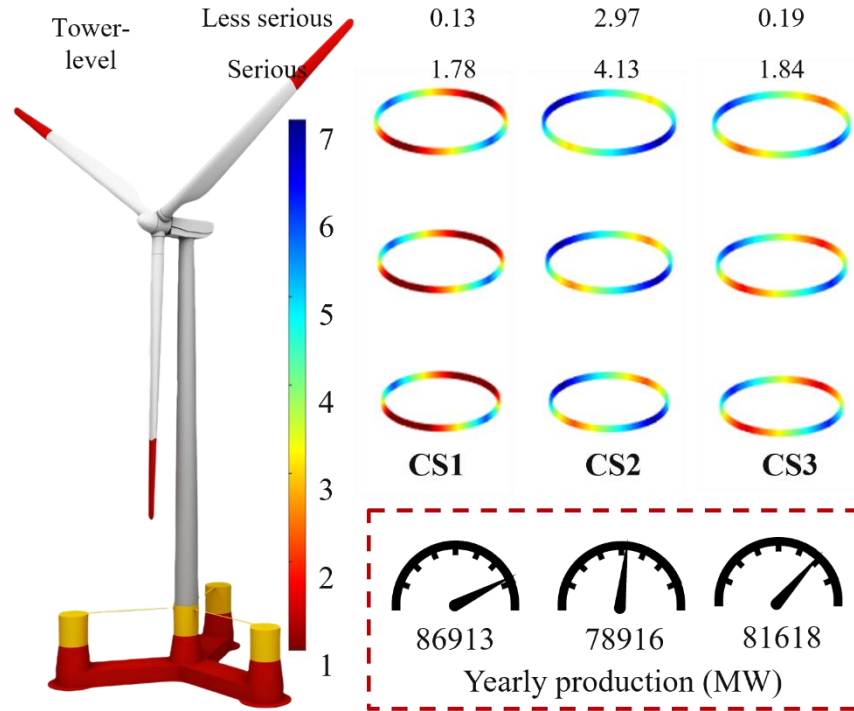


Figure 4-19 CF Reliability of FOWTs over 25 years under different control strategies

Figure 4-19 illustrates the CF reliability of the tower structure under different combinations of consequences and control strategies. It can be observed that from the perspective of a single bolt, reliability is closely related to wind direction distribution, with bolts aligned with the prevailing wind direction being more susceptible to corrosion fatigue damage, while transverse bolts are relatively safer. Under the reference controller (CS1), the FOWT tower exhibits the poorest CF performance, with a value of 0.13 for less serious consequences and 1.78 for serious consequences. When the rated speed is reduced to 9 m/s under CS3, CF performance slightly improves, with improvements of 46.2% and 3.4% for less serious and serious consequences, respectively. A further reduction in rated speed to 7 m/s under CS2 results in a significant improvement in CF performance, with enhancements of 21.8 times and 1.32 times for the two consequences. However, this improvement comes at the cost of reduced turbine capacity, as entering the rated power state earlier reduces overall energy output by 9.20% from CS1 to CS2

and by 6.09% from CS1 to CS3. Furthermore, based on the two-level risk combining reliability and capacity loss the risk in terms of economic loss results is presented in Figure 4-20.

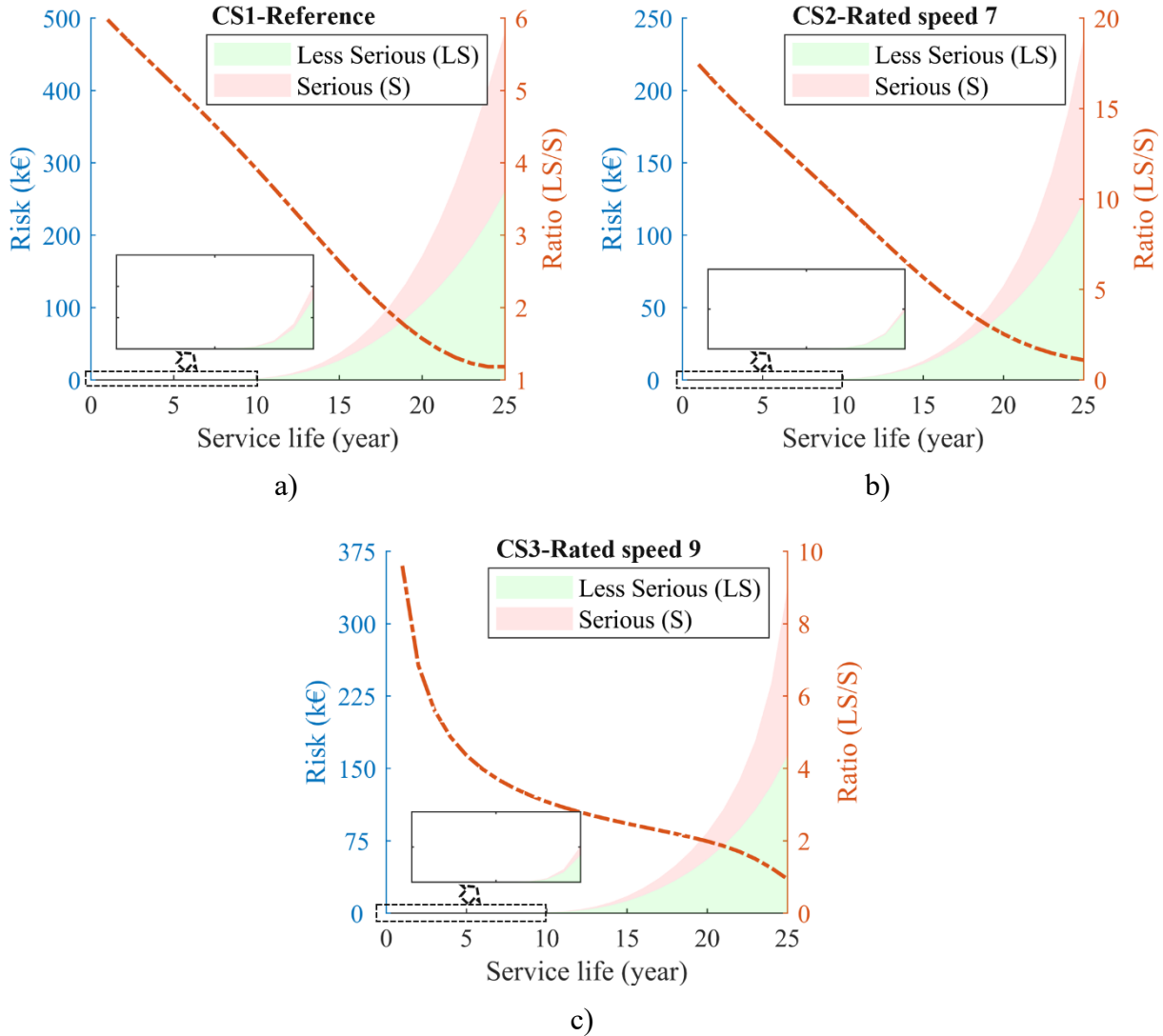
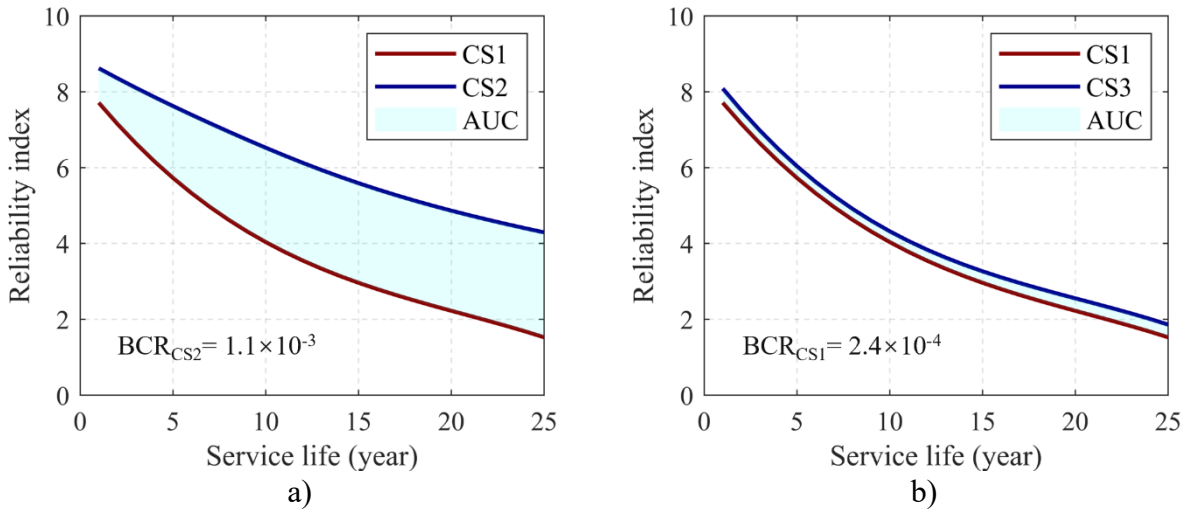


Figure 4-20 Risk assessment of FOWTs under different control strategies. a) CS1; b) CS 2; c) CS 3

Operating at de-rating state can effectively lower the operational risk of FOWT. Compared to the reference controller in Figure 4-20a), the risk under CS2 with a rated speed of 7 m/s in Figure 4-20b) is reduced to half of its original value, and the risk under CS3 with a rated speed of 9 m/s in Figure 4-20c) is reduced to approximately four-fifths of the original value. This demonstrates that control strategy is crucial for managing the life-cycle risk of wind turbines. The line graphs in

the figure represent the ratio of less serious (LS) to serious (S) risks for each year. It can be observed that less serious risks account for a larger proportion of the overall life-cycle risk; however, this proportion decreases as the service life increases. Another point worth noting is that a larger overall risk within the life cycle often corresponds to a lower LS/S ratio, indicating that under high-risk conditions, greater attention needs to be paid to serious consequence events.

In structural maintenance, the cost-effectiveness of each action needs to be considered. This paper uses the benefit-cost ratio (BCR) to compare different actions (Standardization, 2012a). Figure 4-21 compares the BCR of traditional corrective maintenance (CM) and de-rating strategies over the life cycle. It can be observed that as preventive methods, CS2 and CS3 have a higher BCR than corrective methods, with CS2 having a significantly higher BCR than the other two. Therefore, in this analysis, only CS2 is selected as the preventive method. Although corrective methods have a lower BCR, they are the only option after the structure has sustained substantial damage and thus must also be included in the maintenance strategy.



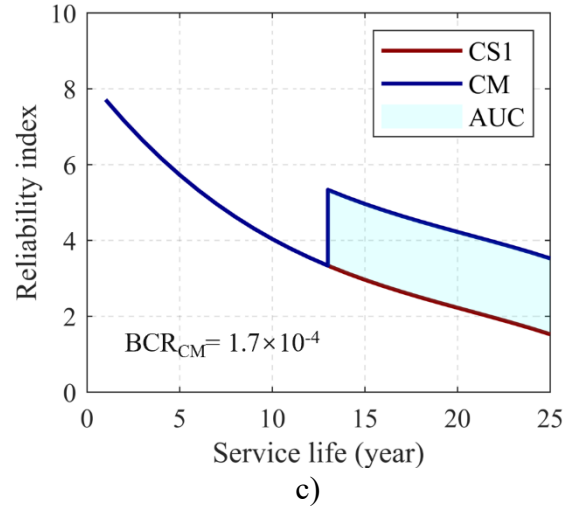


Figure 4-21 Cost-benefit analysis of different operational actions with area under the curve method. a) Strategy C2; b) Strategy C3; c) Corrective Maintenance (CM)

Figure 4-21 shows the comparison of the life-cycle performance of the structure under different O&M strategies, including a 5-year de-rating starting at various times, combined with maintenance and purely maintenance actions. It can be observed that from a performance perspective, early de-rating has a minimal impact on lifecycle performance, whereas late de-rating (start from 15-year) can significantly enhance the CF performance of the wind turbine and reduce the need for one maintenance action. According to the three-stage model of bolt CF cracking in FOWTs described in (Standard, 2005), the fast growth phase in the third stage constitutes the major portion of the time from crack initiation to failure. Therefore, mitigating crack growth in the third stage is more critical than addressing the crack initiation phase during the entire bolt cracking process.

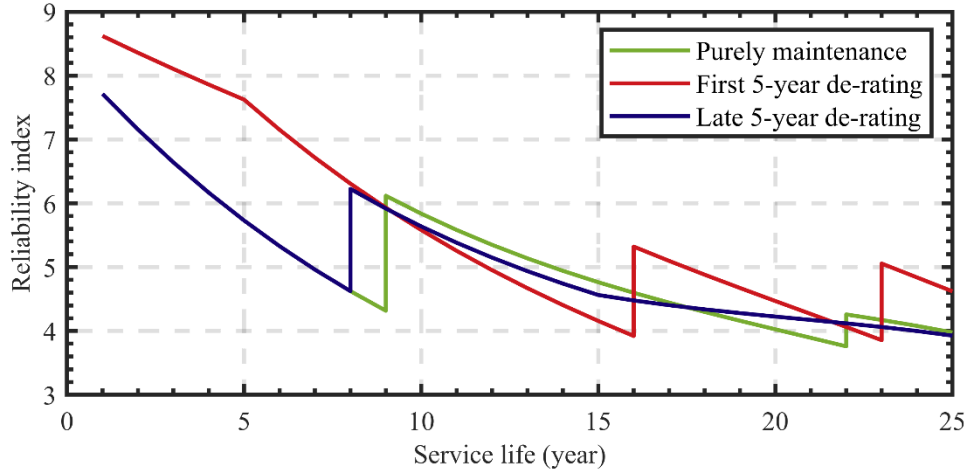


Figure 4-22 Reliability development with different O&M strategies

Furthermore, a GA-based strategy for optimal de-rating timing has been developed for O&M optimization (Mondoro & Frangopol, 2018; J. Zhang, J. Heng, et al., 2024). Corrective maintenance serves as a repair action, while CS2 acts as a preventive measure to delay CF degradation. Two maintenance scenarios are considered in the model: the first aims to reduce the total economic loss over the life cycle (Tao et al., 2023), and the second focuses on the return on investment (ROI) (Lee & Kim, 2007) at the end-of-life, aiming to extend the turbine's lifespan with lower investment to increase total capacity.

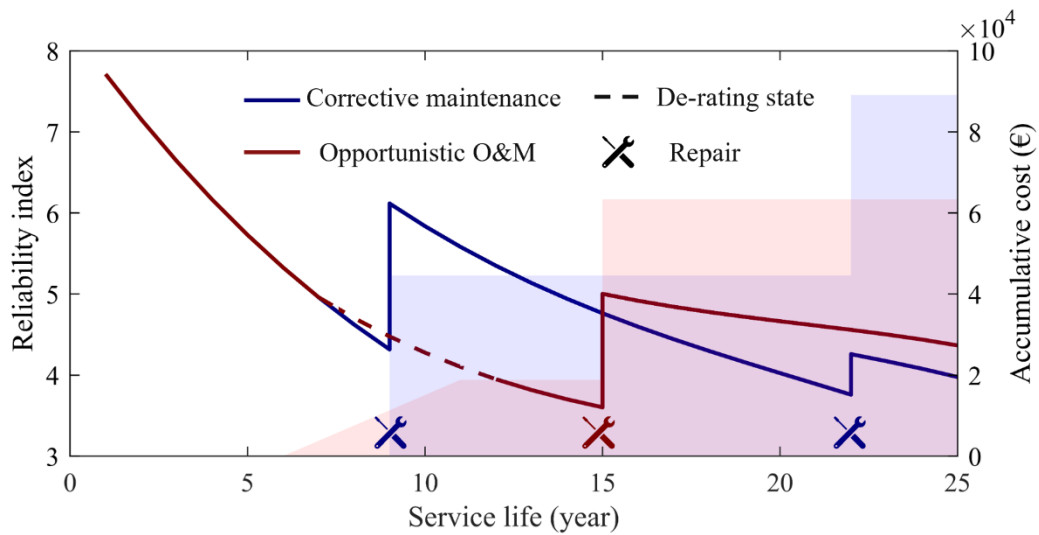


Figure 4-23 Opportunistic O&M scheduling with minimal accumulative cost

It can be observed from Figure 4-23 that the de-rating strategy of CS2 can enhance the CF performance of wind turbines by slowing down the degradation rate. This strategy perfectly aligns with opportunistic maintenance. For different flanges of the wind turbine tower, after some components fail, de-rating can delay the failure time of other components, allowing all components to reach the same maintenance schedule. This improves the utilization efficiency of maintenance vessels, thereby reducing the overall lifecycle costs. Within the life cycle, adopting the proposed opportunistic O&M strategy can significantly reduce the accumulative cost, with reductions of 28.9% compared to traditional reactive maintenance.

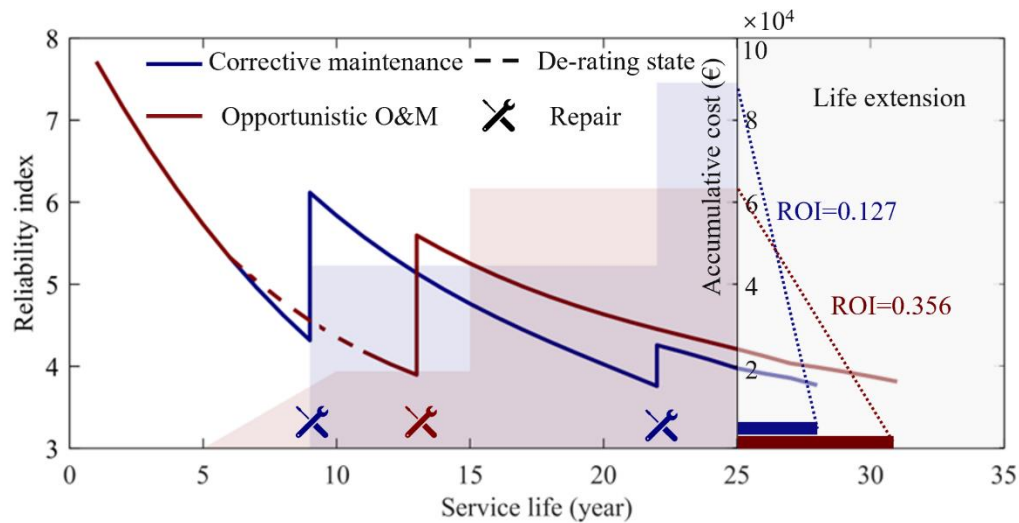


Figure 4-24 Opportunistic O&M scheduling with Maximum ROI

Figure 4-24 presents the optimization results in scenario 2 of ROI based on the end-of-life (EOF) analysis. By extending the lifespan of the wind turbine through O&M with a relatively low investment, the turbine can continue generating capacity beyond its 25-year design life. It can be observed that the proposed opportunistic O&M strategy extends the turbine's lifespan by approximately 6 years, with a total cost of only 63,376 €. From an ROI perspective, this strategy improves ROI by 1.80 times compared to traditional reactive maintenance. This indicates that

combining de-rating with an opportunistic O&M strategy can enhance the overall capacity of the wind turbine over a longer time scale.

4.3.3 Entire structure level

Figure 4-25 illustrates the natural degradation patterns of different components over their entire lifecycle. There are clear differences in the degradation rates of each component. Specifically, the blades and generator exhibit relatively rapid degradation in the early stages of service, with accumulated damage reaching critical thresholds around 14 to 15 years. In contrast, the tower and mooring system experience more gradual degradation in the early years, followed by a sharp increase in failure probability. The tower reaches its critical state around 19.2 years, while the mooring system enters an accelerated degradation phase after 16.3 years. This heterogeneous degradation behavior provides a theoretical basis for optimizing maintenance intervals.

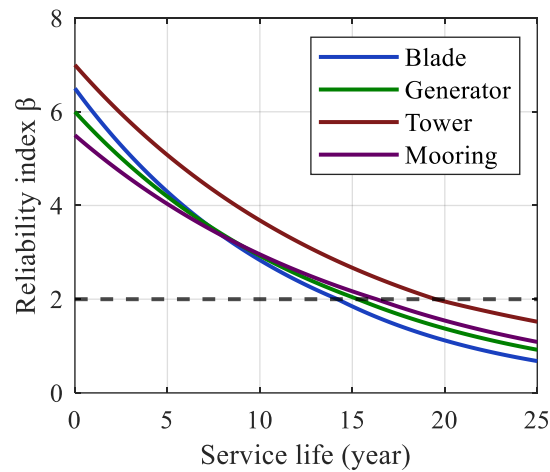


Figure 4-25 Reliability development of each component.

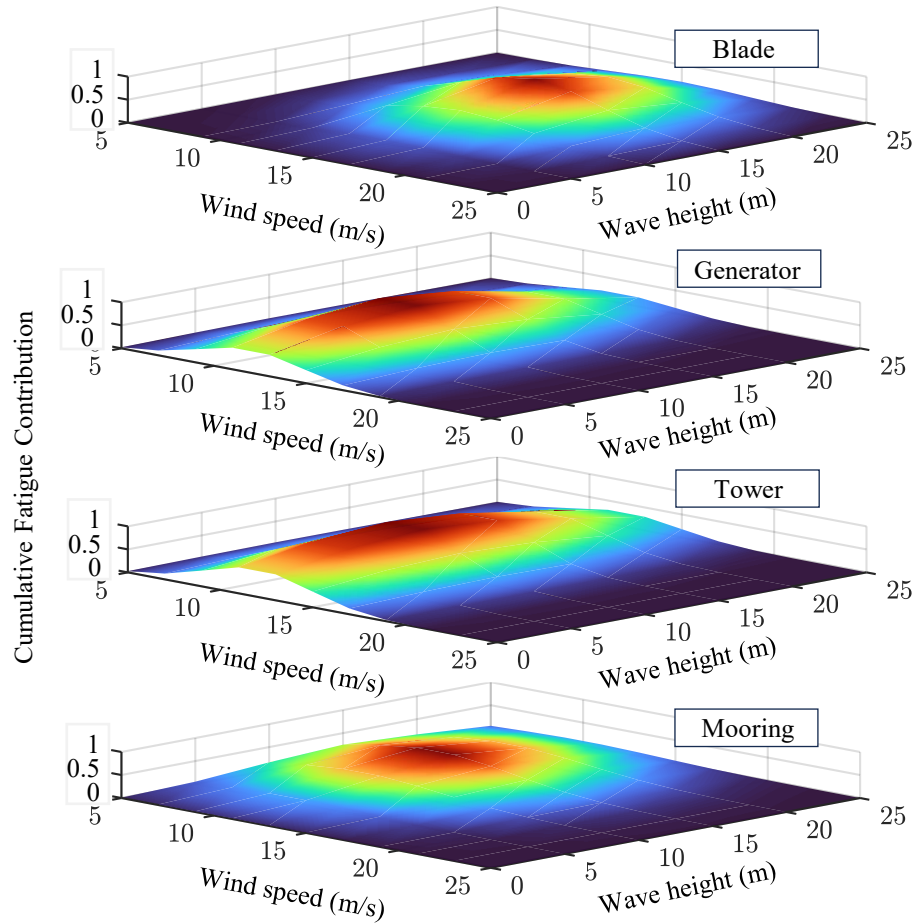


Figure 4-26 Cumulative contribution rates of wind speed and wave height.

Furthermore, we examined how varying wind speeds and wave heights influence the structural response. Figure 4-26 shows the cumulative contribution rates as functions of wind speed and significant wave height. For the FOWT blades, the contribution rate increases with both wind speed and wave height, blade yaw control ensures the blades are always oriented into the wind, so higher wind speeds produce larger aerodynamic loads. The contribution peaks at around 15 m/s, then gradually declines, becoming negligible beyond 23 m/s. This drop-off reflects the local wind-speed distribution, where high-speed events are rare and thus do not contribute appreciably to long-term fatigue damage. In contrast, both the generator and tower exhibit maximal cumulative contributions near the rated wind speed. This reflects the combined effects of pitch control and the wind-speed distribution. Notably, the tower's cumulative contribution remains

sensitive to high wave heights even at elevated wind speeds, producing a skewed distribution toward higher sea states. Finally, for the mooring system, the contribution pattern, akin to the stress distributions shown in Section 3.5, is influenced to some extent by the rated wind speed but is dominated by the wave-height distribution. As a result, its cumulative contribution curve is more gradual and exhibits a lower peak

4.4 Summary

This study integrates site-specific measurements, material test data, multi-physics simulations, and an adapted probabilistic corrosion-fatigue (PCF) model to provide novel insights into the corrosion-fatigue (C-F) degradation of floating offshore wind turbines (FOWTs). Additionally, a Risk & Reliability analysis framework from localized to system-level is proposed using importance sampling. The key findings of this research are succinctly summarized as follows:

1. The degradation of turbine components exhibits distinct temporal and spatial patterns. Under the baseline environmental scenario with mean wind speed of 11.5 m/s and significant wave height of 4.2 m, blades and generators reach critical degradation thresholds within 14–15 years, while the tower approaches critical conditions at 19.2 years and the mooring system shows accelerated deterioration after 16.3 years. The corrosion-fatigue life of high-strength bolts is particularly affected by marine environmental conditions, with their service life in highly corrosive conditions limited to only 20.4 years, approximately 30.4% of their life expectancy under onshore conditions (67.2 years). These heterogeneous degradation patterns provide a theoretical basis for developing differentiated maintenance strategies, where dynamic adjustments to maintenance cycles can delay the degradation of critical components and reduce overall O&M costs.
2. In simulations performed for a 25-year lifecycle under North Sea environmental loading

conditions, switching from the reference controller (CS1) to CS3 (cut-in wind speed 9 m/s) results in a 46.2% improvement in corrosion-fatigue reliability, while reducing power generation capacity by 9.03%. This underscores the crucial role of control parameter optimization in balancing structural safety and economic gains. The tower shows sustained sensitivity to high wave heights, with its cumulative damage contribution exhibiting an asymmetric distribution that increases with wave height at high wind speeds, while mooring system damage is predominantly influenced by wave height. These results highlight the differentiated impact of multi-physics coupling in marine environments on degradation pathways.

3. Using CS2 control (7 m/s cut-in wind speed) reduces the 25-year cumulative risk by 50.9% (to €236.07k), with a benefit-cost ratio (BCR) of 1.1×10^{-3} , far surpassing conventional maintenance strategies. Over the long term, the OOM strategy achieves a 28.88% cost savings and a 9.25% increase in revenue by reducing the frequency of on-site maintenance. Furthermore, the risk profile evolves over the turbine's service life, with the ratio of low-risk/high-risk events (LS/S) steadily decreasing. This indicates the need for risk-based management strategies tailored to different operational phases, optimizing the balance between safety and economic performance.
4. The tower flange (RF1), despite experiencing relatively low stress, shows the lowest reliability due to insufficient design strength, exposing potential weaknesses in traditional structural design. The dynamic characteristics of the floating platform significantly enhance bolt performance, and fixed platforms require M72 bolts to match the corrosion-fatigue resistance of M46 bolts on floating platforms. The study further demonstrates that corrosion-fatigue reliability is governed by both stress amplitude and material strength

degradation, highlighting the importance of considering both factors in long-term reliability assessments.

CHAPTER 5

AI-powered dynamic performance prediction

5.1 *Introduction*

High-fidelity simulations of FOWTs provide detailed insights but involve prohibitive computational costs when applied to long-term or real-time scenarios. Hybrid methods that combine data-driven modeling with physical constraints have been proposed to address this limitation. This chapter follows the degradation assessment of Chapter 4 and establishes the computational basis required for the maintenance strategies presented in Chapters 6 and 7. In particular, the models introduced here serve as the analytical core of a digital twin, providing the data-driven and physics-consistent layer that enables continuous monitoring and rapid prediction.

Physics-informed surrogate models are constructed to reproduce dynamic responses with reduced computational demand while maintaining consistency with governing principles. These models form the essential modeling component of the digital twin, which will subsequently be used to support adaptive operation and opportunistic maintenance strategies.

5.2 *Integrated physics-informed deep learning*

Conventional data-driven methods optimize parameter gradients by minimizing the discrepancy between actual and predicted data, often requiring large datasets to uncover underlying patterns and typically failing to provide interpretable predictions (Luo et al., 2024). PIML, however, integrates rational physical concepts to guide the neural network training process, improving

interpretability by incorporating dynamic equations from partial differential equations (PDEs) (Mousavi et al., 2024), as shown in Figure 5-1. These equations include stiffness (K), mass (M), damping matrices (C), and load relationships (F). However, resonance requires consideration of frequency domain information between loads and structures, which is not fully captured by PDEs. To address this, this study introduces physical information on resonance to guide the extraction of machine learning features and designs a loss function that combines both data loss (JD) and physical loss (JP) related to resonance, with the goal of minimizing the weighted loss function. The PIML analysis process is illustrated in Figure 5-1.

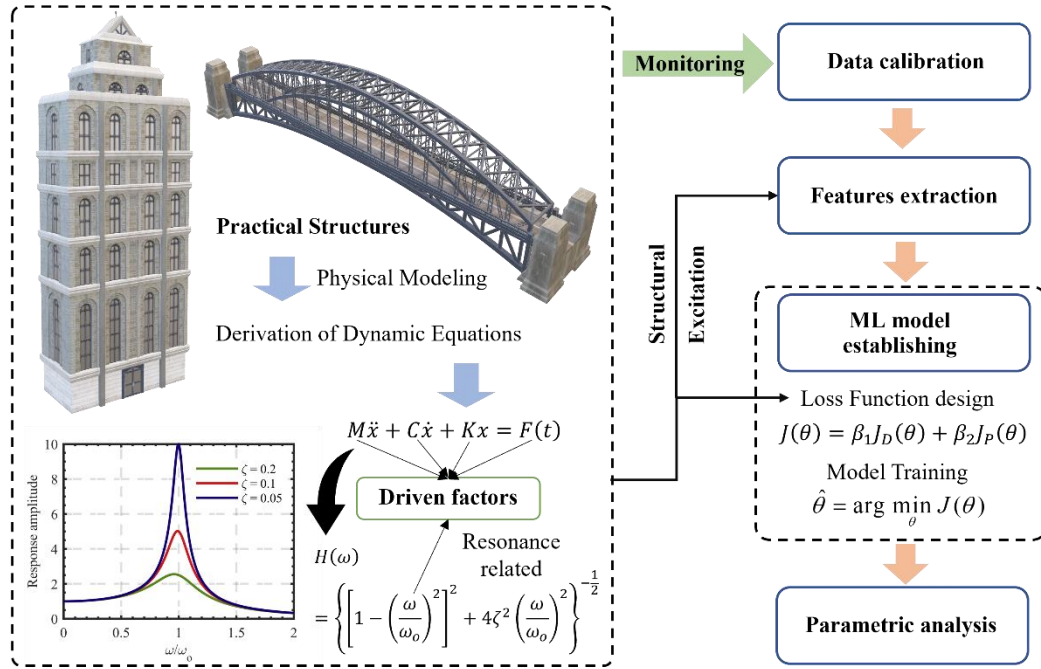


Figure 5-1 Framework of the research

5.2.1 Neural network architecture

This section proposes a regression-oriented Physics-Informed Machine Learning (PIML) architecture for peak value modeling. The regression-based approach allows for straightforward estimation of how the model will respond to changes in the signal, as the underlying function is clearly defined. This feature enables the detection of deviations from normal behavior in the signal.

In contrast, multilayer perceptrons (MLPs) are more complex models, characterized by nested nonlinearity, which retain information from the training data. This "black box" approach fits a single function to the data, resulting in a loss of transparency into the underlying problem (Xu et al., 2022). The use of neural networks (NNs) necessitates careful consideration of various factors. The field of artificial neural networks is vast, with an extensive body of literature on the subject. Relevant references in this study include (Géradin & Rixen, 2014; Haykin, 1998). For any specific application, the primary concern is determining the appropriate network setup. Identifying the correct neural network setup involves several critical factors (Haykin, 1998), including the selection of the network type, transfer/activation functions, input data preprocessing and validation, the number of training patterns, network architecture (layers, neurons, and connectivity), training methods, and weight initialization.

In this study, MLPs are combined with Sigmoid transfer functions. The iterative nature of the weight optimization process makes the curve shape of the transfer function critical, as it greatly influences the number of iterations and the stability of the process. If the weight adjustments are too large for functions with steep gradients, oscillations may occur. The output formulation for a single hidden layer, single output feedforward neural network is given by Equation (5.1).

$$\tilde{y} = \delta_2 \left(\sum_{i=1}^m \left(w_i^{(2)} \delta_1(X) \right) + b^{(2)} \right) X = \sum_{j=1}^n \left(x_j w_{xj}^{(1)} \right) + b^{(1)} \quad (5.1)$$

where $\tilde{y}$ represents the output of the layer; x_j and $w_{xj}^{(1)}$ correspond to the input and weights of the neuron respectively. $b^{(1)}$ denotes the bias of the layer.

The network structure, including the number of layers, connectivity, and number of neurons, can generally be selected arbitrarily. The goal of the iterative process for determining the

architecture is to identify a network structure that provides the best generalization. For this study, a two-layer network is employed for the given application.

As highlighted in the study by (Rafiq et al., 2001), determining the optimal number of neurons requires conducting at least ten trials, with the number of neurons being the sole variable adjusted. The network architecture that provides the best generalization should be chosen. This approach helps reduce the risk of selecting a solution that lacks sufficient generalization ability (Schlechtingen & Santos, 2011). Therefore, this methodology has been adopted in this research. A feedforward network type was selected due to its simplicity, making it a reliable starting point unless a more complex architecture is necessary for the specific application. For this application, the chosen architecture has been validated as appropriate. Each neuron in the hidden layer is connected to the inputs, and each neuron in the output layer is subsequently linked to them. The final network architecture for the dynamic response prediction MLP model is presented in Figure 5-2.

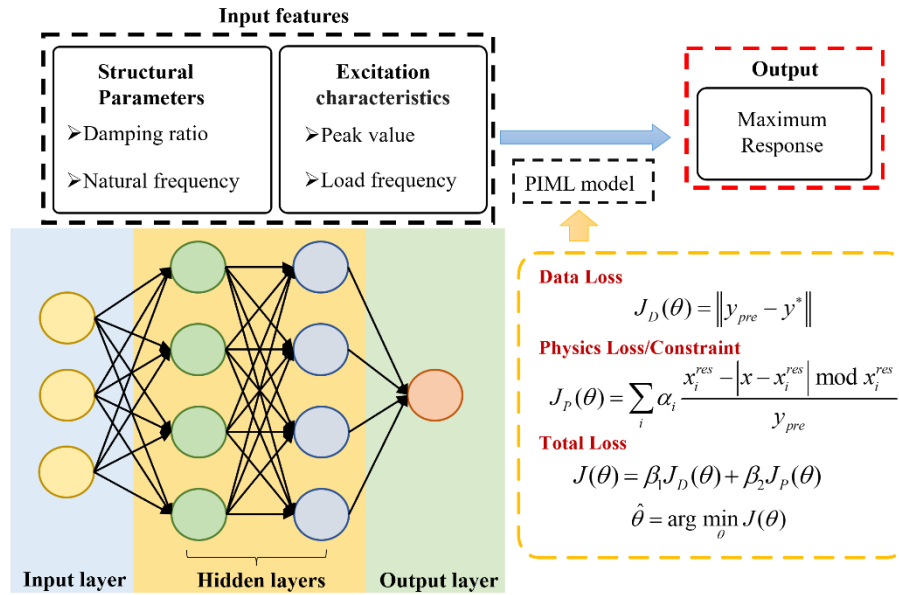


Figure 5-2 Illustration of physics-informed machine learning (PIML)

When training MLPs using the error back-propagation algorithm, the first step involves initializing the weights in both layers with small random values, typically ranging from -0.01 to +0.01 (Tarassenko, 1998). This initialization with small weights helps identify unused input signals, as the weights associated with these signals stay close to their initial values. These unused inputs can then be eliminated, thereby enhancing computational efficiency.

5.2.2 Physical constraints

Typically, structural dynamic analysis examines the response of a structure when subjected to external forces. The forced vibration of a damped structure can be expressed as (Tarassenko, 1998):

$$M\ddot{x} + C\dot{x} + Kx = F(t) \quad (5.2)$$

where, M , C and K are mass, damping and stiffness matrices, respectively.

The effect of resonance can be mathematically described by solving for the dimensionless response amplitude of the system at different forcing frequencies. Assume that the system is subjected to a harmonic loading function with frequency ω and amplitude P_0 :

$$F(t) = P_0 \sin(\omega t) \quad (5.3)$$

The displacement as a function of time can be expressed as:

$$x(t) = \frac{P_0}{K} \sin(\omega t) \quad (5.4)$$

where, P_0 is the maximum applied force and $H(\omega)$ is a dimensionless function that depends on the forcing frequency. Substituting Equation (5.3) and (5.4) into Equation (5.2) and solving for $H(\omega)$, the following expression is obtained:

$$H(\omega) = \left(\left[1 - \left(\frac{\omega}{\omega_o} \right)^2 \right]^2 + 4\zeta^2 \left(\frac{\omega}{\omega_o} \right)^2 \right)^{-\frac{1}{2}} \quad (5.5)$$

$$\omega_o = \sqrt{\frac{k_1}{m}} \quad (5.6)$$

$$\zeta = \frac{c}{2m\omega_o} = \frac{c}{2\sqrt{k_1 m}} \quad (5.7)$$

where ω_o is the natural frequency and ζ is the damping ratio (Figure 5-3).

A periodic force is applied to the system with frequencies ranging from zero (steady force) to twice the system's natural frequency. The dimensionless response amplitude is defined as the maximum displacement from the equilibrium position divided by the displacement caused by a static force of the same magnitude. In other words, the response amplitude equals one when the forcing frequency is zero (Tarassenko, 1998). Resonance occurs when the forcing frequency approaches the system natural frequency.

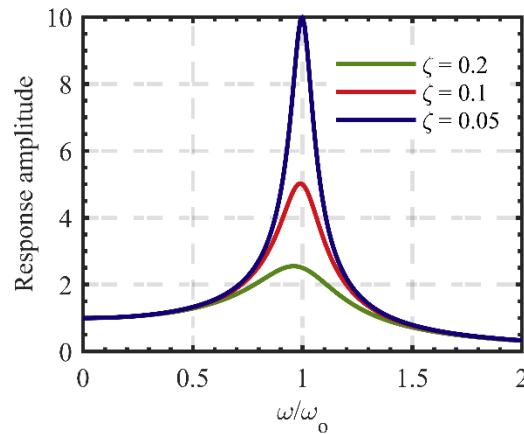


Figure 5-3 Harmonic response functions of a linear spring–mass system

The analysis of most structural systems requires a more complex idealization, even if the response can be described by a single degree of freedom. The generalized-coordinate approach enables the representation of the response of more intricate structural systems using a single, time-dependent coordinate, referred to as the generalized coordinate.

Typically, only a small number, n , of eigenfrequencies are calculated. The result of this computation is a set of natural frequencies, ω , along with their corresponding mode shapes, u_i , where i ranges from 1 to nnn . It can be shown that the eigenmodes are orthogonal (or, in the case of repeated eigenvalues, can be chosen to be orthogonal) with respect to both the mass and stiffness matrices. This orthogonality implies that:

$$\begin{aligned} u_i^T M u_j &= 0 & i \neq j \\ u_i^T K u_j &= 0 & i \neq j \end{aligned} \quad (5.8)$$

The basic assumption in mode superposition is that the displacement can be written as a linear combination of the eigenmodes:

Displacements in the structure are related to the generalized coordinate as:

$$v(x, t) = \varphi(x)Y(t) \quad (5.9)$$

where $Y(t)$ is the time-dependent generalized coordinate and $\varphi(x)$ is a spatial shape function that links the structural degrees of freedom, $v(x, t)$, to the generalized coordinate. For a generalized SDOF system, it is essential to express the restoring forces in the damping and stiffness elements in terms of the relative velocity and relative displacement between the ends of the element:

$$\begin{aligned} \Delta \dot{v}(x, t) &= \varphi(x)\dot{Y}(t) \\ \Delta v(x, t) &= \varphi(x)Y(t) \end{aligned} \quad (5.10)$$

5.2.3 Loss function design

The central idea presented in this context is the optimization of the network hyperparameters θ , which consist of the weight W_θ , b_θ , parameters of the neural network. This optimization allows the PIML to not only interpret measurement data but also align with the underlying physical phenomena (J. Zhang, X. Lei, et al., 2024).

The data loss $J_D(\theta)$ based the measurements

$$J_D(\theta) = \|y_{pre} - y^*\| \quad (5.11)$$

where y_{pre} is the dynamic response predicted by the PIML method, while y^* is the actual dynamic response.

The core of resonance phenomena lies in the difference between natural frequencies and loading frequencies. It is proposed that the predicted outcomes should cover a broader frequency range for structural responses near resonance points, in contrast to those at frequencies farther away. To address this, the physics loss function incorporates the difference between the loading frequency and the structure's natural frequency as a key guiding factor. Since resonance at lower-order natural frequencies can significantly amplify the load, a remainder function is used to represent the proximity between the loading frequency and the lower-order structural frequencies. For frequencies near resonance, response amplification is necessary.

In the context of PIML, the optimization process aims to minimize the loss function. To achieve this, the reciprocal of the predicted values is utilized, ensuring that the response is maximized at the resonance points. This approach guarantees that as the predicted frequency approaches the actual resonance frequency, the corresponding structural response is properly amplified, aligning with the physical reality of increased responses at resonance within the PIML grid. Consequently, the physics loss introduces a constraint for the neural network that models the relationship between the output features and the structural fundamental frequencies.

$$J_p(\theta) = \sum_i \alpha_i \frac{x_i^{res} - |x - x_i^{res}| \bmod x_i^{res}}{y_{pre}} \quad (5.12)$$

where x_i^{res} is the i th natural frequency of the structure, x is the load frequency, and α_i represents the weighting coefficient for this mode of vibration.

The total loss $J(\theta)$ is then defined as

$$J(\theta) = \beta_1 J_D(\theta) + \beta_2 J_P(\theta) \quad (5.13)$$

where β_1 and β_2 represent the weighting coefficients for data loss and physics loss, respectively.

The model will be trained and optimized to minimize the objective function defined as follows:

$$\hat{\theta} = \arg \min_{\theta} J(\theta) \quad (5.14)$$

5.3 Illustrative Example for classical resonance-driven structures

5.3.1 Case 1: Single degree of freedom (SDOF) system

The single-degree-of-freedom (SDOF) system is a fundamental concept in structural dynamics and mechanical engineering. It consists of a mass point, a spring, and a damping element. The mass represents the inertial properties of the structure, the spring models its stiffness, and the damping element accounts for energy dissipation. This simplified model enables engineers to focus on the essential dynamics of the system, free from the complexities of multi-component structures. Despite its simplicity, the SDOF system serves as an effective tool for understanding more complex structural systems and their responses to various loading conditions.

The fundamental frequency of the SDOF system is distinct and considerably different from the higher-order primary frequencies, resulting in a clear resonance effect. Therefore, the forced vibration of the SDOF system (as depicted in Figure 5-4) is initially used to validate the proposed PIML algorithm.

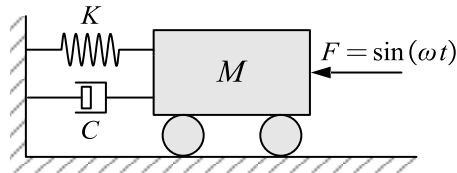


Figure 5-4 Simulation model of a single freedom

The single-degree-of-freedom structural system exhibits a distinct first-order natural frequency that is directly proportional to the structure's mass and inversely proportional to its spring stiffness. As a result, significant peaks are observed in the defined variable space. Figure 5-5 presents a four-dimensional representation of the maximum displacement response of the structure, plotted against excitation frequency, stiffness, and mass. The color gradient on the color bar indicates the extreme values of the displacement response, measured in millimeters.

As shown in Figure 5-5, a peak response band indicative of resonance appears on the xoy plane, with a concentrated distribution along the linear relationship between mass and stiffness. This occurs because resonance requires the structure's natural frequency to remain consistent with a fixed load frequency, which is determined by the linear relationship between stiffness and mass.

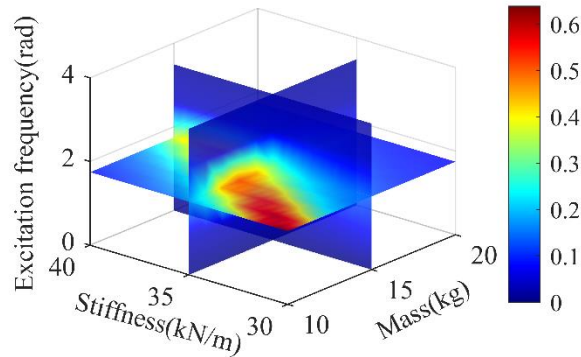


Figure 5-5 A four-dimensional representation of the displacement response

The maximum response of the structure is observed where the displacement cloud intersects with the natural frequency reference line, demonstrating that the proposed PIML method can successfully identify the structure's resonance. To further highlight the local resonance information captured by the algorithm, the analysis space is divided into four equal segments based on stiffness and mass. Figure 5-6 illustrates the distribution of vibration response peaks at various excitation frequencies. The diagram clearly shows that an excitation frequency of approximately 1.7 rad

within the analyzed region triggers the maximum vibration of the structure. This phenomenon is attributed to the constant excitation amplitude and the maximum displacement generated by the combination of the smallest stiffness and mass.

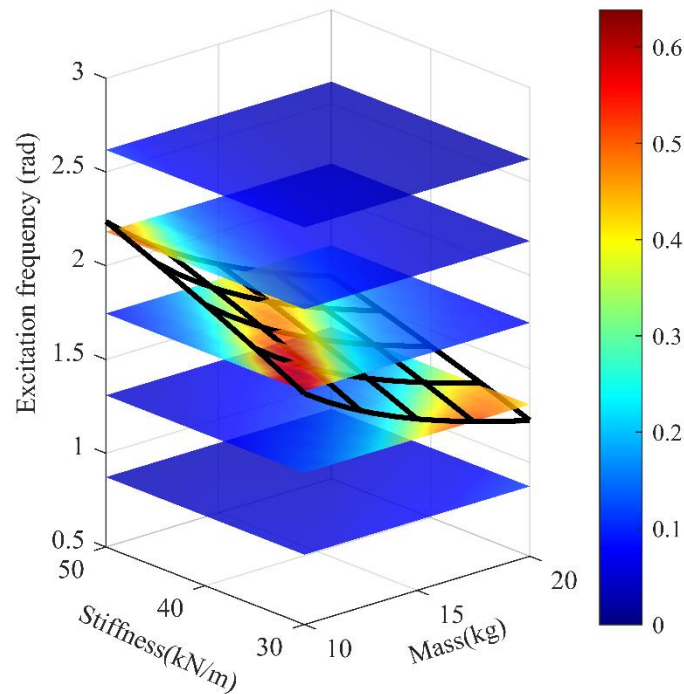


Figure 5-6 A four-dimensional representation of the displacement response under varying loading frequencies

5.3.2 Case 2: Vehicle-Bridge coupled system

The vehicle-bridge coupled system is a critical subject of study in structural dynamics and transportation engineering. It focuses on the dynamic interaction between vehicles and bridges, considering how both components mutually influence and respond to each other ([Géradin & Rixen, 2014](#)). Understanding this interaction is vital for designing safe and efficient transportation

infrastructure, and for evaluating the dynamic performance and durability of bridges subjected to moving vehicle loads.

The vehicle-bridge interaction (VBI) system (shown in Figure 5-7) consists of three subsystems: the train, the track, and the bridge. These subsystems are spatially coupled through nonlinear wheel/rail interactions and track/bridge interactions. The dynamic equations of motion for the coupled system can be expressed as follows:

$$\begin{aligned} M_n \ddot{u}_n + C_n \dot{u}_n + K_n u_n &= F_n \\ M_t \ddot{u}_t + C_t \dot{u}_t + K_t u_t &= F_t \\ M_b \ddot{u}_b + C_b \dot{u}_b + K_b u_b &= F_b \end{aligned} \quad (5.15)$$

where M , C and K are the mass, damping, and stiffness matrices, respectively. The subscripts "n", "t" and "b" refer to the vehicle, track, and bridge subsystems, respectively. The vectors $\ddot{u}$, $\dot{u}$, u and F represent acceleration, velocity, displacement, and forces, respectively.

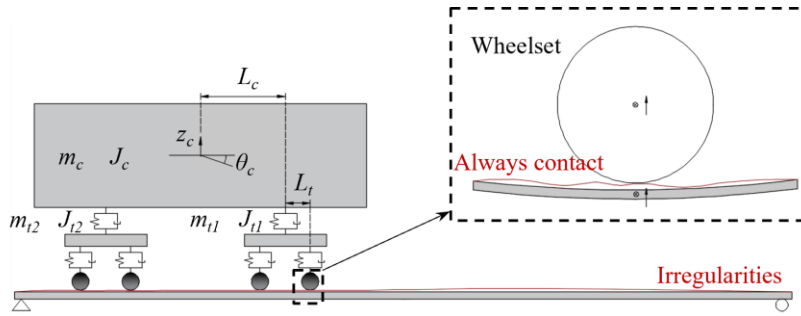


Figure 5-7 Illustration of the vehicle-bridge coupling system

For a simply-supported bridge, the critical speeds associated with resonance can be derived analytically (Miller, 2005) and are summarized in Table 5-1. In the table, V_{br} denotes the resonance train speed (km/h), while f_{vn} and f_{ln} are the n th vertical and lateral natural frequencies of the bridge (Hz), respectively. L_b is the length of the bridge span (m).

Table 5-1 The resonance speed condition

Descriptions	Speeds (km/h)
Basic resonance speed in vertical direction	$V_{br} = \frac{3.6f_{vn}L_b}{i}; n = 1,2,3,\dots; i = 1,2,3,\dots$
Basic resonance in lateral direction	$V_{br} = \frac{3.6f_{ln}L_b}{i}; n = 1,2,3,\dots; i = 1,2,3,\dots$

Given the fundamental frequency ranges for railway bridges, the speeds linked to the first lateral and second resonant conditions significantly exceed current operational train speeds. Special attention should be given to the first vertical resonance in the dynamic design of high-speed railway bridges, as its resonance significantly amplifies, primarily due to the first flexural mode.

$$\omega_n^2 = n^2\pi^2 \sqrt{\frac{EI_y}{\bar{m}L_b^4}}; \omega_n = 2\pi f_{vn} \quad (5.16)$$

where, $\bar{m}$ is the unit mass per meter; E is the Young's modulus.

The numerical examples assume an ICE-3 train (Zhai & Zhai, 2020) with eight vehicles, operating at speeds ranging from 100 km/h to 400 km/h in 10 km/h increments. These trains traverse simply-supported concrete bridges, with span lengths ranging from 30 m to 50 m. Table 5-2 summarizes the range of factors considered in this study.

Table 5-2 Range of influencing factors in the VBI system

Part	Symbol	Parameter	Units	Upper	Lower
Material	ρ	Concrete density	kg/m ³	2000	3000
	E	Concrete elastic modulus	GPa	30	40
	A	Section area	m ²	5	10
Geometry	J	Torsional moment of inertial	m ⁴	10	20
	I_z	Bending moment of inertia about the Z axis	m ⁴	5	10
	I_y	Bending moment of inertia about the Y axis	m ⁴	50	70
Structure	ξ	Bridge damping	-	0.03	0.1

The material properties, geometrical features, and structural damping are considered when determining the bridge parameters. The bridge parameter vector $\mathbf{X}_B$ is constructed as follows:

$$\mathbf{X}_B = [\rho \quad E \quad A \quad J \quad I_z \quad I_y \quad \xi] \quad (5.17)$$

Based on the parameter ranges presented in Table 5-2, a total of 1000 sample sets were generated, with 700 sets used for model training, 150 for validation, and the remaining 150 for testing. The trained PIML model was compared with the actual simulation results to validate the accuracy of the algorithm and its ability to capture the resonance effect.

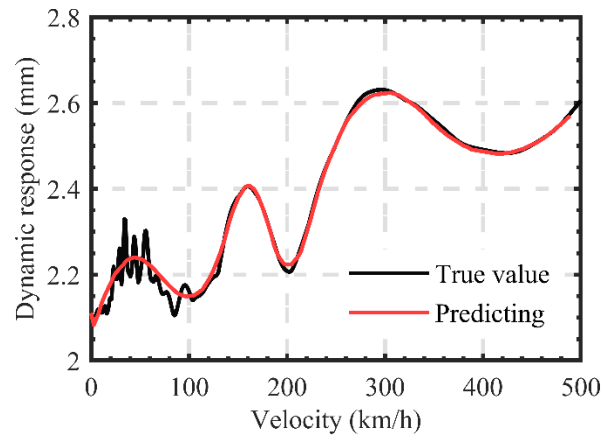


Figure 5-8 Maximum displacement at bridge mid-span against velocity.

Figure 5-8 shows the variation in response with vehicle speed, computed and plotted by the PIML for a VBI system with specified parameters. As observed, the proposed PIML method can accurately match the actual bridge dynamic response, capturing the resonance peak of the bridge, particularly in the speed range of 100 to 300 km/h, which is critical for high-speed rail.

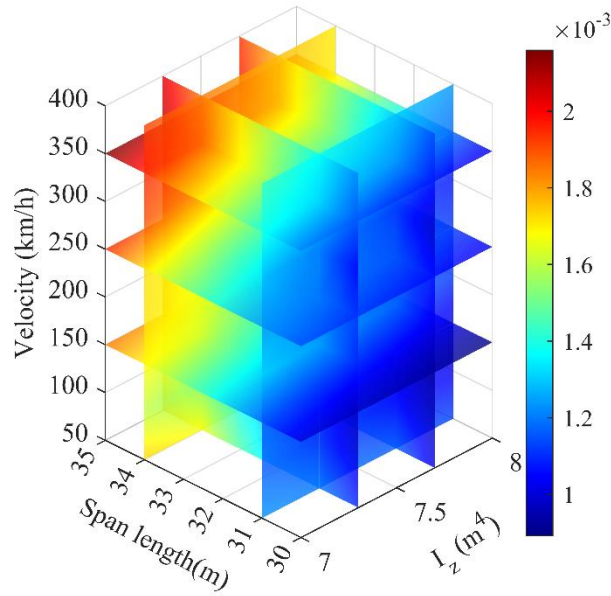


Figure 5-9 Maximum acceleration distribution at mid-span of the bridge.

The moment of inertia is the most influential factor in the bridge's dynamic response. The features are not monotonically related to the bridge's dynamic response due to the resonance effect. For the example shown, the resonance effect occurs near a speed of 200 km/h, where the maximum power response is observed.

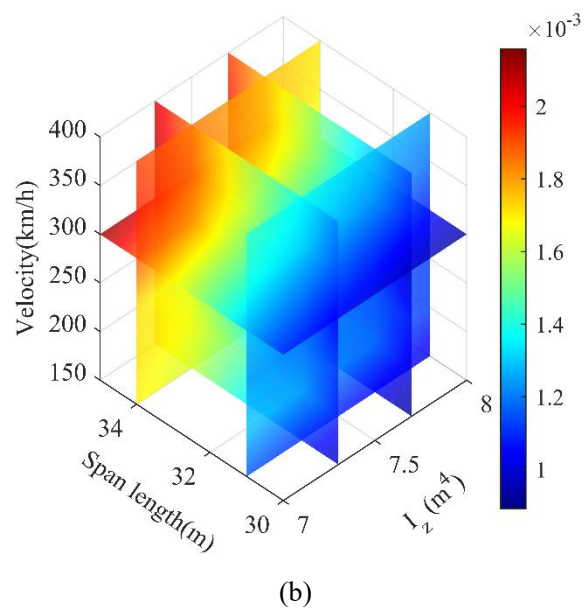
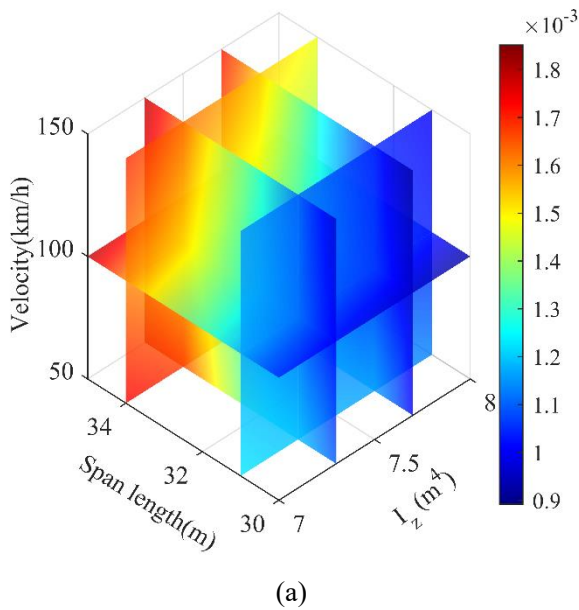


Figure 5-10 A four-dimensional representation of maximum acceleration at mid-span of the bridge at different running speeds. a) 50-150km/h, b) 150-400km/h.

5.3.3 Case 3: Tall buildings

The PIML architecture is further demonstrated using field sensing data. The building in focus is a 108-story, 484 m (1,588 ft) commercial skyscraper completed in 2010 in West Kowloon, Hong Kong. It is part of the Union Square project atop Kowloon Station. The monitoring system consists of four accelerometers, each with a sampling frequency of 100 Hz, strategically placed at heights of 52, 179, 299, and 405 meters. This configuration ensures comprehensive coverage of dynamic responses at critical points along the structural vertical span, providing a robust dataset for structural health monitoring and assessment. Typhoon Hato, a strong tropical cyclone that impacted South China in August 2017, is considered for the study. It was the thirteenth named storm and the fourth typhoon of the Pacific season. Forming as a tropical depression east of Luzon on August 19 (Xin et al., 2020), it intensified rapidly and became a Category 3-equivalent typhoon by August 23. The storm caused significant damage, totaling US\$6.82 billion, with wind gusts reaching 240 km/h (150 mph) (He et al., 2022). Both Hong Kong and Macau had their tropical cyclone signals raised to the highest category in anticipation of the storm, which inflicted more than US\$1 billion worth of damage in each of those areas ((HKO), 2017). Wind speed and direction data from Hong Kong's monitoring station are shown in Figure 5-11, collected using Doppler SODARs with a measurement time resolution of 1 minute.

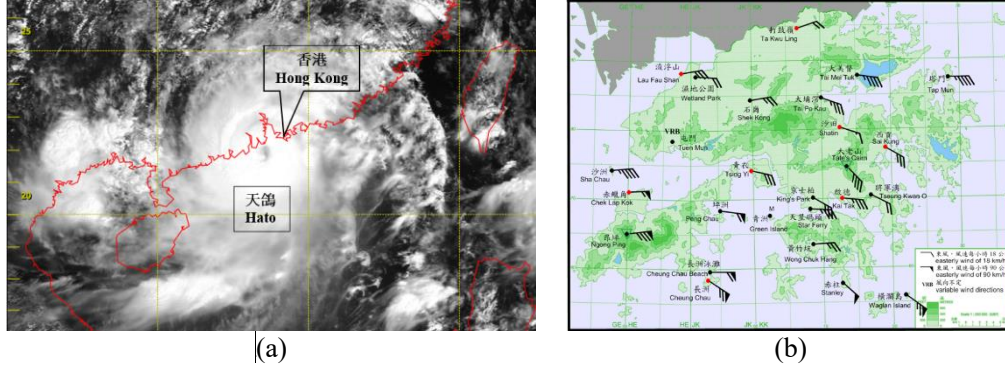


Figure 5-11 Distribution of Typhoon Hato. a) Visible satellite imagery from Himawari-8 Satellite. b) Wind direction and speed recorded at various station in HK. (Yang et al., 2019)

Figure 5-12 illustrates the relationship between the normalized dynamic response and the wind speed of Typhoon Hato after data normalization from HKO observation.

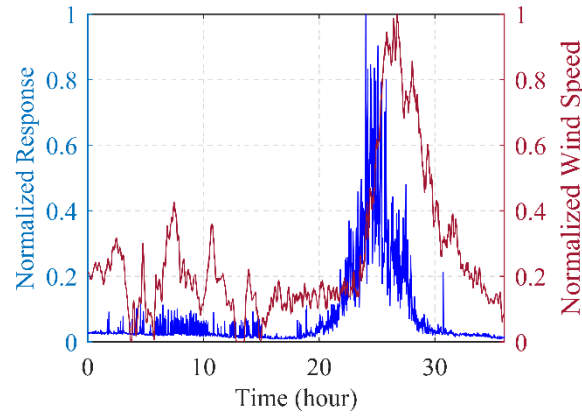


Figure 5-12 Recorded wind speeds and responses.

To accommodate the limited length and redundancy of the original response time-series data, a sliding window method of 10 hours is used for data segmentation and feature extraction, with a 0.1-hour overlap between each window (shown in Figure 5-13). This segmentation results in a total of 534 samples for further dataset construction.

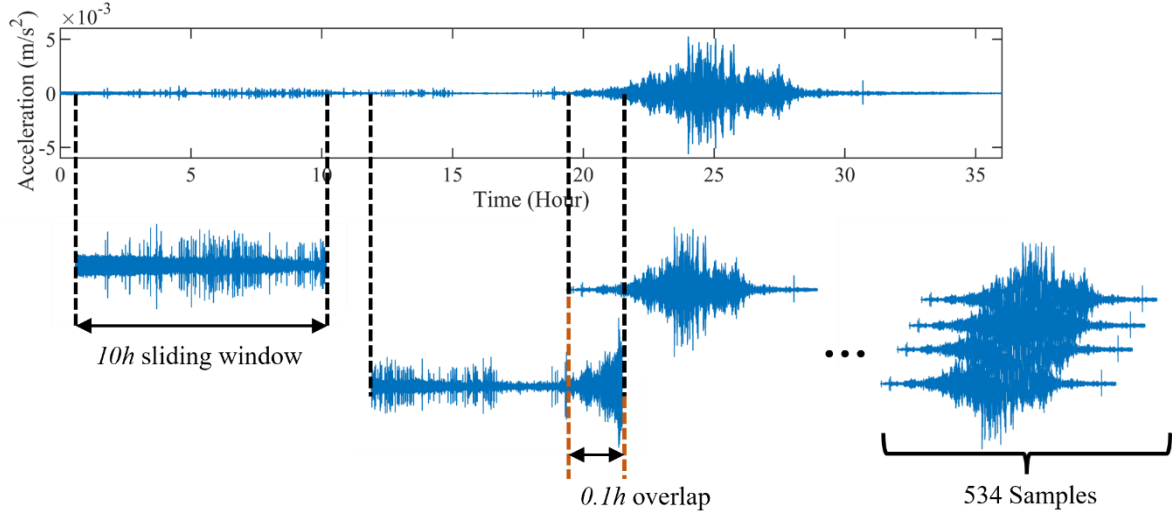


Figure 5-13 Data Segmentation Method via Sliding Time Window.

For each sliding window, peak wind speed is extracted, and the maximum entropy method is applied for time-frequency transformation (Chen et al., 2021). The positions where frequency energy is concentrated are extracted as representative values of load frequency. Structural information, including natural frequency, is extracted from the response time series using the random decrement method (Yang et al., 2019). The feasibility of this method is validated through comparison of extracted frequency domain data from the 484m building with data from other high-rise buildings under strong wind conditions (Ghorbani et al., 2020; Ulrych & Bishop, 1975). Wind parameters and frequency domain information of the dynamic system are shown in Figure 5-14

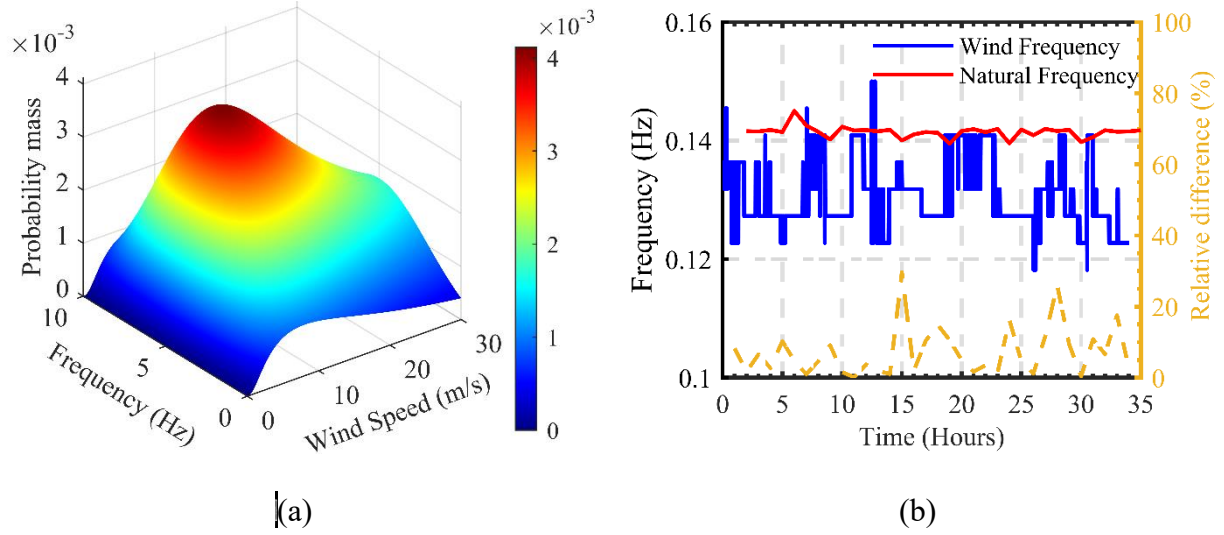


Figure 5-14 Feature extraction from original data a) Wind speed distribution; b) Frequency

domain information

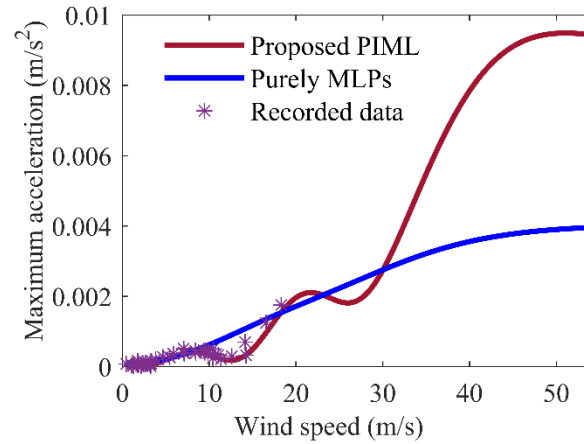


Figure 5-15 Predictive performance of the proposed PIML method

The natural frequency of the building is used in the trained PIML model to validate regression performance. Figure 5-15 illustrates the prediction performance of the PIML model with added physical information, compared to the purely data-driven MLPs. The wind speed ranges from 0 to 50 m/s . Recorded data shows peak wind-induced vibrations at wind speeds of 7 m/s and 20 m/s , as shown in Figure 5-15. The proposed PIML method can accurately capture the positions and response amplitudes of these resonance points and predict resonance phenomena at higher wind

speeds. In contrast, the MLP method, without incorporating resonance effects, only captures the monotonic trend of structural response increase with wind speed. This occurs due to the scarcity of data points under resonance conditions within the training data. Without physical information, the network tends to dismiss these resonance points as outliers, but the inclusion of physical phenomena guides the network to prioritize these critical data points. This demonstrates that incorporating physical insights can reduce data requirements for capturing special phenomena, leading to an efficient PIML framework combining limited data with essential physical knowledge.

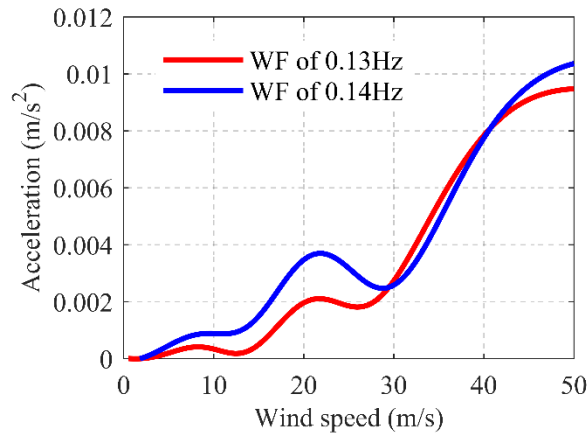


Figure 5-16. Dynamic behavior under different Wind Frequency (WF).

Figure 5-16 compares the change in dynamic behavior with varying wind frequencies, as a function of wind speed, using the well-trained PIML model. It shows that wind speed is not the only significant factor influencing wind-induced vibration responses; variations in wind load frequency also notably affect structural dynamic performance.

5.4 *Dynamic response prediction for FOWTs*

For wind turbines, resonance sources may arise from the inherent structural frequencies of the tower or the blade rotational speed. In addition, the dynamic response of the turbine structure is significantly influenced by the relationship between the inflow wind speed and the rated wind

speed. This characteristic is greatly affected by the control strategies of FOWTs. As shown in Figure 5-17, for instance, in the case of the tower, the bending moment at the tower base in the Fore-Aft direction reaches its maximum near the rated wind speed (10.59 m/s). Therefore, for FOWTs, in addition to considering the resonance frequency related to wind speed, the amplitude and its relationship with the rated wind speed also require further consideration.

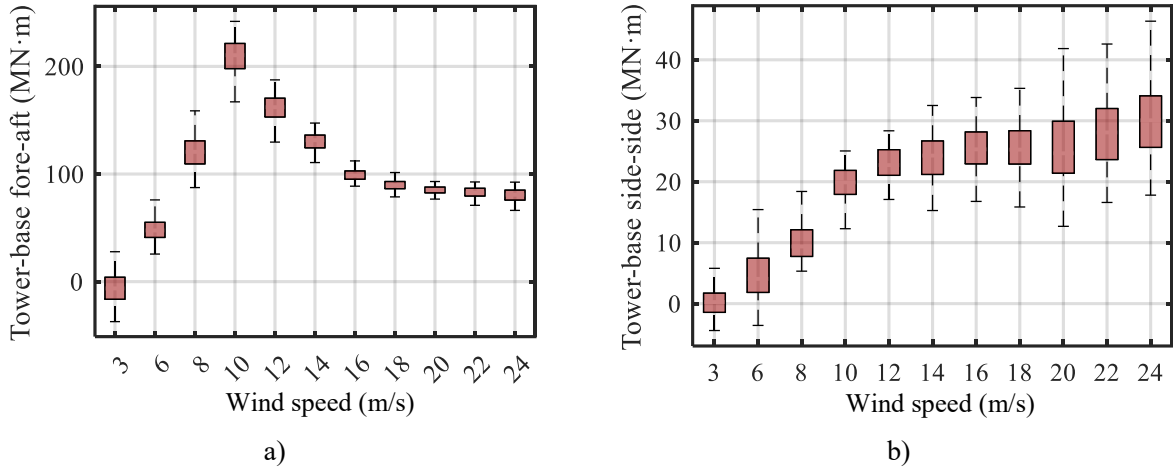


Figure 5-17 Tower base moment responses by the OpenFAST model. (a) Fore-Aft and (b) Side-to-Side.

In this study, we propose a physics-informed neural network (PINN) framework for modeling the structural dynamic response of floating offshore wind turbines (FOWTs). The neural network is designed to predict the structural response of the FOWT, denoted by:

$$u_{pred}(t) = \mathcal{N}(t, F_{wind}(t), F_{wave}(t), f_{load}(t); \theta) \quad (5.18)$$

where $u_{pred}(t)$ represents the predicted structural response at time t , and $F_{wind}(t)$, $F_{wave}(t)$ are the wind and wave loadings respectively, $f_{load}(t)$ is the local dominant frequency extracted from the loading signal, and θ denotes the neural network parameters.

To ensure both accuracy of data fitting and adherence to underlying physical principles, the total loss function for the network training is formulated as:

$$\mathcal{L} = \mathcal{L}_{data} + \lambda_{phys}\mathcal{L}_{phys} + \lambda_{freq}\mathcal{L}_{freq} + \lambda_{mean}\mathcal{L}_{mean} \quad (5.19)$$

where λ_{phys} , λ_{freq} , and λ_{mean} are hyperparameters controlling the relative importance of each loss component.

The data-driven loss is expressed as a mean squared error (MSE):

$$\mathcal{L}_{data} = \frac{1}{N} \sum_{i=1}^N \left(u_{pred}(t_i) - u_{data}(t_i) \right)^2 \quad (5.20)$$

where $u_{data}(t_i)$ is the measured or numerically simulated structural response at time t_i , and N denotes the total number of data points.

The physics-based loss incorporates structural dynamics equations, formulated through residuals as follows:

$$\mathcal{L}_{phys} = \frac{1}{N} \sum_{i=1}^N \left(M u_{pred}''(t_i) + C u_{pred}'(t_i) + K u_{pred}(t_i) - [F_{wind}(t_i) + F_{wave}(t_i)] \right)^2 \quad (5.21)$$

where M , C , and K represent equivalent structural mass, damping, and stiffness, respectively; $u_{pred}'(t_i)$ and $u_{pred}''(t_i)$ denote predicted velocity and acceleration at time t_i .

To capture the frequency-dependent response characteristics, we adopt a time-windowed short-time Fourier transform (STFT) approach to identify local dominant load frequencies. Specifically, the load signal is partitioned into multiple segments of fixed duration T_w , potentially with overlapping segments, to improve temporal resolution. Within each time window centered at t_c , the local frequency spectrum is obtained via:

$$\hat{F}(t_c, f) = \int_{t_c - T_w/2}^{t_c + T_w/2} F(\tau) w(\tau - t_c) e^{-j2\pi f \tau} d\tau \quad (5.22)$$

where $F(\tau)$ is the chosen windowing function (e.g., Hamming window). The dominant local frequency is then determined by:

$$f_{load}(t_c) = \arg \max_f |\hat{F}(t_c, f)| \quad (5.23)$$

The frequency-based loss is designed to reflect the structural response amplification when load frequencies approach the natural frequency of the FOWT. This loss is formulated as:

$$\mathcal{L}_{freq} = \frac{1}{N_w} \sum_{c=1}^{N_w} [\phi(|f_{load}(t_c) - f_n|) - R_{pred}(t_c)]^2 \quad (5.24)$$

where $\phi(\Delta f) = \exp(-\alpha \Delta f^2)$ is a Gaussian weighting function emphasizing smaller frequency differences, controls sensitivity, $\Delta f = |f_{load}(t_c) - f_n|$, is the predicted response amplitude or energy indicator at the time-window center, and N_w is the total number of windows.

Finally, a mean-based loss enforces constraints on the predicted mean response within each window, aligning it with an expected constant value, indicative of resonance or characteristic response level:

$$\mathcal{L}_{mean} = |\mu(u_{pred}) - C| \quad (5.25)$$

where $\mu(u_{pred})$ denotes the average predicted response within each time window.

By minimizing the total loss function $\mathcal{L}$, this PINN framework effectively combines observational data and physical insights, thereby enhancing the capability to accurately model the dynamic behavior of FOWTs under complex environmental loading conditions.

$$R^2(y_k, \hat{y}) = 1 - \frac{MSE(y_k, \hat{y})}{MSE(y_k, \bar{y})} = 1 - \frac{\sum_k (y_k - \hat{y}_k)^2}{\sum_k (y_k - \bar{y}_k)^2} \quad (5.26)$$

where $\bar{y}$ is the mean of the ground truth data. The R^2 -score measures the predictive power of a given model with respect to the predictive power of the trivial model which always forecasts the mean value of the observed data (in this case, $R^2 = 0$). This metric varies in the range $(-\infty, 1]$, the upper bound obtained in case of a perfect forecasting.

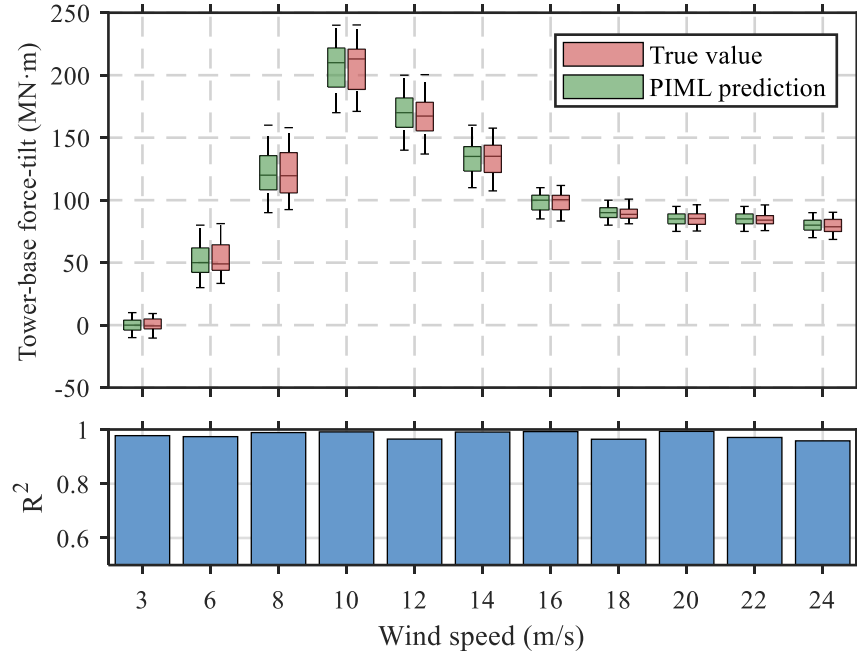
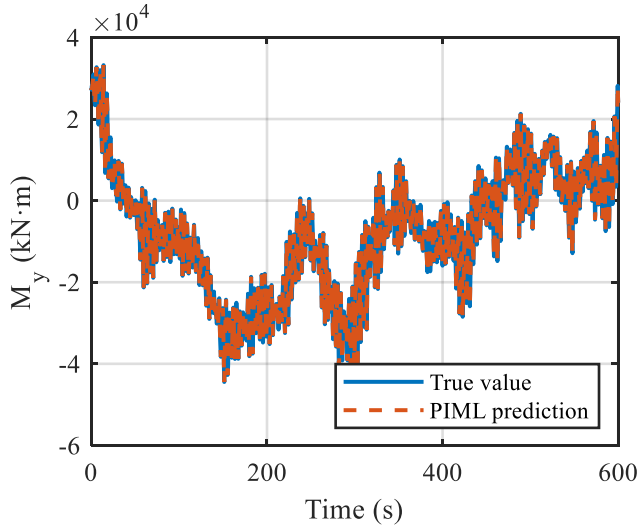
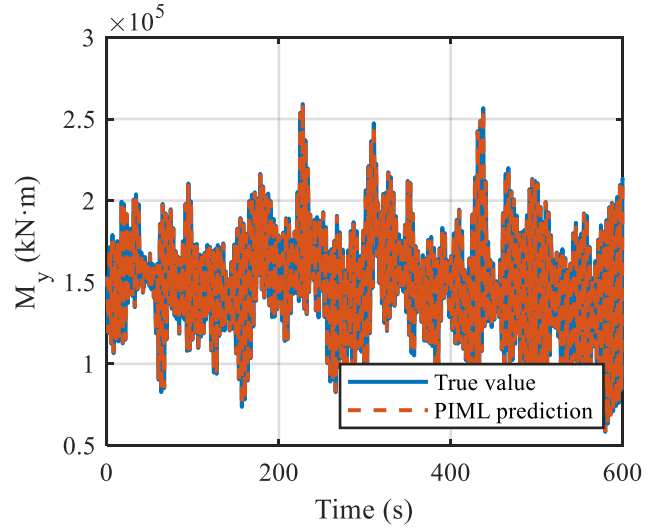


Figure 5-18 PIML-predicted dynamic response distribution of FOWT.

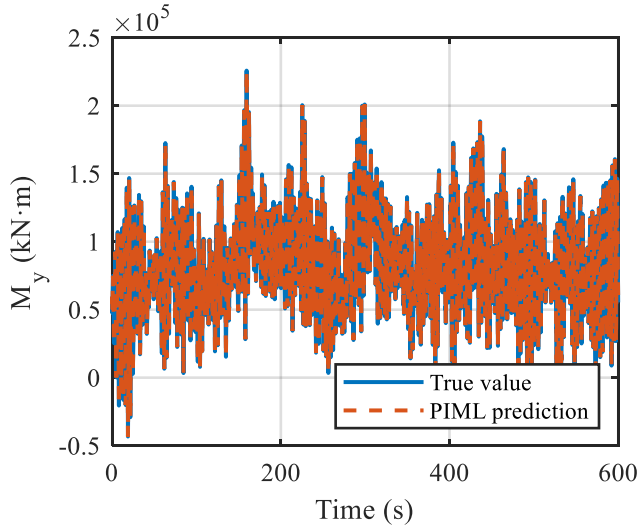
Figure 5-18 compares the structural response distributions of different FOWT components across varying wind speeds, as predicted by the proposed PIML approach and observed in actual simulations. Focusing on the Fore-Aft tower base bending moment, a control-sensitive response identified in Figure 5-18, the results demonstrate that the proposed method can accurately and efficiently replicate the dynamic behavior of FOWTs. Notably, the PIML model successfully captures the critical peak response near the rated wind speed, a characteristic phenomenon essential for structural reliability assessment.



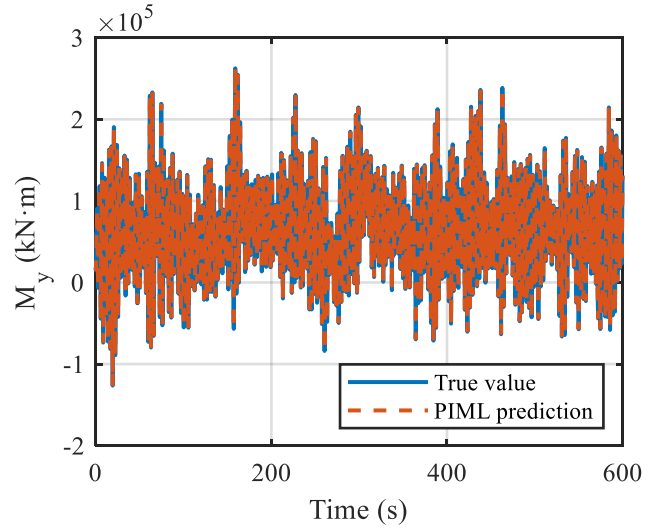
a)



b)



c)



d)

Figure 5-19 Predicted dynamic response of FOWT under different wind speeds using the proposed PIML method. a) 5 m/s; b) 10.59 m/s; c) 20 m/s; d) 30 m/s.

Furthermore, Figure 5-19 presents a time-domain comparison between the high-frequency structural response signals predicted by the proposed PIML algorithm and those obtained from actual simulations. Taking the tower base bending moment as an example, the response histories are shown under four representative operating conditions: sub-rated wind speed (5 m/s), rated wind speed (10.59 m/s), high wind speed (20 m/s), and shutdown condition (30 m/s). The prediction

accuracy is quantitatively assessed using the coefficient of determination R^2 , as defined in Equation 5.24. The corresponding R^2 values for the four cases are 0.954, 0.963, 0.966, and 0.947, respectively, indicating consistently high accuracy across diverse operational scenarios. These results affirm the model's capability in capturing both the amplitude and temporal features of high-frequency structural responses with strong fidelity.

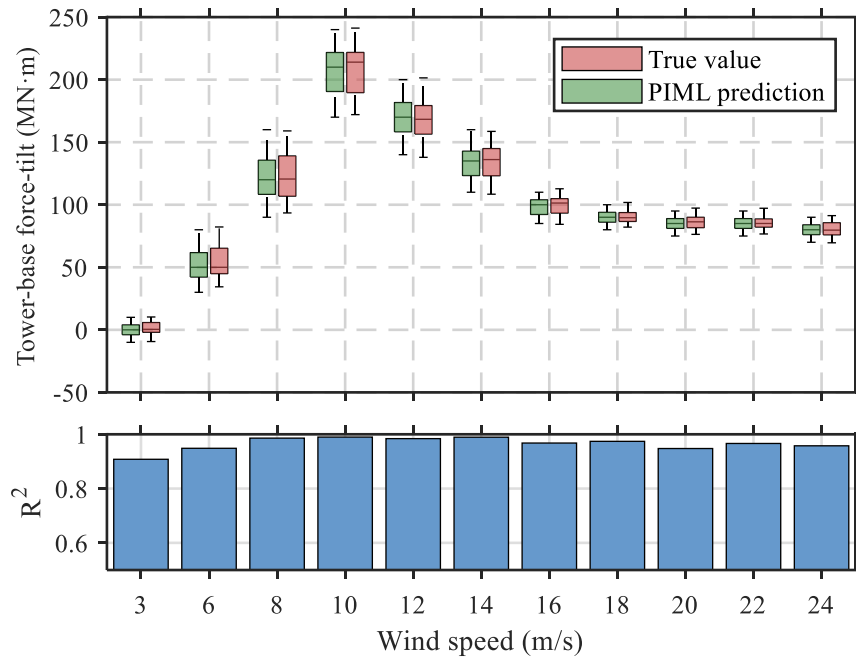
The proposed PIML framework demonstrates notable advantages in predicting dynamic responses under realistic conditions with limited data availability. Table 5-3 provides additional validation beyond the experiments with a complete training set (case 0). Several supplementary cases are investigated, including scenarios with only medium-to-low wind speed samples (case 1), scenarios lacking samples in the rated wind speed region (case 2), and scenarios with only a small number of low wind speed samples (case 3).

Table 5-3 Case study setup for the PIML experiment

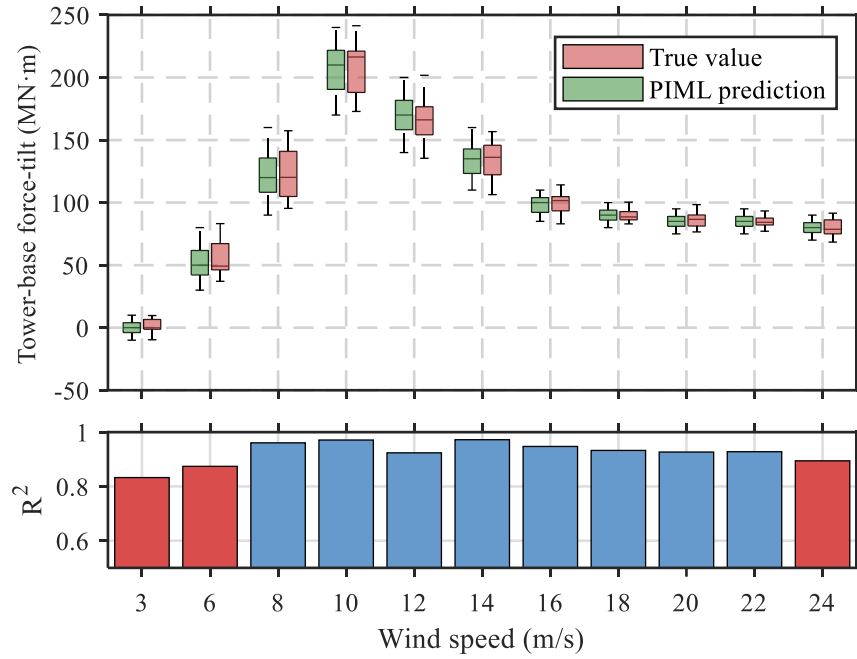
Item	Wind speed (m/s)										
	3	6	8	10	12	14	16	18	20	22	24
case 0											
case 1											
case 2											
case 3											

Figure 5-20 compares the prediction performance of PIML for the dynamic responses of the FOWT under different wind speed excitations across various cases, together with the corresponding R^2 values. In the figure, red denotes values below 0.9. For Case 1, even in the absence of training data in the high-wind-speed region, PIML still achieves accurate predictions of the dynamic responses in this range. The minimum R^2 reaches 0.942, indicating that PIML can infer the turbine's dynamic behavior under extreme conditions, such as typhoons, from normal operational records. Case 2 represents a scenario where the recorded data are incomplete, specifically lacking samples near the rated wind speed region. Although the results are affected to

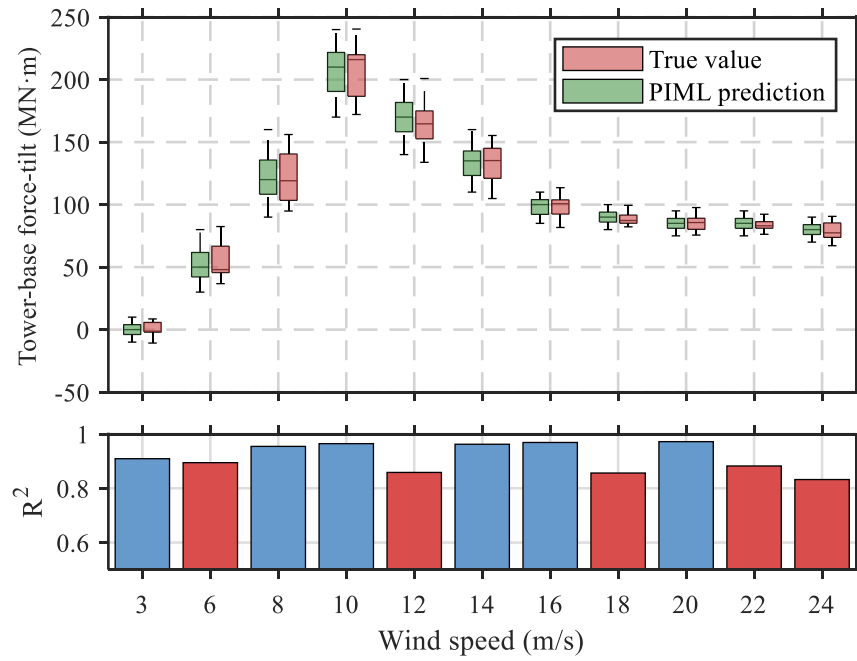
some extent, the PIML approach still achieves an R^2 of 0.9281 in the rated region, which is of primary concern. This demonstrates that the integration of control strategies into the loss function enables the model to effectively capture the actual trend of turbine dynamics. Finally, Case 3 reflects the situation of a newly installed turbine that has only experienced low wind speeds, without exposure to medium- or high-speed regions. Even in this case, PIML is able to capture the dynamic response with high accuracy ($R^2 > 0.85$), demonstrating the robustness of the proposed framework under varying data availability conditions.



a)



b)



c)

Figure 5-20 Predicted dynamic response of FOWT using the proposed PIML method. a) Case 1;

b) Case 2; c) Case 3.

5.5 *Summary*

This chapter presents a novel methodology PIML for modeling structural dynamic performance. By embedding the critical physical phenomenon of resonance directly into the design of the loss function, the model seamlessly fuses data-driven learning with fundamental engineering principles. Three representative resonance-sensitive structures were used to validate the approach. Furthermore, a time-sequential PIML framework incorporating a sliding window technique was proposed to account for the interaction between control strategies and resonance frequency in FOWTs. This model was successfully applied to predict the dynamic responses of FOWTs under realistic operating conditions. The key findings are summarized as follows:

- (1) The proposed method was validated through numerical simulations on a single-degree-of-freedom system under forced vibration and a vehicle-bridge interaction system. Results confirm that the PIML approach can accurately capture dynamic responses and reproduce resonance phenomena at critical frequency bands, demonstrating strong physical consistency and numerical robustness.
- (2) When applied to field measurements of a high-rise building under Typhoon Hato (maximum sustained wind speed 185 km/h), the PIML method achieved significantly higher accuracy compared with conventional machine learning models, even when trained on a limited dataset. This highlights the value of embedding physical constraints in reducing data requirements and improving generalizability. The model enabled detailed

parameter analysis and facilitated comparisons across varying wind speeds and excitation frequencies.

- (3) Long-term predictive analyses were conducted to assess structural response trends under evolving climate conditions from 1985 to 2045. The model identified shifts in dynamic behavior over time, confirming that the structural design remains resilient under a wide spectrum of environmental scenarios. These results establish PIML as a reliable tool for long-term structural health and safety assessments under climate uncertainty.
- (4) The methodology demonstrated high fidelity in simulating the dynamic responses of FOWTs, particularly in capturing the peak response near the rated wind speed. By integrating wavelet-based temporal decomposition and a sliding time window mechanism, the PIML model effectively reproduced the time-domain response signals across operational regimes. At wind speeds of 5 m/s, 10.59 m/s (rated), 20 m/s, and 30 m/s (shutdown), the R^2 values were 0.954, 0.963, 0.966, and 0.947, respectively, highlighting the model strong predictive accuracy across diverse loading conditions.

In conclusion, this chapter proposes a physics-informed machine learning framework tailored for efficient and accurate prediction of the dynamic behavior of FOWTs under varying environmental conditions. The model captures critical resonance effects, reduces reliance on large datasets, and offers a powerful solution for high-throughput simulations required in lifecycle-wide analysis. It serves as a foundational tool for future predictive assessments and decision-making in offshore wind engineering.

CHAPTER 6

Opportunistic O&M management for FOWTs

6.1 *Introduction*

As noted in Section 1.1, O&M costs can account for as much as 25%–30% of the total wind power life cycle cost (He & Li, 2014; Wu et al., 2021), conventional maintenance strategies have been limited in their ability to address the dynamic and uncertain offshore environment. Consequently, optimization strategies for maintenance scheduling, fault prediction, and resource allocation have become mainstream research topics. This chapter builds upon the predictive capabilities introduced in Chapter 5, where physics-informed models were established as the core layer of a digital twin. On this basis, the digital twin is extended from passive prediction to active decision support, providing the foundation for turbine-level O&M optimization.

Opportunistic maintenance strategies are formulated by integrating predictive degradation information from the digital twin with adaptive control adjustments and scheduling decisions. Through this linkage, turbine-level reliability, cost, and energy generation objectives are addressed in preparation for the wind farm–level strategies of Chapter 7.”

6.2 *Opportunistic operation and maintenance*

6.2.1 **Concept of opportunistic maintenance**

Maintenance actions for wind turbines are generally aimed at improving performance to ensure operational efficiency throughout the life cycle (J. Cheng et al., 2023). Due to the complex

environment of offshore wind turbines, inspection and maintenance typically require the use of maintenance vessels, which limits the timeliness and accuracy of these activities (Ren et al., 2021). Reactive maintenance, as shown in Figure 6-1a), where repairs are done only after failures occur, presents major challenges for offshore wind turbines. The remote locations and harsh conditions make it difficult to diagnose and fix problems quickly, leading to long downtimes and high repair costs (Karyotakis & Bucknall, 2010). While this approach may seem cost-effective at first, unexpected outages and extensive repairs result in high long-term costs, making it less ideal. Condition-based maintenance (CBM) improves on this by using diagnostic tools to monitor the condition of turbine parts (J. Cheng et al., 2023; Ramírez & Sørensen, 2009). This proactive approach schedules maintenance based on the actual health of the components, preventing major failures and reducing downtime, as shown in Figure 6-1b). Though CBM has higher initial costs, it offers long-term benefits like lower maintenance costs and increased reliability.

Building on the advantages of CBM, opportunistic strategy is further proposed to optimize maintenance efficiency by capitalizing on planned downtimes or scheduled maintenance events to address additional repair needs (Ramírez & Sørensen, 2009). By addressing multiple issues at once when the turbine is already offline, this method reduces the need for frequent maintenance visits, cuts overall maintenance costs, and minimizes downtime, thereby improving the efficiency and reliability of offshore wind turbines (Liu et al., 2021). Therefore, performing more maintenance actions simultaneously is key to an opportunistic strategy. As discussed in Section 4.3.2, de-rating can effectively prevent corrosion fatigue cracking caused by stress cycles and thus can be used as a preventive measure to delay wind turbine degradation. This approach aims to synchronize the maintenance schedules of all components as closely as possible. Based on this, an opportunistic operation and maintenance (OppOM) strategy combining de-rating and corrective maintenance (as

shown in Figure 6-1c) is proposed. By timely placing the wind turbine in a de-rated state to delay the degradation of certain components, the utilization efficiency of maintenance vessels is improved, thereby enhancing cost-effectiveness.

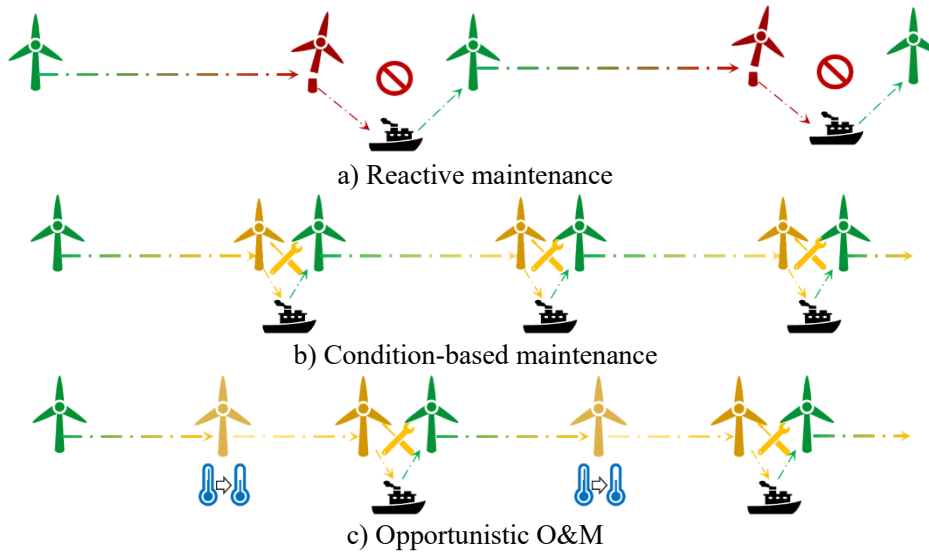


Figure 6-1 Definition of different management types

The core idea of OppOM is to combine de-rating strategies, which temporarily reduce the operational load on components, with maintenance actions, such as repair or replacement. By integrating these two elements, OM achieves synchronization of maintenance tasks, allowing multiple components to be serviced in a single maintenance trip. This reduces the number of trips required and significantly lowers fixed costs associated with vessel mobilization, crew deployment, and logistical operations.

6.2.2 Collaborative Synergies of Operation and Maintenance

The dynamic coupling between structural degradation and operational control in offshore wind turbines necessitates an integrated approach to lifecycle management. As established in Section 4.1, turbine control strategies significantly influence structural dynamic responses - particularly in blade root bending moments and tower base stresses - which subsequently accelerate fatigue

damage accumulation in critical components. This interdependence reveals a fundamental limitation in conventional OM strategies that treat maintenance scheduling and power generation operations as decoupled processes. To address this gap, we propose an Opportunistic Operation-Maintenance (OppOM) framework that strategically coordinates de-rating actions with traditional maintenance activities, creating a symbiotic relationship between power output modulation and component reliability management.

The OppOM framework introduces de-rating as a proactive operational lever to reshape maintenance opportunity windows. Unlike reactive maintenance triggers (e.g., component failures) or passive environmental constraints, de-rating enables active creation of maintenance synchronization points through controlled power output reduction. This controlled degradation pacing allows operators to align multiple components' maintenance schedules within consolidated weather windows, as illustrated in Figure 7. The economic viability stems from two compensatory mechanisms: 1) Reduced cumulative production losses through optimized maintenance clustering, and 2) Extended maintenance intervals enabled by degradation rate modulation.

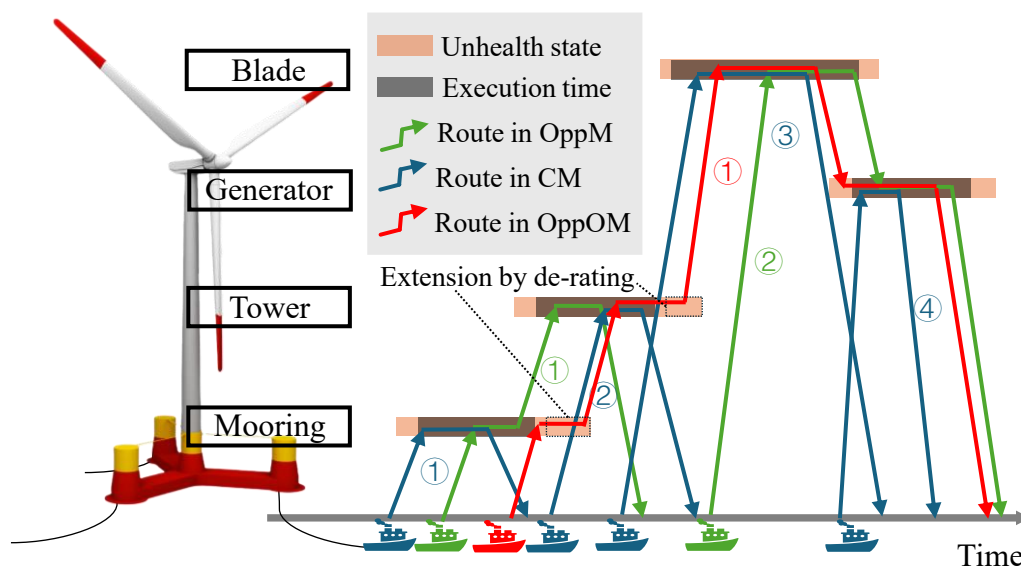


Figure 6-2 Concept of opportunistic operation and maintenance (OppOM).

Three distinctive advantages emerge from this operational-maintenance synergy. First, de-rating serves as a global degradation moderator, simultaneously attenuating fatigue damage progression across all structural components. Second, it introduces operational flexibility during inaccessible periods, where temporary 10-20% de-rating can maintain structural integrity until the next feasible maintenance window. Third, the framework enables dynamic cost balancing between immediate production losses and long-term maintenance savings, facilitated by real-time decision models incorporating electricity market prices and component performance redictions.

This section presents a detailed mathematical model for OppOM of FOWTs, emphasizing cost-effective and structurally reliable maintenance strategies. We consider an offshore wind turbine consisting of four critical structural components, indexed by $i \in \{1,2,3,4\}$, namely blade (1), nacelle (2), tower (3), and mooring system (4). The planning horizon is discretized into daily time intervals, indexed by $t \in \{0,1,2, \dots, T\}$.

The binary decision variable $z_{i,t}$ indicates whether repair actions are carried out on component i at day t , where $z_{i,t} = 1$ represents repair action executed, and $z_{i,t} = 0$ otherwise. This ensures that maintenance actions, when performed, are coordinated to address multiple components simultaneously, as illustrated in [Figure 6-3](#).

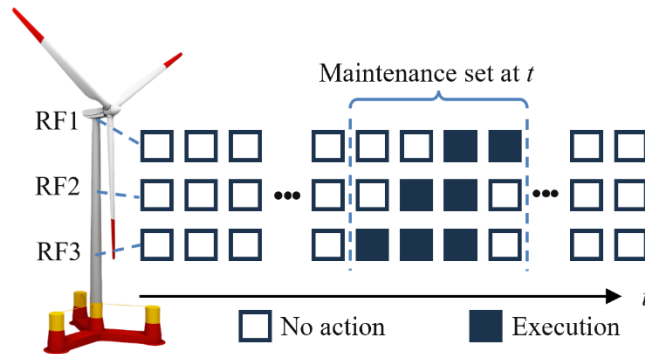


Figure 6-3 The schematic diagram of maintenance action variables in OppOM.

A second binary variable y_t captures vessel mobilization status at day t , where $y_t = 1$ if at least one component undergoes repair on day t , and $y_t = 0$ otherwise, formulated explicitly by the constraints:

$$y_t \geq z_{i,t} \quad (6.1)$$

$$y_t \leq \sum_{i=1}^4 z_{i,t} \quad (6.2)$$

The constraints guarantee that the vessel is mobilized only when at least one repair is scheduled, and no unnecessary dispatches occur.

Additionally, we introduce a binary variable $dr_t \in \{0,1\}$ to represent structural-level operational de-rating at day t , where $dr_t = 1$ indicates active de-rating and $dr_t = 0$ indicates normal operation.

To promote opportunistic maintenance, we require that each vessel dispatch involves repairs on a minimum number M of components, represented by the constraint:

$$\sum_{i=1}^4 z_{i,t} \geq M \cdot y_t, \quad M \geq 2 \quad (6.3)$$

De-rating is considered as an alternative strategy applicable only when no repairs are performed, ensuring a clear distinction between repair activities and structural-level de-rating operations. This is captured by the constraint:

$$\sum_{i=1}^4 z_{i,t} + dr_t \leq 1 \quad (6.4)$$

Repair actions are explicitly modeled as parallel activities, meaning multiple structural components can be serviced simultaneously during a single vessel dispatch. The total downtime

due to repairs on day t , denoted as τ_t , is dictated by the longest individual repair duration among the components scheduled for maintenance on that day

$$\tau_t = \max_{i \in \{1,2,3,4\}} \{\tau_i \cdot x_{i,t}\} \quad (6.5)$$

By considering repairs in parallel, the model significantly reduces overall downtime and associated production losses, enhancing operational efficiency.

To ensure structural integrity and operational safety, each component's reliability level $R_{i,t}$ must be maintained above a specified minimum threshold $R_i^{\min}$:

$$R_{i,t} \geq R_i^{\min} \quad (6.6)$$

6.2.3 Multi-attribute function on FOWT

FOWTs inherently span multiple disciplines including structural engineering, fluid dynamics, control theory, economics and environmental science, and their real-world performance emerges from the complex interplay among these domains. A change in structural health (e.g., degradation rate or maintenance schedule) not only alters reliability but also impacts downtime, energy yield and carbon balances; likewise, operational strategies such as de-rating or preventive maintenance carry economic consequences while feeding back into system efficiency and emission profiles (Kang & Soares, 2020). As a result, any decision that optimizes one metric (say, minimizing carbon footprint) can ripple through others (like increasing lifecycle cost or reducing availability), making isolated assessments unreliable. A truly comprehensive evaluation therefore demands a multi-attribute framework that simultaneously captures health state, power production dynamics, cost drivers and environmental impacts, as shown in Figure 6-4, allowing trade-offs to be quantified and governed in a coherent, systems-level optimization.

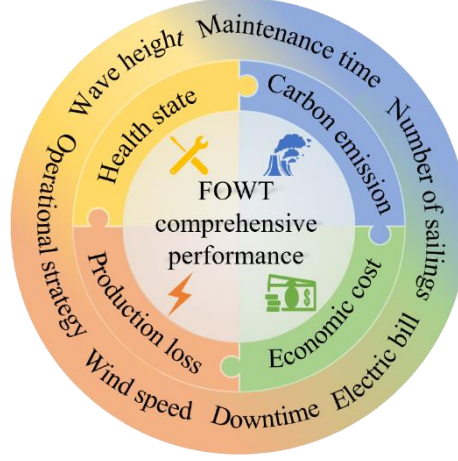


Figure 6-4 Multi-attribute function on FOWT

Health state

The health state assessment of FOWTs is essential for maintaining operational safety and long-term reliability. This section proposes a structural reliability-based model that integrates external environmental loads, internal control strategies, and maintenance actions. Building on the foundation established by Nielsen and Sørensen (2011), this model quantifies the structural health state using a time-dependent reliability index.

The structural reliability index $R(t)$ is formulated as:

$$R(t) = R_0 - \gamma_1 t - \gamma_2 S(t) + \gamma_3 M(t) \quad (6.7)$$

where R_0 is initial reliability; γ_1 denotes the natural degradation rate coefficient; γ_2 captures the effect of cumulative environmental loads; γ_3 measures the beneficial impact of maintenance; $S(t)$ is the cumulative environmental load up to day t ; and $M(t)$ is the cumulative maintenance effect by day t .

Maintenance actions are modeled as:

$$M(t) = \sum_{i=1}^n \delta_i \cdot z_{i,t} \quad (6.8)$$

where δ_i indicates the effectiveness of repairing component i ; $z_{i,t}$ denotes whether component i is repaired on day t .

Power production

Power production is a key indicator of FOWT performance, directly linked to economic output and system efficiency. It is influenced by wind conditions, maintenance-induced downtime, and operational strategies such as de-rating.

The total energy produced on day t is:

$$E(t) = \int_0^{24} P(v(t, \tau)) \cdot [1 - I_d(t, \tau)] \cdot \eta(t) d \quad (6.9)$$

where $I_d(t, \tau)$ is a binary indicator set to 1 if the turbine is shut down at time τ due to repairs or de-rating; $\eta(t)$ represents the system efficiency on day t , which is influenced by the health state; τ is the total downtime used to determine values of $I_d(t, \tau)$.

When structural de-rating is applied (i.e., $dr_t = 1$), the rated power is reduced:

$$P_{dr}(t) = P_{rated} \cdot (1 - \lambda(t)) \quad (6.10)$$

where $\lambda(t)$ is the de-rating coefficient (0–1).

The corresponding energy loss from de-rating is:

$$E_{dr}(t) = E_{nom}(t) - E_{dr}(t) \quad (6.11)$$

Economic cost

This section develops a comprehensive economic framework that quantifies the financial implications of maintenance decisions, vessel logistics, production losses, and operational

strategies such as power de-rating.

The total cost over a planning horizon T is defined as the sum of four major components: vessel mobilization cost, repair cost of individual components, downtime-induced production loss, and energy loss due to de-rating:

$$C_{total} = \sum_{t=1}^T \left[C_{dp}(t) + \sum_{i=1}^n C_i(t) \cdot z_{i,t} + C_{dt}(t) + C_{dr}(t) \right] \quad (6.12)$$

where C_{total} is the cumulative economic cost over the time horizon T ; the subcomponents are described as follows.

For each component i , repair activities incur a cost $C_i(t)$ when executed at time t . The binary decision variable $z_{i,t} \in \{0,1\}$ indicates whether a repair is performed:

Thus, the total repair cost at time t is the sum of component-wise costs:

$$\sum_{i=1}^n C_i(t) \cdot z_{i,t} \quad (6.13)$$

Maintenance operations in offshore environments often require the dispatch of specialized vessels.

A binary variable $y_t \in \{0,1\}$ is introduced to indicate whether any component is repaired on day t . The vessel mobilization cost is modeled as:

$$C_{dp}(t) = C_{ves} \cdot y_t \quad (6.14)$$

where C_{ves} is the fixed mobilization cost for deploying a maintenance vessel.

While repairs are conducted, turbines are temporarily taken offline, leading to lost power generation and associated revenue loss. The downtime duration on day t is denoted by τ_t , and the corresponding cost is given by:

$$C_{dt}(t) = c_{dt} \cdot \tau_t \quad (6.15)$$

where c_{dt} is the unit downtime cost, reflecting the opportunity cost of unavailable energy. This cost includes both direct energy sales loss and potential penalties from unfulfilled energy contracts.

De-rating strategies, while beneficial in extending component life and reducing failure risk, result in a deliberate reduction of power output. On any day t , if de-rating is applied, energy production is curtailed. The resulting energy loss is denoted $E_{dr}(t)$, and the associated cost is calculated as:

$$C_{dr}(t) = c_e \cdot E_{dr}(t) \quad (6.16)$$

where c_e represents the unit price of electricity. This cost term captures the economic trade-off of applying de-rating, especially under high market prices or grid obligations.

Carbon emission

Carbon emissions are a key metric in environmental performance evaluation of FOWTs. This section considers both emission reductions from renewable energy production and emissions resulting from maintenance operations.

Carbon emission reduction is computed as:

$$CO_2^{\text{red}}(t) = e_{\text{trad}} \cdot E(t) \quad (6.17)$$

where e_{trad} is the emissions factor for displaced fossil energy.

Maintenance-related emissions are:

$$CO_2^{\text{rep}}(t) = y_t \cdot e_{\text{ves}} + \sum_{i=1}^n z_{i,t} \cdot e_{\text{rep},i} \quad (6.18)$$

where e_{ves} indicates emissions from a single vessel deployment; $e_{\text{rep},i}$ denotes the emissions from repairing component i .

The net carbon impact is:

$$CO_2^{net}(t) = CO_2^{red}(t) - CO_2^{rep} \quad (6.19)$$

Multi-attribute function

Due to the presence of coupling factors, there are often intersecting or mutually exclusive relationships among the factors. For instance, maintenance actions can improve the condition state but also generate carbon emissions, thereby affecting sustainability. This necessitates a comprehensive consideration of multiple indicators to achieve a balanced state in the lifecycle maintenance of FOWTs. This study employs a multi-attribute utility function (Tao et al., 2023) to integrate different indicators. As a common method in decision theory for handling multi-objective problems, the multi-attribute utility (MAU) function fully considers the decision-makers' risk attitudes towards the indicators (Mateo, 2012). Decision-makers first normalize individual indicators based on their risk attitudes and then conduct multi-indicator comprehensive analysis through weight coefficients. For single-factor utility functions, an exponential function form is generally adopted, as shown in Equation 6.20.

$$U_i(x_i) = A - B \cdot e^{-\frac{x_i}{RT}} \quad (6.20)$$

where U_i represents the utility value of the single indicator i ; A and B are scaling constants, controlled by the range of the single indicator; RT denotes the Risk Tolerance, reflecting attitude towards data uncertainty and failure risk, as shown in Figure 6-5. Specifically, when RT is negative, it indicates risk-seeking (RS); when RT is zero, it indicates risk-neutral (RN); and when RT is positive, it indicates risk aversion (RA).

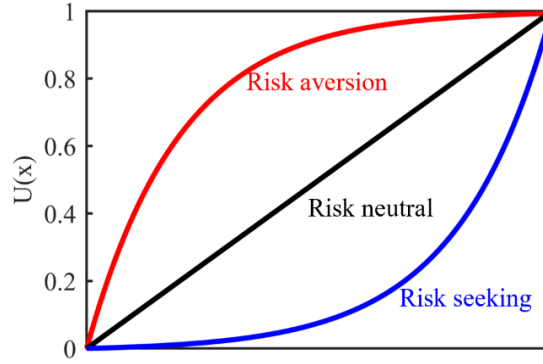


Figure 6-5 Utility functions in MAU.

6.3 *An integrated DBN-POMDP framework for Systematic modeling*

6.3.1 Hybrid DBN model for long-term degradation

FOWTs are subjected to various environmental loads, including wind, waves, and currents, which contribute significantly to the degradation phenomena over time. Therefore, accurately modeling the failure behavior of these systems necessitates considering these degradation effects (Kang & Soares, 2020). The degradation process is primarily driven by cumulative external shocks and internal material aging (Santos et al., 2016). The long-term performance degradation of structures typically involves both time-dependent and environment-dependent factors (Darmawan & Stewart, 2007; Frangopol & Liu, 2019). The time-dependent degradation is often characterized using statistical methods based on historical data and underlying physical mechanisms. In this study, the degradation process is modeled using a Weibull distribution (Le & Andrews, 2016). This section presents a comprehensive description of the integrated degradation model and decision-making framework developed in this study. The proposed framework integrates Dynamic Bayesian Network (DBN), Weibull natural degradation model, and Partially Observable Markov Decision Process (POMDP). Specifically, the framework consists of the following logical layers: firstly, environmental effects on structural degradation are quantified through stress-history analysis of

wind, wave, and current loads; secondly, individual degradation sub-models are constructed by inputting stress histories into the Weibull natural degradation model and the Paris crack growth model, respectively; subsequently, these two distinct degradation mechanisms are integrated into a unified probabilistic degradation model using DBN; finally, a decision-making strategy for structural inspection and maintenance is optimized through the POMDP framework based on this probabilistic model.

FOWTs are exposed to complex and varying environmental conditions. Environmental loads, including wind and wave critically impact structural degradation processes. Utilizing measured or simulated data, this study applies spectral analysis and the Rainflow Counting Method to extract the number of stress cycles n_i and corresponding stress ranges $\Delta\sigma_i$, which can be obtained from section 3.4.

The Weibull distribution, extensively employed in reliability engineering, effectively characterizes the natural degradation of structures over time. Its probability density function (PDF) and hazard rate function are expressed as follows:

$$f(t; \alpha, \beta) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\alpha}\right)^\beta\right], \lambda(t) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1} \quad (6.21)$$

where α denotes the scale parameter, representing the characteristic lifetime, and β is the shape parameter, dictating the trend of the degradation rate.

To reflect the acceleration effect of environmental stresses on natural degradation, relationships between scale parameter β , shape parameter β , and mean stress $\bar{\sigma}$ are fitted based on experimental data:

$$\alpha(\bar{\sigma}) = \alpha_0 \left(\frac{\bar{\sigma}}{\sigma_0}\right)^{-\gamma}, \quad \beta(\bar{\sigma}) = \beta_0 + k \ln\left(\frac{\bar{\sigma}}{\sigma_0}\right) \quad (6.22)$$

where α_0 represent initial parameters at reference stress σ_0 , while γ and k are material or

structural constants determined through experimental fitting, signifying sensitivity to environmental loading.

Fatigue crack growth significantly contributes to the failure of offshore structures. The Paris law, widely used for describing crack length growth per stress cycle (Lee & Kwon, 2023), is mathematically expressed as:

$$\frac{da}{dN} = C(\Delta K)^m \quad (6.23)$$

where a is crack length, N represents stress cycle count, and parameters C and m determined via fatigue experiments, represent crack growth rate and material sensitivity to loading, respectively. The stress intensity factor range ΔK directly correlates with the stress history, reflecting the stress concentration at the crack tip:

$$\Delta K = Y\Delta\sigma\sqrt{\pi a} \quad (6.24)$$

where geometric factor Y depends on crack location and structural geometry, determined through finite element analysis or experimental data.

Integrating and discretizing Paris' law probabilistically yields the transition probability from crack length state a_i to a_j :

$$P(a_{t+1} = a_j | a_t = a_i) = \int_{a_j}^{a_{j+1}} f(a | a_i, \Delta\sigma) da \quad (6.25)$$

Dynamic Bayesian Networks (DBNs) are probabilistic graphical models suitable for describing state evolution and observation integration in dynamically uncertain systems. Here, DBN integrates the natural degradation and fatigue crack growth mechanisms.

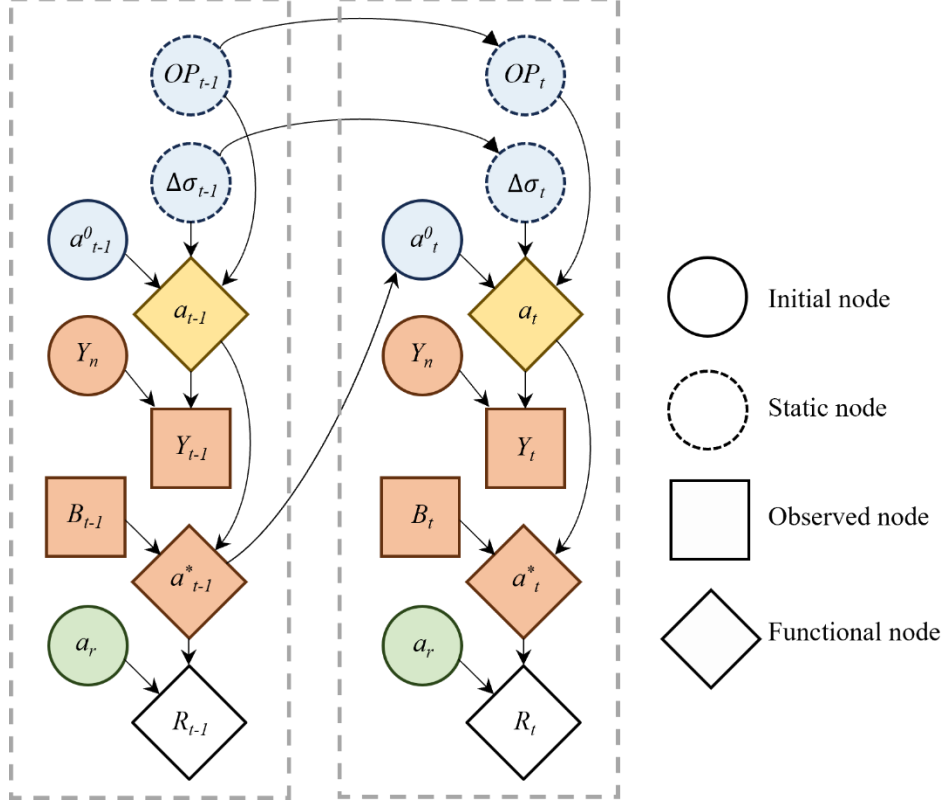


Figure 6-6 DBN node configuration

This study defines a state vector

$$S_t = (d_t, a_t) \quad (6.26)$$

where d_t denotes the natural degradation state modeled by the Weibull distribution; a_t represents the crack length state modeled by the Paris crack growth model.

State dynamics over time are represented using Conditional Probability Tables (CPTs):

$$P(S_{t+1}|S_t) = P(d_{t+1}|d_t, \alpha, \beta) \cdot P(a_{t+1}|a_t, \Delta\sigma) \quad (6.27)$$

assuming independence between natural degradation and fatigue crack growth mechanisms.

Inspection results are incorporated into DBN as observational nodes O_t , modeled using Probability of Detection (POD) curves widely used in structural inspections (Zhao & Haldar, 1996):

$$P(O_t = o|a_t) = \frac{1}{1 + (X_0/a_t)^b} \quad (6.28)$$

where X_0 and b represent characteristic inspection parameters, calibrated through experiments or field data, reflecting inspection precision and reliability.

Through Bayesian updating within the DBN framework, observational data updates the state probability distributions effectively. The updating procedure includes:

- 1) Forward propagation (prediction step): Predicting future state distributions based on current probabilities and transition probabilities.
- 2) Backward updating (correction step): Adjusting predictions based on observational data.

The baseline annual failure rates of the main wind turbine components (as listed in Table 6-1) were initially taken from (Le & Andrews, 2016). In their study, these values were used as indicative parameters derived from literature surveys and statistical sources, and applied within a Petri Net degradation framework. As a result, some component-level rates, such as the relatively higher tower failure rate compared to the blade, may not fully reflect field experience but rather serve to illustrate the modelling methodology. By incorporating degradation physics and operational data into the DBN framework, the failure probabilities were dynamically updated over time. This modification improves the representativeness of the results, ensuring that the estimated failure rates are more consistent with realistic degradation behaviour and operating conditions, while still retaining the advantages of the probabilistic modelling framework.

Table 6-1 Time-dependent degradation model parameters

Component	Annual failure rate	Functional failure
Blade	0.0348	$\alpha=1.2, \beta=2.88$
Generator	0.052	$\alpha=1.2, \beta=1.92$
Tower	0.067	$\alpha=1.2, \beta=14.93$
Mooring	0.006	$\alpha=1.2, \beta=16.67$

6.3.2 POMDP modeling

The Partially Observable Markov Decision Process (POMDP) is a decision optimization

framework designed to operate under uncertainty and incomplete system state observability. Given that the degradation states of FOWT components are not directly accessible and both environmental loads and degradation evolution are inherently uncertain, a POMDP is employed to dynamically optimize inspection and maintenance strategies (Kim et al., 2018). The probabilistic degradation and observation models provided by the DBN are incorporated into the POMDP to form a closed-loop decision-feedback mechanism.

The POMDP model is defined as a tuple $\langle S, A, \Theta, T, O, R, \gamma \rangle$, where:

- S is the system state space, defined as $S_t = (d_t, a_t)$, with d_t representing natural degradation and a_t representing crack length.
- $A = \{DN, IM\}$ is the action space, including "Do Nothing" (DN) and "Inspection and Maintenance" (IM). The effects of the repair actions is illustrated in Figure 6-7.

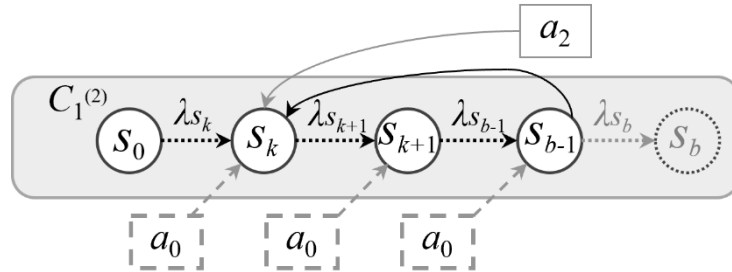


Figure 6-7 MDP showing repair actions taken for components.

- $O = \{o_D, o_{ND}, o_0\}$ is the observation space, where o_D and o_{ND} are the outcomes of crack detection and non-detection, respectively, and o_0 denotes no observation.
- $T(s'|s, a) = P(S_{t+1} = s' | S_t = s, a_t = a)$ is the state transition model provided by DBN:
 - For $a = DN$: $T(s'|s, DN) = P(d_{t+1}|d_t) \cdot P(a_{t+1}|a_t, \Delta\sigma)$
 - For $a = IM$: the post-maintenance state $s^* \sim f(s^*|o_t, s)$ is first updated using Bayesian inference, and the transition becomes $T(s'|s, IM) = P(s'|s^*)$

- $Z(o|s, a)$ is the observation model, defined by the probability of detection (POD) curve:

$$Z(o | s, a) = \begin{cases} POD(a_t), & a = IM, o = o_D \\ 1 - POD(a_t), & a = IM, o = o_{ND} \\ 1, & a = DN, o = o_0 \\ 0, & \text{Otherwise} \end{cases} \text{ with } POD(a) = \frac{1}{1 + (X_0/a)^b} \quad (6.29)$$

where X_0 and b are inspection-specific parameters.

- $R(s, a)$ is the reward function. In this study, the multi-attribute utility formulation described in Section 2.3 is directly used as the reward model, incorporating factors such as operational benefits, failure penalties, and maintenance costs.
- $\gamma \in [0,1)$ is the discount factor reflecting the importance of future rewards.

Since the true system state is not directly observable, the POMDP framework maintains a belief state $b(s)$, representing a probability distribution over possible states. Upon executing action a_t and receiving observation o_{t+1} , the belief is updated according to:

$$b_{t+1}(s') = \tau(b_t, a_t, o_{t+1}) = \eta Z(o_{t+1}|s', a_t) \sum_{s \in S} T(s'|s, a_t) b_t(s) \quad (6.30)$$

where η is a normalization constant ensuring $b_{t+1}(s')$ sums to one. The transition and observation models T and Z are derived from the DBN, enabling tight integration between probabilistic modeling and decision optimization.

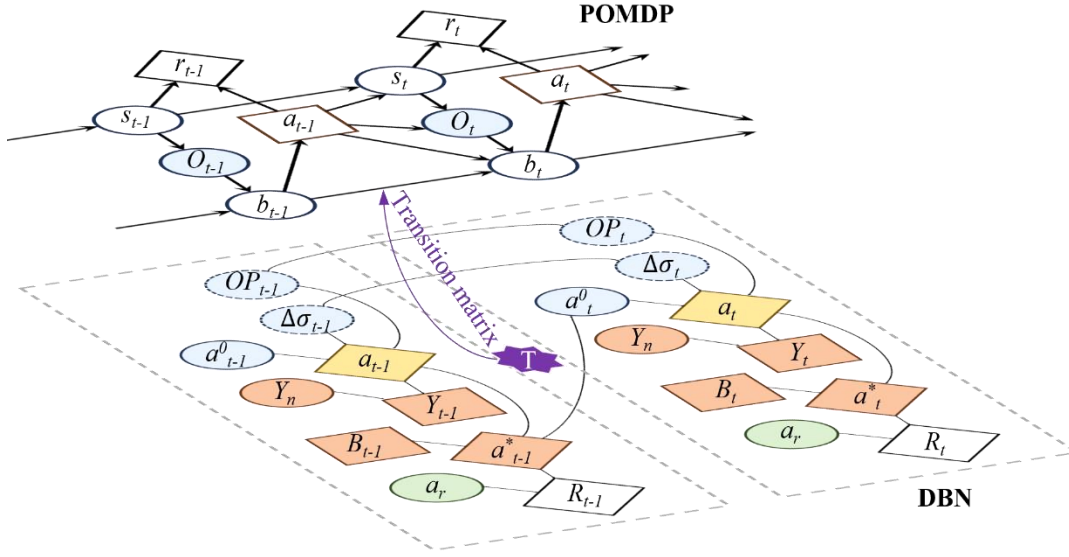


Figure 6-8 DBN and POMDP coupled model

To solve the POMDP, this study adopts point-based solution methods suitable for high-dimensional belief spaces (Pineau et al., 2006). These methods approximate the value function $V(b)$ over selected belief points:

$$V(b) = \max_{a \in A} \left[\sum_{s \in S} b(s) R(s, a) + \gamma \sum_{o \in O} P(o|b, a) V(b') \right] \quad (6.31)$$

where b' is the updated belief state after taking action a and observing o .

The optimal policy $\pi^*(b)$ is derived as:

$$\pi^*(b) = \arg \max_{a \in A} \left[\sum_{s \in S} b(s) R(s, a) + \gamma \sum_{o \in O} P(o|b, a) V(b') \right] \quad (6.32)$$

In summary, the POMDP-based decision-making framework leverages the DBN probabilistic inference to dynamically update the belief state and optimize inspection and maintenance actions.

6.4 *Deep reinforcement learning in optimization solution*

6.4.1 Actor-critic architecture

Throughout the lifecycle of a structure, structural deterioration caused by environmental factors often significantly impacts its service performance and design lifespan (J. Zhang, J. Heng, et al., 2024). Therefore, timely inspection and maintenance are required to ensure its operational condition. In the context of maintenance scheduling for FOWTs, Actor-Critic (AC) Reinforcement Learning provides a robust approach to optimize decision-making by learning from interactions with the environment. The AC framework combines value-based and policy-based methods, offering stability and efficiency in handling continuous and high-dimensional action spaces. This method is particularly well-suited for applications where the agent needs to balance the immediate costs of maintenance actions against the long-term benefits of extending the structure's operational life and reducing the risk of failure (Marugán, 2023).

The Actor-Critic method consists of two primary components: the actor and the critic. The actor, represented by a policy network, selects actions based on the current policy. The critic, represented by a value network, evaluates these actions by estimating the value function. The actor updates the policy to maximize the expected cumulative reward, while the critic updates the value function to better estimate future rewards, providing a baseline to reduce the variance of policy updates (Grondman et al., 2012), as shown in Figure 6-9.

Initially, the actor's policy $\pi(a|s;\theta)$ and the critic's value function $V(s;\omega)$ are initialized with random parameters θ and ω , respectively. At each time step t , the actor selects an action a_t based on the current policy:

$$a_t \sim \pi(a|s_t; \theta_t) \quad (6.33)$$

The environment then transitions to a new state s_{t+1} and provides a reward r_t . The critic evaluates the new state by estimating the value function $V(s_{t+1}; \omega_t)$, and the TD error is computed as:

$$\delta_t = r_t + \gamma V(s_{t+1}; \omega_t) - V(s_t; \omega_t) \quad (6.34)$$

The critic's parameters are updated using the TD error, following Equation 6.35.

$$\omega_{t+1} = \omega_t + \alpha_c \delta_t \nabla_{\omega} V(s_t; \omega_t) \quad (6.35)$$

where α_c is the learning rate for the critic. Concurrently, the actor updates the policy parameters using Equation 6.36.

$$\theta_{t+1} = \theta_t + \alpha_a \delta_t \nabla_{\theta} \log \pi(a_t | s_t; \theta_t) \quad (6.36)$$

where α_a is the learning rate for the actor.

Consider the practical example of managing the maintenance of a FOWTs. The state s includes metrics since the last inspection. Immediate rewards r balance the cost of actions against benefits such as improved condition and reduced failure risk. During each time step, the actor selects an action. The environment transitions to a new state, providing feedback in the form of rewards and new observations. The critic evaluates this feedback to refine the value function, while the actor updates the policy to enhance future decision-making.

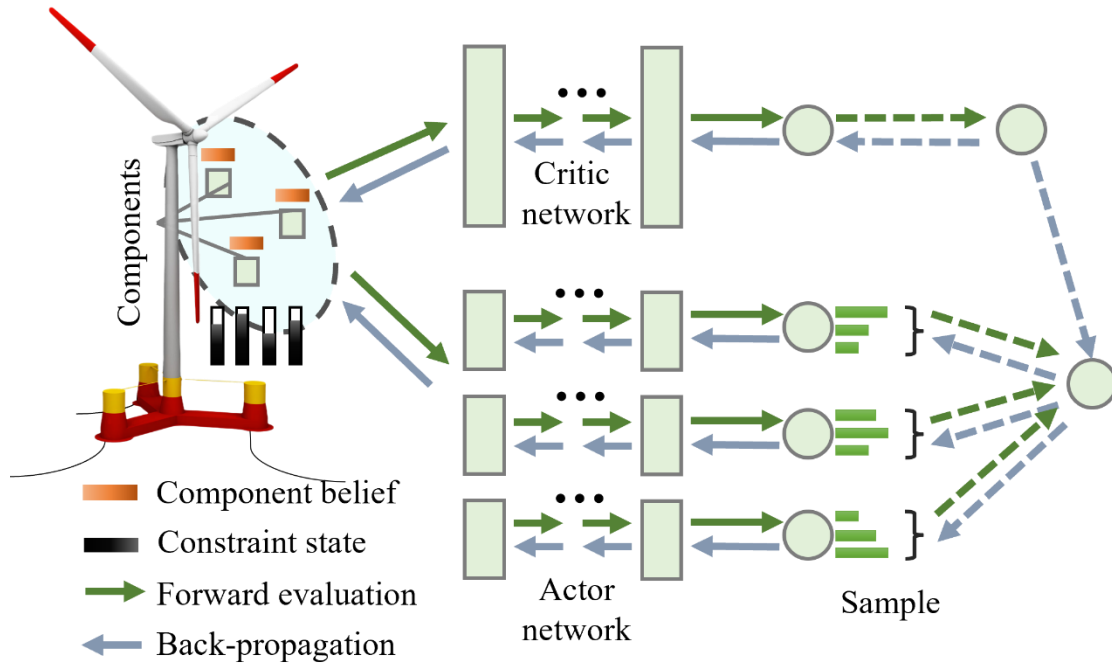


Figure 6-9 Architecture of actor-critic network

6.4.2 A3C reinforcement learning

Building on the AC framework, we further enhance the maintenance scheduling approach by implementing the Asynchronous Advantage Actor-Critic (A3C) algorithm (Marugán, 2023). A3C leverages the benefits of parallel training and asynchronous updates, which significantly improve the learning efficiency and stability of reinforcement learning models. In the A3C framework, as shown in Figure 6-10, multiple parallel agents interact with separate instances of the environment. These agents independently explore different parts of the state space, collect experiences, and update their local parameters. Each agent maintains local copies of the global policy and value function parameters (Grondman et al., 2012). Periodically, the local parameters are synchronized with the global parameters, leading to a more stable and efficient learning process.

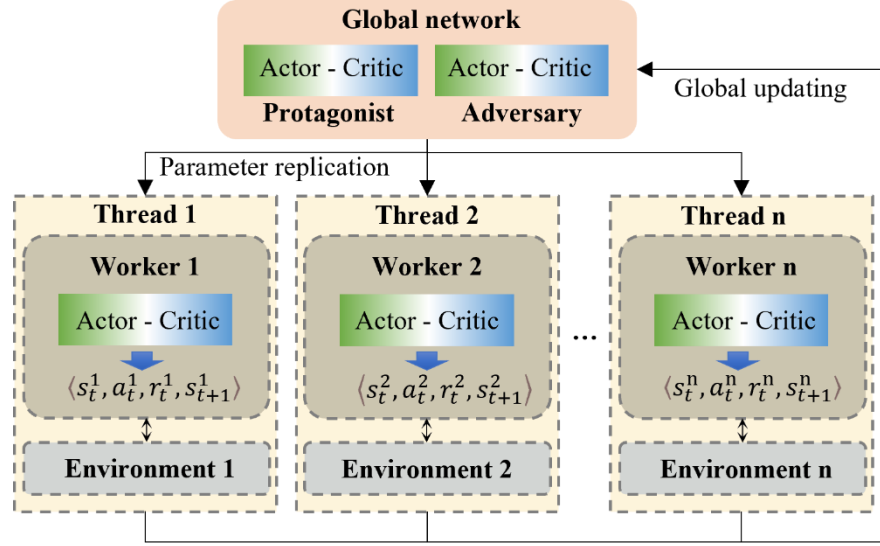


Figure 6-10 Framework of A3C

6.5 Application in a Dynamic marine environment

6.5.1 Opportunistic O&M scheduling

To further validate the performance gains of our proposed “Operations–Maintenance Synergy” strategy (OppOM) over the traditional “Opportunistic Maintenance” approach (OppM), we conducted a control experiment in which all de-rating trigger variables introduced in Section 3.2 were fixed at zero, reducing the model to pure OppM, and the CBM (condition-based maintenance) policy was retained solely as a non-optimized baseline (M. Chen et al., 2020). Figure 6-11 presents the convergence trajectories of the mean reward (raw and smoothed) during 0–15 000 training episodes under the A3C framework for both strategies. During the initial exploration phase (0–500 episodes), both methods start around -0.5 and exhibit large fluctuations (the shaded region denotes the standard deviation), with OppM smaller action space producing slightly narrower variance. In the rapid convergence phase (1 000–3 000 episodes), the agents begin to exploit positive feedback from the environment, OppM simpler policy structure yields a steeper ascent, whereas OppOM higher-dimensional action set updates more conservatively, yet by about 3 000 episodes it

overtakes OppM. From 3 000 to 6 000 episodes, both smoothed curves enter a fine-tuning and stabilization phase, with OppM oscillating around 0.75 and OppOM around 0.80, and both variances markedly contracting. In the final plateau phase (11 000–15 000 episodes), OppM converges to 0.77, while OppOM (red curve) converges to 0.84. These results demonstrate that although OppOM converges more slowly in the early stages due to its policy complexity, its greater expressive power ultimately yields a superior long-term average return, confirming the effectiveness of synergistically optimizing operations and maintenance.

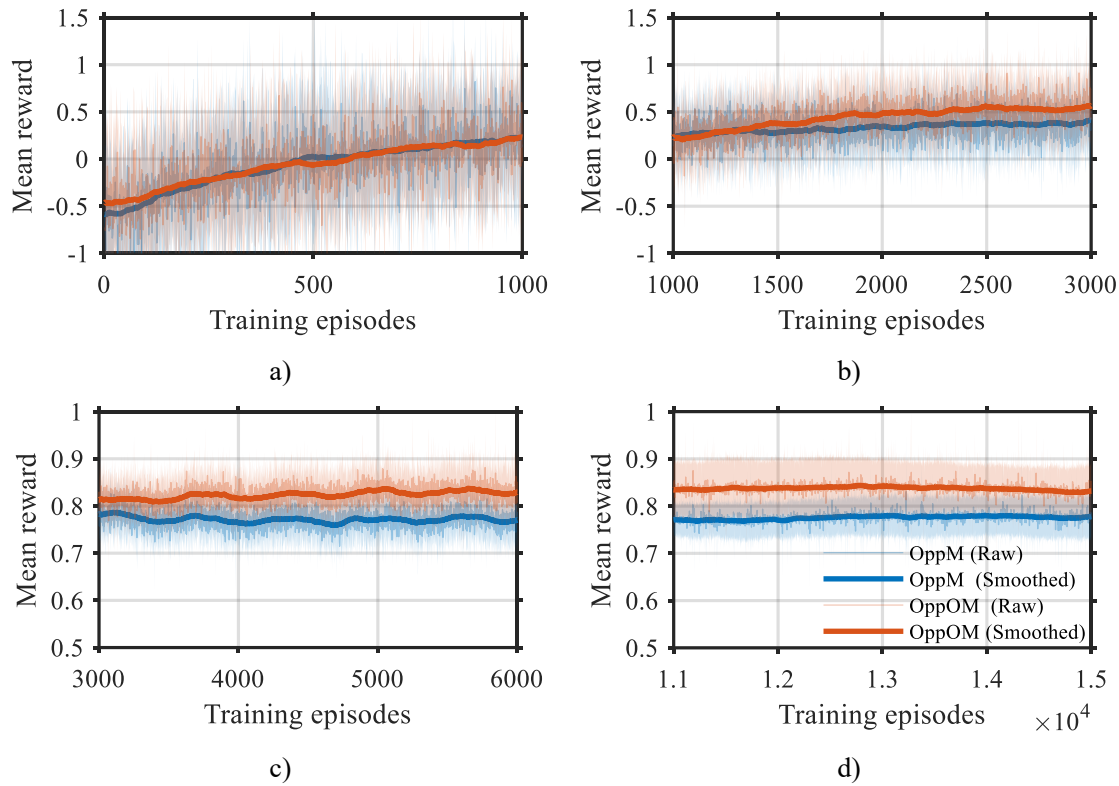


Figure 6-11 Key training phase analysis of A3C in OppM and OppOM. a) initial exploration; b) rapid convergence; c) Fine tuning; d) Stable performance.

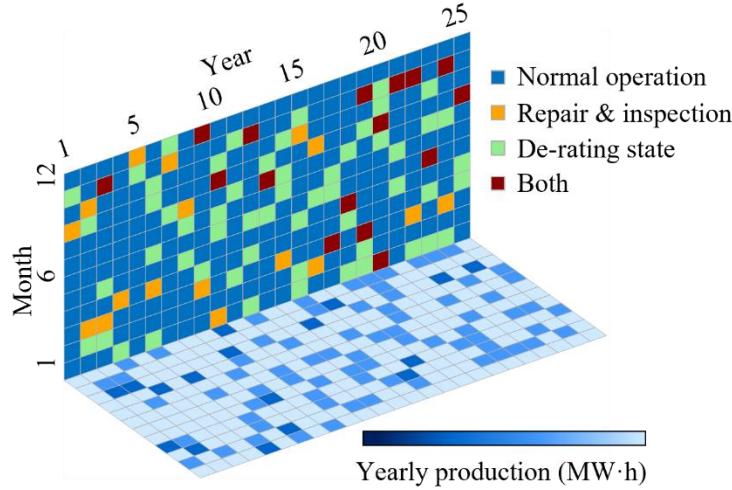


Figure 6-12 Optimal OppOM schedule by the proposed DT framework with low-fidelity.

Figure 6-12 illustrates the distribution of different operational and maintenance states over the 25-year service life under the OppOM strategy. The results reveal that the structure remains in a predominantly stable operational state throughout the lifecycle. During the initial five years, only minimal repair actions are required to meet performance and reliability standards, with de-rating occurring only once, indicating low initial degradation and minimal intervention needs. As the service period progresses, the frequency of de-rating events increases noticeably, while the frequency of repairs does not rise proportionally. This trend suggests that the de-rating strategy effectively slows down the overall degradation rate of structural components, allowing the system to maintain operational integrity without requiring frequent intrusive maintenance. In the final five years of operation, both repair and de-rating events occur more frequently, reflecting the natural aging and accumulated wear of the system. Nevertheless, even under these conditions, the power output remains consistently stable across the entire lifecycle. Notably, no sharp drops in energy production are observed during months when de-rating or repair actions are implemented. This underscores the robustness of the OppOM strategy in maintaining operational continuity and ensuring reliable power generation, even under conditions of progressive structural degradation.

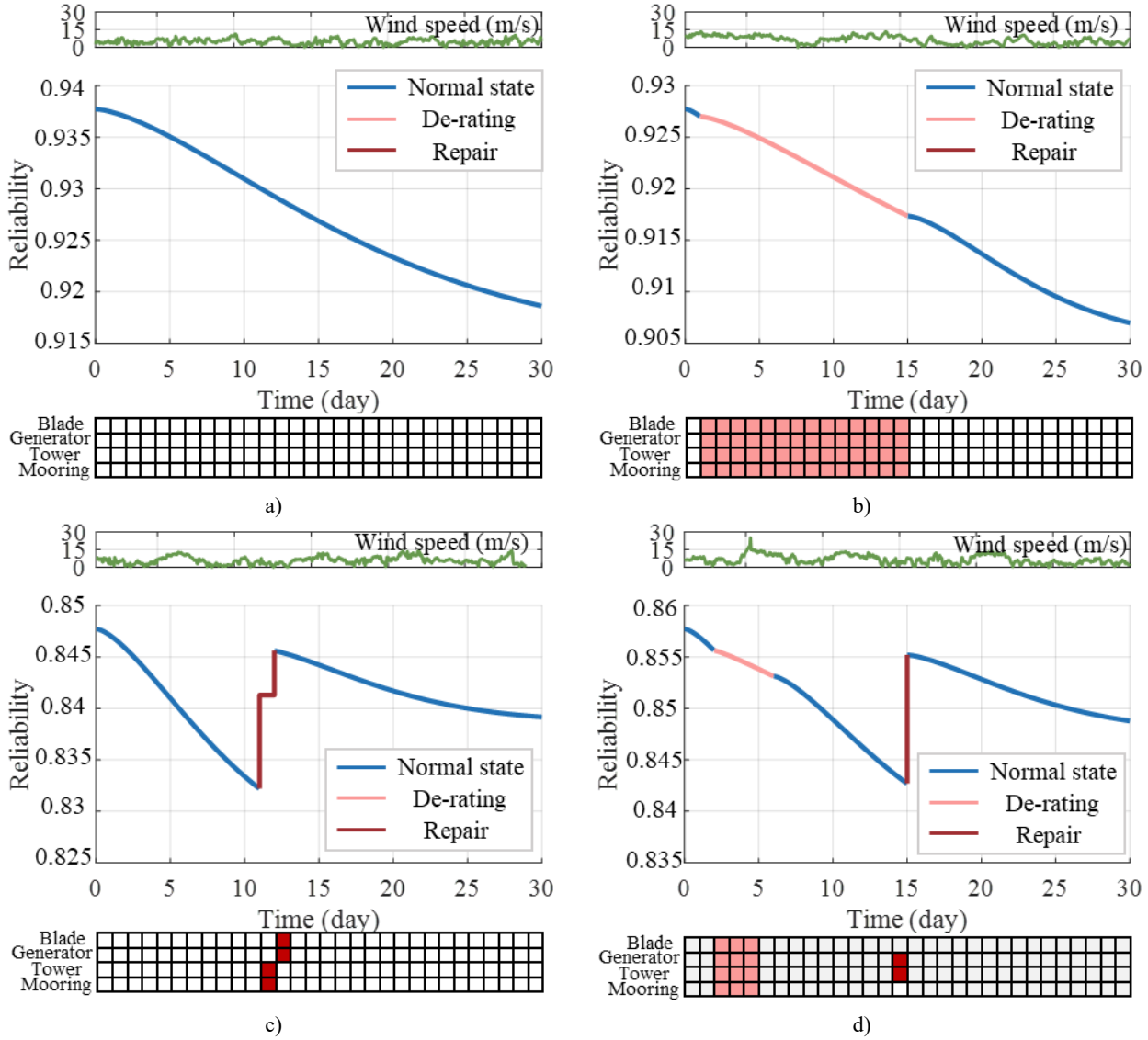


Figure 6-13 Detailed performance development of four selected typical actions. a) Non-action; b) De-rating state; c) Repair action; d) Both action.

Furthermore, [Figure 6-13](#) presents the evolution of reliability metrics across selected representative months, offering a deeper insight into how the OppOM strategy dynamically adapts to varying environmental and operational conditions. [Figure 6-13a](#)) illustrates a relatively stable month characterized by low wind speeds. The reliability index evolves slowly, following a trend closely resembling a Weibull distribution, which reflects a natural and gradual degradation process in the absence of significant external stressors. [Figure 6-13b](#)) captures a scenario where de-rating

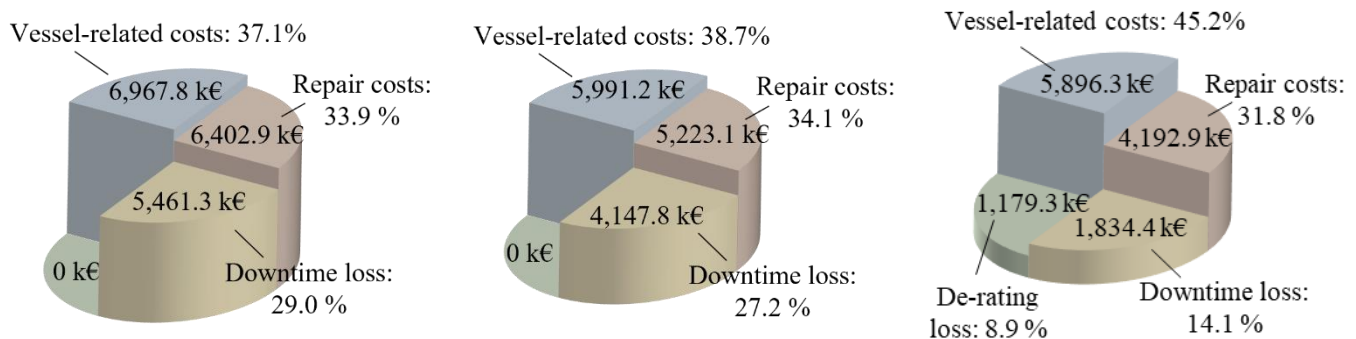
actions were applied from day 2 to day 15. During this period, wind speeds remained persistently high, posing a considerable risk of accelerated structural deterioration. The model effectively implements de-rating during these high-risk intervals, resulting in a noticeably flatter reliability trajectory. This highlights the capacity to proactively mitigate damage accumulation by adapting the operational profile to real-time wind conditions. [Figure 6-13c](#)) depicts a month in which only repair actions were triggered. A comprehensive offshore maintenance event was executed, during which all four critical components underwent repairs over a 2-day period. Importantly, this activity coincided with a moderate-to-low wind regime, ensuring operational safety during offshore operations while minimizing downtime-related energy losses. The algorithm's ability to align maintenance scheduling with favorable environmental windows further enhances O&M efficiency. [Figure 6-13d](#)) showcases a more complex scenario where both de-rating and repair actions were deployed. Here, de-rating was applied prior to reaching the maintenance threshold, successfully delaying structural degradation during high wind speed periods. Maintenance was then triggered during a subsequent low-wind interval. These results confirm that the A3C-based optimization framework effectively orchestrates both proactive and reactive actions, executing de-rating during peak stress windows and scheduling physical interventions during calm periods. In summary, the proposed A3C algorithm provides a robust and adaptive decision-making framework for dynamic O&M coordination. By continuously evaluating real-time wind profiles and structural health indicators, the model can intelligently deploy and adjust maintenance and control strategies, enhancing structural longevity while preserving energy production efficiency.

6.5.2 Comparison of different strategies

[Figure 6-14](#) provides a comprehensive breakdown of lifecycle costs associated with different operational and maintenance strategies, including economic losses from vessel deployment, direct

repair costs, and production losses due to both downtime and de-rating. The results clearly show that the CBM strategy incurs the highest overall expenditure, with a total cost of €18,832k. This is primarily due to the frequent need for offshore deployment to maintain structural integrity, resulting in substantial vessel and repair-related expenses. In comparison, the OppM strategy demonstrates improved cost-efficiency, with a total lifecycle cost of €15,352.1k. This reduction is largely attributable to its ability to effectively anticipate and act on maintenance triggers, thereby minimizing unplanned downtime. Under OppM, downtime-related production loss is reduced to €4,147.8k, a notable improvement over CBM. The proposed OppOM yields the most cost-effective outcome, with a total lifecycle cost of only €13,102.6k. By integrating real-time de-rating control into the O&M decision-making process, OppOM significantly alleviates structural degradation, effectively reducing the frequency of required physical maintenance interventions. Although the introduction of de-rating incurs some production loss, the combined loss from de-rating and downtime is limited to €3,013.7k, substantially lower than that of both CBM and OppM. These results demonstrate that de-rating, when strategically coordinated with O&M activities, offers a high return on investment: modest reductions in short-term energy output can be offset by long-term savings in maintenance costs and operational disruptions.

A comprehensive multi-aspect evaluation of the three strategies including safety, economic performance, and energy yield is further illustrated in [Figure 6-15](#).



a) b) c)
Figure 6-14 Total cost and cost distribution under different maintenance strategies. a) CBM; b) OppM; c) OppOM.

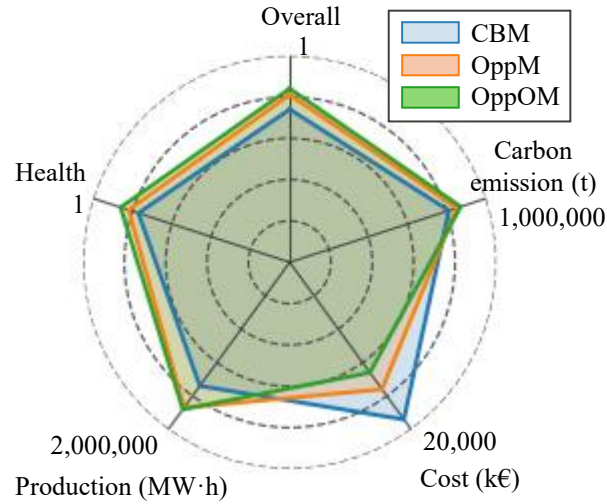


Figure 6-15 Comprehensive performance of FOWT (CBM; OppM; OppOM)

Figure 6-15 presents a comparative overview of key performance indicators over the 25-year service life for the three O&M strategies. The proposed OppOM strategy consistently outperforms both OppM and CBM across all metrics. The overall composite performance scores, normalized across multiple dimensions, are 0.84 for OppOM, 0.81 for OppM, and 0.74 for CBM, indicating a clear hierarchical advantage. In terms of structural health, CBM tends to treat components independently, initiating repairs only after degradation reaches a predefined threshold. This conservative approach results in a higher tolerance for degradation accumulation, yielding a relatively low average reliability index of 0.82 over the lifecycle. In contrast, both OppM and OppOM implement proactive maintenance actions during each service opportunity, often addressing components that have not yet crossed failure thresholds. This leads to improved health trajectories, with average reliability indices of 0.84 for OppM and 0.87 for OppOM, highlighting the benefit of coordinated, preemptive maintenance strategies. From an operational perspective,

CBM also suffers from frequent offshore interventions, longer downtime durations, and higher associated costs. Its total energy production over 25 years stands at 1,480,231.7 MWh, with corresponding CO₂ emissions avoided totaling 767,358.4 tons. In comparison, both opportunity-based strategies demonstrate substantial advantages by reducing offshore deployment frequency and aggregating multiple maintenance tasks per trip. This results in lower maintenance costs and greater emissions reductions. While both OppM and OppOM outperform CBM, key distinctions exist between the two. OppOM further integrates de-rating control to slow down component degradation by reducing operational loads during high-risk periods. Although this incurs modest short-term production losses, it substantially reduces downtime and offshore repair demand. Over the full service life, this trade-off proves advantageous: OppOM achieves a total energy yield of 1,661,121.5 MWh and a net CO₂ offset of 853,541.1 tons, surpassing OppM 1,647,823.3 MWh and 825,194.3 tons, respectively.

These findings confirm that the coordinated use of control and maintenance under OppOM not only improves structural resilience but also enhances lifecycle energy performance and environmental impact, making it a compelling solution for future offshore wind O&M frameworks.

6.6 *Summary*

This Section study proposes an integrated opportunistic operation and maintenance strategy that combines turbine control policies with human-in-the-loop maintenance actions. To address the compounded degradation of wind turbines caused by material aging and long-term loading during service, a probabilistic degradation modeling framework was developed based on DBN. The DBN model explicitly defines the state variables, transition probabilities, and observation models, enabling a quantitative representation of uncertainty in the degradation evolution process. Through

Bayesian updating, real-time inference of system health states is achieved, resulting in a belief distribution that reflects the most probable structural condition at any given time.

Building on this, a decision-making framework is constructed within the partially observable Markov decision process (POMDP) paradigm. This framework establishes a state-to-action mapping that incorporates a multi-objective evaluation across safety, economic cost, energy yield, and carbon emissions. These aggregated metrics serve as the optimization objective in a lifecycle-aware maintenance planning process. The policy is dynamically optimized using the A3C reinforcement learning algorithm, enabling global coordination of control and maintenance strategies throughout the turbine lifecycle.

- (1) An in-depth analysis of the degradation behavior of major components, including the blades, generator, tower, and mooring system reveals distinct deterioration trajectories. Specifically, the blades and generator exhibit relatively rapid degradation, reaching critical damage thresholds around years 14 to 15. In contrast, the tower and mooring system deteriorate more slowly in the early years, but enter a phase of accelerated failure thereafter. The tower, for instance, approaches its critical state at approximately 19.2 years, while the mooring system begins to deteriorate rapidly after year 16. These heterogeneous degradation characteristics provide a strong rationale for component-specific maintenance scheduling, enabling optimized interval adjustments that prolong structural health while minimizing maintenance frequency and cost.
- (2) The combined DBN-POMDP framework demonstrates significant advantages in capturing the temporal evolution of structural degradation under complex, non-stationary environmental conditions. By leveraging the Bayesian updating mechanism, the method enables accurate real-time state estimation even under partial observability. Optimal

- decision policies are obtained via dynamic programming, resulting in a robust and adaptive O&M strategy. Compared to traditional condition-based methods, this approach offers greater flexibility and precision in both monitoring and action planning, particularly under the uncertainty and volatility inherent in offshore wind environments.
- (3) Over a 25-year lifecycle simulation with standard North Sea weather windows and average accessibility constraints, the proposed opportunistic operation and maintenance strategy resulted in a total cost of €13,102.6k, compared to €15,352.1k for conventional opportunistic maintenance and €18,832k for traditional condition-based maintenance. While de-rating may lead to minor short-term production losses, the long-term economic benefit from reduced intervention frequency and downtime outweighs this loss.
- (4) The OppOM strategy achieves the best overall results. Its average reliability index over the service period reaches 0.87, outperforming OppM (0.84) and CBM (0.82), indicating stronger performance in structural integrity preservation. Despite some power curtailment during de-rating events, the OppOM strategy's ability to reduce peak stresses results in less frequent shutdowns. Over 25 years, it delivers a total energy yield of 1,661,121.5 MWh, surpassing both OppM (1,647,823.3 MWh) and CBM (1,480,231.7 MWh). Additionally, by minimizing offshore operations and maximizing energy production, OppOM achieves the highest carbon reduction potential, with 853,541.1 t CO₂ avoided, compared to 825,194.3 t for OppM and 767,358.4 t for CBM.
- (5) In conclusion, although de-rating introduces minor short-term output losses, it plays a critical role in extending structural service life, reducing operational risk, and minimizing lifecycle cost and environmental impact. The proposed OppOM strategy thus presents a holistic, adaptive, and economically viable approach to lifecycle management for

offshore wind turbines, effectively balancing structural safety, economic efficiency, and environmental sustainability.

CHAPTER 7

Wind-farm level management with OppOM

7.1 *Introduction*

Turbine-level optimization provides detailed control and maintenance strategies, yet large-scale deployment requires system-level coordination. Chapter 1 identified the necessity of addressing wake interactions, shared resources, and multi-turbine dependencies at the wind farm scale.

This chapter extends the opportunistic maintenance strategies of Chapter 6 from the turbine level to the wind farm level.

A wind farm-level framework is developed that integrates wake effects, heterogeneous turbine states, and logistic constraints. The framework enables coordinated OppM and facilitates decision-making that accounts for both local turbine performance and overall system operation.

7.2 *Wake effect for different FOWTs*

Wake models are pivotal in studying the complex interactions between wind turbines and optimizing wind farm performance ([González-Longatt et al., 2012](#)). A wake, formed downstream of a wind turbine due to energy extraction, is characterized by reduced wind speeds and increased turbulence intensity ([Shakoor et al., 2016](#)). These wake effects not only diminish the power output of downstream turbines but also increase structural loads and fatigue damage. The dynamics of wakes, including wind speed distribution, turbulence intensity, wake expansion, and meandering, are critical for wind farm performance and operational optimization. Current wake modeling

approaches must strike a balance between computational accuracy and efficiency to support large-scale wind farm layouts and design optimization.

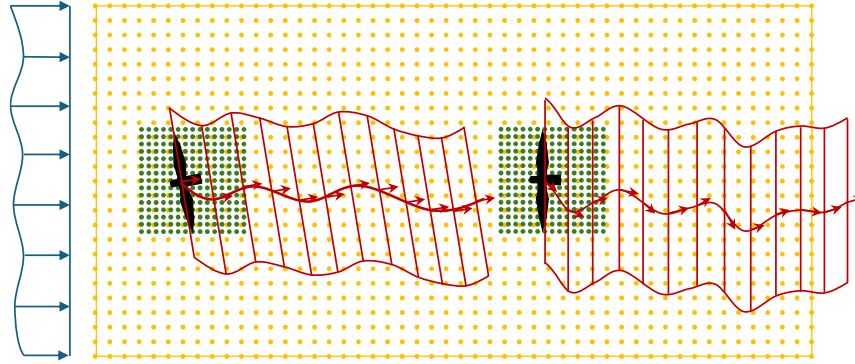


Figure 7-1 Wake planes, wake volumes, and zones of wake overlap for a two-turbine wind farm.

The Dynamic Wake Meandering (DWM) model, as a medium-fidelity wake modeling approach, uses physical approximations to capture essential wake dynamics while maintaining computational efficiency (Larsen et al., 2008; Larsen et al., 2013). The DWM model divides wake dynamics into two primary components: the evolution of the wake deficit and the stochastic motion of wake meandering (Ye et al., 2024). The wake deficit represents the wind speed reduction caused by upstream turbine energy extraction and is modeled using the thin shear layer approximation. Based on the Reynolds-averaged Navier-Stokes equations, the model describes the dynamic variations of axial and radial velocity distributions within the wake:

$$V_x \frac{\partial V_x}{\partial x} + V_r \frac{\partial V_x}{\partial r} = \frac{1}{r} \frac{\partial}{\partial r} \left(r v_T \frac{\partial V_x}{\partial r} \right) \quad (7.1)$$

where V_x are the axial and radial velocities, respectively, while v_T represents the eddy viscosity, accounting for turbulence diffusion effects. The eddy viscosity is expressed as:

$$v_T(x, r) = F_{v,Amb}(x) k_{v,Amb} T_{IAmb} \overline{V_{Wind}} R + F_{v,Shr}(x) k_{v,Shr} \max \left(\frac{D_{Wake}(x)}{2}, \left| \frac{\partial V_x}{\partial r} \right| \right) \quad (7.2)$$

In this formulation, the first term captures the effect of ambient turbulence intensity on wake expansion, while the second term accounts for the turbulence induced by the wake shear layer. By dynamically adjusting the eddy viscosity, the model effectively captures the wake's expansion rate and turbulence characteristics.

Wake meandering is influenced by large-scale ambient turbulence, resulting in stochastic lateral and vertical motions of the wake centerline. The DWM model employs a passive tracer approach to model wake meandering and uses low-pass filtering to capture its transient characteristics. This approach reflects the dynamic shifts in the wake centerline and shape under varying flow conditions, particularly the transition from circular to elliptical wake shapes under yawed inflow. Additionally, in the near-wake region, significant velocity deficits and radial expansions occur due to pressure gradients. The DWM model incorporates a near-wake correction to improve accuracy in this region, providing refined initial conditions for far-wake evolution:

$$V_{\text{Wake},x}(r)|_{n_p=0} = -\overline{V_{\text{Rel}}} C_{\text{NearWake}} a(r) \quad (7.3)$$

where C_{NearWake} denotes the near-wake expansion coefficient, and $a(r)a(r)a(r)$ represents the axial induction factor.

FAST.Farm, as a medium-fidelity multi-physics simulation tool, integrates the DWM model as one of its core components. Through a modular design, FAST.Farm combines wake modeling with high-fidelity dynamic response calculations for individual turbines. High-resolution grids are employed around individual turbines to capture local wind speeds and turbulence, driving aerodynamic load calculations within the OpenFAST module. Simultaneously, low-resolution grids encompass the entire wind farm to model the background wind field and overall wake propagation. This multi-scale grid approach ensures global and local computational consistency through efficient data interpolation, balancing accuracy and efficiency.

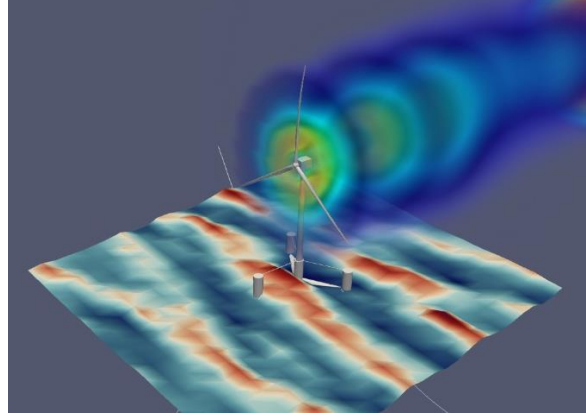


Figure 7-2 OpenFAST simulation of wind turbine wake effects

For offshore wind farms, FAST.Farm incorporates wave modeling capabilities to study the coupled effects of waves and wakes on turbine dynamics. Wave propagation is modeled using linear wave theory, with wave parameters such as height, wavelength, and period defined by input spectra (e.g., JONSWAP spectrum). Hydrodynamic loads are calculated using the Morison equation:

$$F = C_m \rho V \ddot{u} + C_d \frac{1}{2} \rho A u |u| \quad (7.4)$$

where C_m and C_d are the inertia and drag coefficients, respectively, ρ is the water density, V and A are the structural volume and frontal area, and u and $\ddot{u}$ denote fluid velocity and acceleration. By incorporating the combined effects of waves, wind flow, and wakes, the model comprehensively simulates the dynamic performance of offshore wind farms.

The DWM model in FAST.Farm provides an efficient and accurate solution for wake simulations. By integrating wake dynamics, ambient turbulence effects, and multi-scale grid methodologies, the model captures the complex interactions between wind turbines within a wind farm (Jonkman & Shaler, 2021). Additionally, the inclusion of wave modeling extends FAST.Farm's applicability to offshore scenarios, enabling dynamic analyses across diverse

environmental conditions. This comprehensive modeling capability supports the optimization of wind farm design and enhances operational performance.

Adjustments in the rotational speed of upstream wind turbines directly impact wake characteristics, consequently affecting the inflow conditions and dynamic performance of downstream turbines. Specifically, a reduction in the rotational speed of the upstream turbine alters the rotor thrust coefficient (CT) and induction factor (a), as described by momentum theory.

According to Betz momentum theory, the axial velocity deficit within the wake V_{wake} relates to the axial induction factor (a) by the following equation:

$$V_{wake} = V_{\infty}(1 - 2a) \quad (7.5)$$

where, V_{∞} represents the free stream wind speed. Lowering the upstream turbine's rotational speed reduces blade loading, consequently decreasing the thrust coefficient CT and axial induction factor a. This leads to a reduced axial velocity deficit in the wake, effectively increasing the wind speed downstream within the wake region.

Moreover, FAST.Farm modeling, based on Dynamic Wake Meandering (DWM) theory, considers wake advection, deflection, and low-frequency oscillations. Notably, decreasing the upstream turbine speed modifies the turbulent diffusion characteristics within the wake vortices, enhancing the recovery rate toward the free stream wind condition downstream.

Specifically, the FAST.Farm turbulent viscosity model describing wake evolution can be represented as:

$$v_T(x, r) = F_{vAmb}(x)k_{vAmb} \frac{FiltTI_{Amb}}{FiltV_{wind,x}R} + F_{vShr}(x)k_{vShr} \max\left(\frac{D_{wake}(x)}{2}, \left|\frac{\partial V_x}{\partial r}\right|, \frac{D_{wake}(x)}{2} \min|rV_x(x, r)|\right) \quad (7.6)$$

A reduction in upstream turbine speed affects the axial velocity gradient $\partial V_x / \partial r$ distribution, weakening the turbulent viscosity effect within the wake shear layer. This adjustment accelerates wake diffusion and wind speed recovery. Therefore, upstream turbine de-rating significantly influences downstream turbine inflow conditions by lowering thrust coefficients, induction factors, and modifying turbulent diffusion in wake vortices. This ultimately results in increased downstream wake wind speeds and reduced negative impacts on downstream turbine performance and structural integrity.

7.3 *Climate change modelling*

Given the challenges of fully integrating weather models with deterioration models, this section presents a simplified weather model that accounts for the following factors:

- (1) The impact of global warming;
- (2) Seasonal and daily variations in weather parameters; and
- (3) The randomness of weather.

Seasonal variations are modeled using the sinusoidal model developed by Phu Tho et al. [7], while a Gaussian random process is used to characterize the randomness of weather.

$$\psi(t) = \bar{\psi}(t) + \psi_{sd}(t) + \psi_{GP}(t) \quad (7.7)$$

where t is the time parameter (in hours); $\psi_{sd}(t)$ is the time-varying mean baseline of the model; $\psi_{sea}(t)$ represents the seasonal and daily variations in environmental temperature; and $\psi_{GP}(t)$ is the stochastic component modeled as a Gaussian process.

$$\psi_{sd}(t) = \alpha_1 \sin\left(\frac{2\pi t}{365.25 \times 24} + \alpha_2\right) + \alpha_3 \sin\left(\frac{2\pi t}{24} + \alpha_4\right) \quad (7.8)$$

where α_s ($s=1,2,3,4$) are model parameters determined by fitting the model to actual environmental

data.

According to the IPCC 2023 report, the average temperature from 2011 to 2020 was approximately 1.1°C higher than that of 1850-1900. Even under the most optimistic scenarios of reduced carbon dioxide emissions, temperatures are expected to rise by 1.4°C by 2100 (Pincioli et al., 2021). Based on existing research (Dong & Zhao, 2021), it is assumed that the annual average temperature changes linearly over time; thus, $\bar{\psi}(t)$ can be expressed as:

$$\bar{\psi}(t) = \psi_0 + t \cdot k_T \quad (7.9)$$

where ψ_0 represents the annual average temperature (°C) at the beginning of the analysis, and k_T (°C/yr) denotes the annual average temperature rise. Additionally, the surface chloride content of concrete, $C_s(t)$ (expressed as a percentage by weight of the binder), is predicted by the following equation (CHANGE, 2007):

$$C_{s,sub} = 4.12 \cdot A_c \cdot R_{wb} \cdot C_{sea} \cdot (1 - \exp(-0.56t/(365.25 \times 24))) \quad (7.10)$$

where C_{sea} represents the chloride concentration in seawater, which is 1.93% (Bastidas-Arteaga et al., 2013); R_{wb} is the water-to-binder ratio; and A_c is a correction factor for the binder type, which is 0.9 (Anthoni, 2006; Shi et al., 2021).

Climate change has a profound impact on the global distribution of wind speeds, affecting not only the mean wind speed but also higher-order statistical moments such as standard deviation, skewness, and kurtosis (Shi et al., 2021). These changes generally follow a linear trend over time (Liu et al., 2022). In this study, the temporal variation in the mean wind speed and standard deviation is modeled using Equation (7.11), offering a quantitative framework to capture the progressive effects of climate change on wind characteristics.

$$\bar{W}_s(t) = \bar{W}_{s,0} + t \cdot k_W \quad (7.11)$$

where $\bar{W}_s(t)$ represents the annual average wind speed (m/s) at the start of the analysis, and k_W

denotes the annual average temperature rise.

For wave height, a fitting analysis based on measured data shows a linear relationship between wave height and wind speed under marine conditions (Jung & Schindler, 2019). Consequently, this study employs a linear function to model the correlation between the two variables. The fitting results between wave height and wind speed are presented in Figure 7-3.

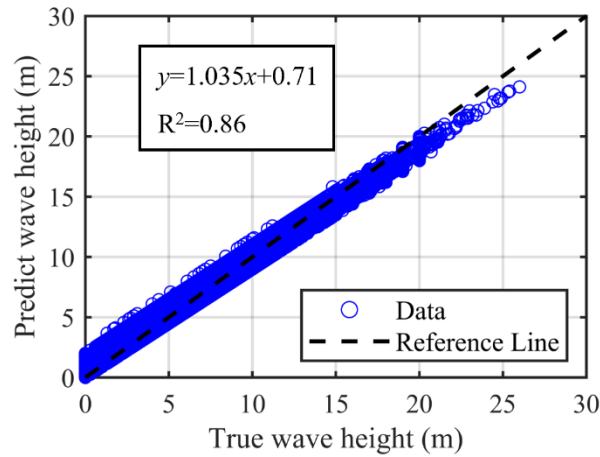


Figure 7-3 Fitting results between wind speed and wave height

Using seawater temperature data from the National Data Buoy Center for CAPE ELIZABETH - 45NM NW of Aberdeen, WA (https://www.ndbc.noaa.gov/station_page.php?station=46041), spanning from January 1, 1988, to the end of 2023, and incorporating the environmental model, a regression analysis was performed to fit the model parameters. Initially, the temperature data was normalized to extract the seasonal and daily temperature variations. Following this, the parameters in (t) were regressed, as shown in Figure 7-4.

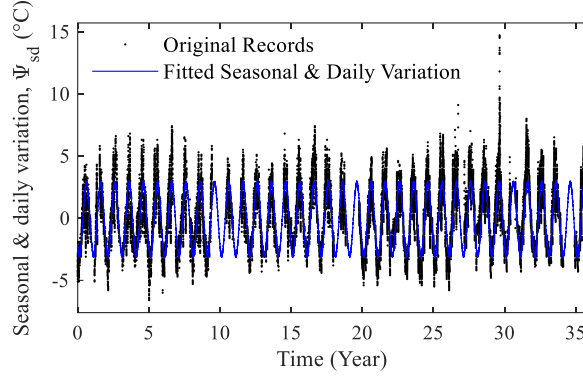


Figure 7-4 Comparisons of actual data and fitted model of seasonal and daily variation of temperature

After obtaining the seasonal and daily variations, the next step involves modeling the residual error using Gaussian processes (GP). Herein, Karhunen-Loève expansion (KLE) is employed to discretize the GP $\Psi_{GP}(t)$. KLE is based on the spectral decomposition of the covariance function $C(t_1, t_2)$ (where t_1 and t_2 are two arbitrary time points) and expresses the random process $\Psi_{GP}(t)$ as a combination of orthogonal functions $f_i(t)$:

Once the seasonal and daily variations are obtained, the next step is to model the residual error using Gaussian processes (GP). In this approach, Karhunen-Loève expansion (KLE) is used to discretize the $\Psi_{GP}(t)$. KLE relies on the spectral decomposition of the covariance function $C(t_1, t_2)$ (where t_1, t_2 are two arbitrary time points) and expresses the random process $\Psi_{GP}(t)$ as a sum of orthogonal functions $f_i(t)$:

$$\psi_{GP}(t) \simeq \bar{\psi}_{GP}(t) + \sigma_{\psi_{GP}}(t) \cdot \sum \sqrt{\lambda_i} \xi_i(\theta) f_i(t) \quad (7.12)$$

where $\bar{\psi}_{GP}(t)$ μ and $\sigma_{\psi_{GP}}(t) \cdot \sigma$ are the mean and standard deviation (STD) of $\Psi_{GP}(t)$, respectively, which are directly obtained from the mean and STD of residual errors; $\xi_i(\theta)$ represents a set of standard Gaussian variables; n_{KLE} denotes the number of truncated discretization terms; and λ_i are the eigenvalues of the covariance function $C(t_1, t_2)$, which are derived from the following

expression:

$$\int C(t_1, t_2) f_i(t_2) dt_2 = \lambda_i f_i(t_1) \quad (7.13)$$

Assuming that the covariance function $C(t_1, t_2)$ follows an exponential form, the solution to Equation (7.13) can be derived analytically:

$$C(t_1, t_2) = \exp(-|t_1 - t_2|/b_e) \quad (7.14)$$

where b_e represents the correlation length (in hours). To determine b_e , an autocorrelation analysis is performed to assess how the autocorrelation coefficient varies with Δt .

By fitting Equation (7.14), the parameter b was found to be 1094.9 hours, as shown in Figure 7-5. Next, random sampling of $\Psi_{GP(t)}$ was carried out using the Karhunen-Loève Expansion (KLE), as depicted in Figure 7-6. A comparison between the sampled stochastic temperature model and actual temperature data demonstrates that the proposed approach successfully captures the temporal variability and inherent randomness of temperature fluctuations.

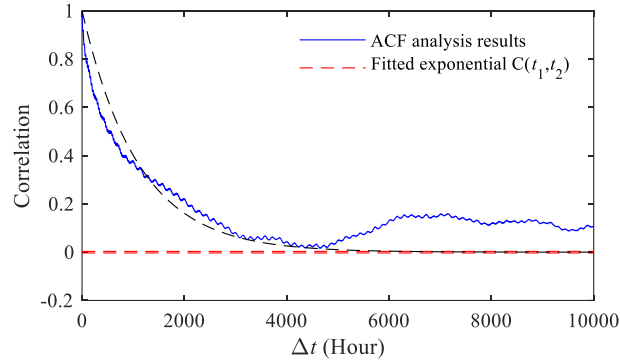


Figure 7-5 Comparisons of ACF analysis results and fitted $C(t_1, t_2)$

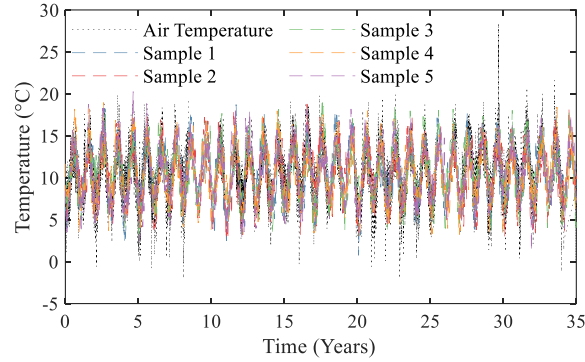


Figure 7-6 Comparisons of actual temperature records and sampled stochastic temperature model

Based on the framework provided by (Mukherjee & Sivaramakrishnan, 1981), this study considers three climate change scenarios: no global warming, expected global warming, and pessimistic global warming, as outlined in Table 7-1. The expected global warming scenario assumes a mix of alternative and fossil fuels, with current birth rates maintained and no widespread adoption of clean technologies (equivalent to RCP2.6-RCP4.5 scenarios), leading to a temperature rise of only 2.5°C over a century. The pessimistic global warming scenario, on the other hand, involves heavy reliance on fossil fuels, significant population growth, and a lack of policies encouraging clean technology adoption (equivalent to RCP6-RCP8.5 scenarios), resulting in a temperature increase of 6.5°C over 100 years.

Table 7-1 Annual average temperature rises under different scenarios

Scenario No	T1	T2	T3
$k_T(^{\circ}\text{C}/\text{yr})$	0	2.5×10^{-2}	6.5×10^{-2}

7.4 Mathematical modeling in wind farms

This section expands the mathematical model from single offshore wind turbine maintenance to

an entire offshore wind farm, consisting of three turbines. The formulation aims to systematically address opportunistic maintenance (OM) strategies, incorporating component-level repairs, structural-level operational de-rating, environmental impact analysis (CO₂ emissions), and minimizing variability in total power generation. Key features of this model extension include parallel maintenance within individual turbines, sequential maintenance among different turbines, independent de-rating decisions per turbine, and maintaining stable total farm energy output.

Consider a wind farm with three turbines, indexed by $j \in \{1,2,3\}$. Each turbine comprises four critical structural components, indexed by $i \in \{1,2,3,4\}$ (blade, nacelle, tower, and mooring system). The planning horizon is discretized into daily intervals, indexed by $t \in \{0,1,2,\dots,T\}$.

For each turbine j , a binary decision variable $z_{i,j,t}$ indicates repair actions on component i of turbine at day t :

$$z_{i,j,t} \in \{0,1\}, \quad \forall i,j,t \quad (7.15)$$

where $z_{i,j,t} = 1$ represents a repair action executed, and $z_{i,j,t} = 0$ otherwise.

A binary variable $y_{j,t}$ represents vessel mobilization status for turbine j on day t :

$$y_{j,t} \geq z_{i,j,t} \quad (7.16)$$

$$y_{j,t} \leq \sum_{i=1}^4 z_{i,j,t} \quad (7.17)$$

where $y_{j,t} = 1$ if at least one component in turbine j is repaired on day t , and $y_{j,t} = 0$ otherwise.

Additionally, binary variables $dr_{j,t}$ represent structural-level operational de-rating decisions for each turbine j independently:

$$\sum_{i=1}^4 z_{i,j,t} + dr_{j,t} \leq 1 \quad (7.18)$$

where $dr_{j,t} = 1$ indicates active de-rating and $dr_{j,t} = 0$ indicates normal operation for turbine j .

Within each turbine j , component repairs occur simultaneously (parallel execution), defining total turbine downtime $\tau_{j,t}$ as:

$$\tau_{j,t} = \max_i \{\tau_{i,j} z_{i,j,t}\} \quad (7.19)$$

where $\tau_{j,t}$ is the duration of repair for component i of turbine j .

Across turbines, maintenance is conducted sequentially due to limited vessel and crew availability.

Thus, total daily downtime D_t^{farm} is:

$$D_t^{farm} = \sum_{j=1}^3 D_{j,t} \quad (7.20)$$

Reliability of each component $R_{i,j,t}$ must exceed its threshold $R_{i,j}^{min}$:

$$R_{i,j,t} \geq R_{i,j}^{min} \quad (7.21)$$

where $R_{i,j,t}$ is the reliability of component i in turbine j at day t .

7.5 *Application on a Three-FOWT wind farm*

7.5.1 Description of the wind farm

The layout of semi-submersible floating offshore wind farms involves multiple critical components, including the design of floating platforms, configuration of mooring systems, subsea cable routing, and the spatial arrangement of wind turbines. In this study, the WindFloat Atlantic project in Portugal is selected as a representative case to illustrate the practical deployment approach and technical characteristics of such floating wind farms. WindFloat Atlantic is the world's first commercial semi-submersible floating offshore wind farm and the first of its kind in continental Europe. Commissioned in 2020, the project is located approximately 20 kilometers off

the coast of Viana do Castelo, Portugal. It represents a milestone in the advancement of floating wind technology, transitioning from demonstration to full-scale commercial operation.

The project has a total installed capacity of 25 MW and comprises three MHI Vestas V164-8.4 MW wind turbines mounted on semi-submersible floating platforms utilizing WindFloat technology. The operations and maintenance base is situated at the Port of Viana do Castelo, where real-time monitoring and coordination of offshore activities are conducted. Due to limited publicly available data on the exact layout of the WindFloat Atlantic project, this study adopts an assumed inter-turbine spacing of 1 km within the life-cycle assessment framework. This assumption is consistent with industry practices, where turbine spacing typically ranges from 4D to 10D (D representing rotor diameter) as noted by (Carter, 1982). For the 15 MW turbines used in this study, with a rotor diameter of 240 meters, a 1 km spacing ensures adequate mitigation of wake effects.

Furthermore, to investigate the structural degradation under the most unfavorable operational conditions, wind turbine alignment is oriented along the prevailing wind direction as indicated by the site's wind rose diagram. Following the conclusions of Section 3.2, which identified maximum wind speed distribution as a critical factor influencing structural fatigue, the layout adopted in this study features three turbines arranged in parallel along the dominant wind direction to simulate the worst-case deterioration pathway (see Figure 7-7).

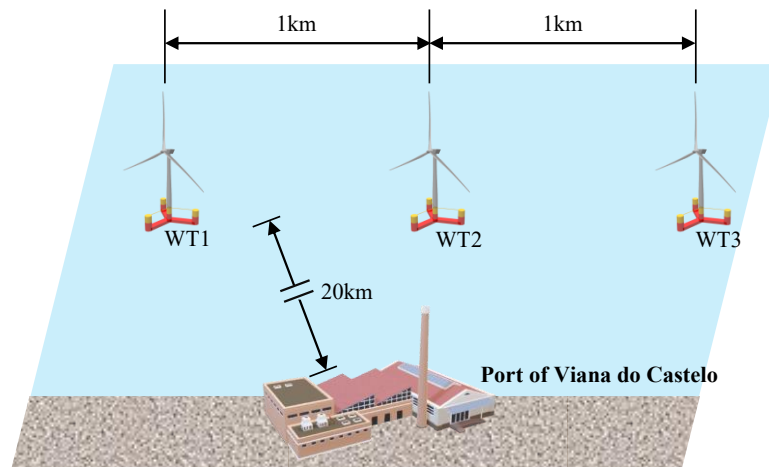


Figure 7-7 Turbine layout aligned with dominant wind direction

7.5.2 Dynamic performance of FOWTs

A key distinction between wind farm-scale dynamic analysis and single-turbine evaluation lies in the influence of wake effects on inter-turbine wind speed propagation. As upstream turbines extract energy from the wind, they generate a downstream wake characterized by reduced wind speed and increased turbulence. This altered inflow significantly affects the aerodynamic loading and dynamic performance of downstream turbines. Figure 7-8 presents a comparative analysis of wind speed distributions across a three-turbine layout under three typical upstream inflow conditions, rated wind speed (10.59 m/s), moderate high wind speed (15 m/s), and extreme high wind speed (21 m/s). The results demonstrate a clear trend: as upstream wind speed increases, the relative intensity of the wake effect decreases, allowing higher wind energy availability at downstream turbines.

- At an upstream inflow of 11 m/s, the wake significantly reduces downstream wind speeds. Turbine T2 receives a mean wind speed of only 7.62 m/s, while T3 drops further to 6.83 m/s, indicating substantial energy loss due to wake interference.
- At 15 m/s upstream inflow, the wake weakens. T2 and T3 record improved mean wind speeds of 13.06 m/s and 12.61 m/s, respectively, retaining a larger portion of the wind energy.
- When the upstream turbine operates under a strong inflow of 21 m/s, the wake effect becomes even less pronounced. T2 and T3 maintain high mean wind speeds of 19.64 m/s and 19.47 m/s, suggesting minimal aerodynamic shadowing.

These findings emphasize the critical role of inflow variability and wake propagation in determining turbine-specific loading conditions. As each turbine within a farm operates under unique and temporally evolving wind profiles, accounting for wake-induced wind speed disparities

is essential for accurate dynamic performance evaluation, control coordination, and predictive maintenance planning at the wind farm scale.

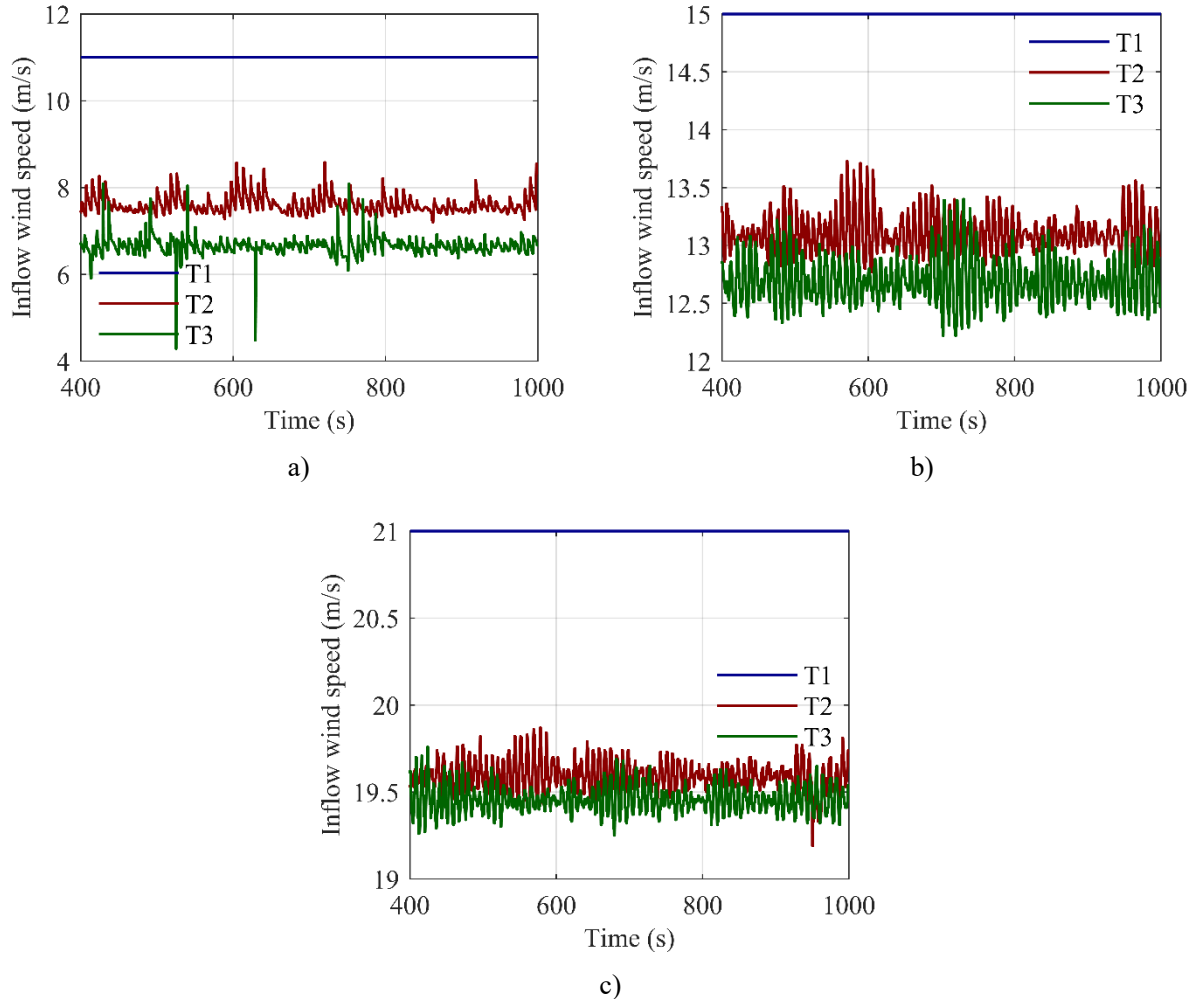


Figure 7-8 Wind speed distribution of the turbine under different inflow wind speeds. a) 11 m/s; b) 15 m/s; c) 21 m/s.

Building on the wind speed distributions illustrated in [Figure 7-10](#), [Figure 7-9](#) further analyzes the dynamic performance of turbines WT1, WT2, and WT3, using blade response as a representative indicator. The results reveal a clear influence of wake effects on structural behavior: downstream turbines exhibit significantly lower dynamic responses compared to the upstream turbine, primarily due to reduced inflow wind energy caused by upstream wake interference. However,

consistent with the trend observed in Figure 7-8, this disparity in dynamic response diminishes as the upstream inflow velocity increases. At higher wind speeds, the wake deficit is less severe, allowing downstream turbines to regain a portion of the aerodynamic loading experienced by the lead turbine. Consequently, the difference in blade response across turbines is reduced under strong wind conditions. These observations highlight the dynamic sensitivity of turbine components such as blades to spatial variations in wind field characteristics induced by turbine-turbine interactions. Accurate modeling of such wake-modulated structural behaviors is essential for developing effective wind farm-level control strategies and load management approaches.

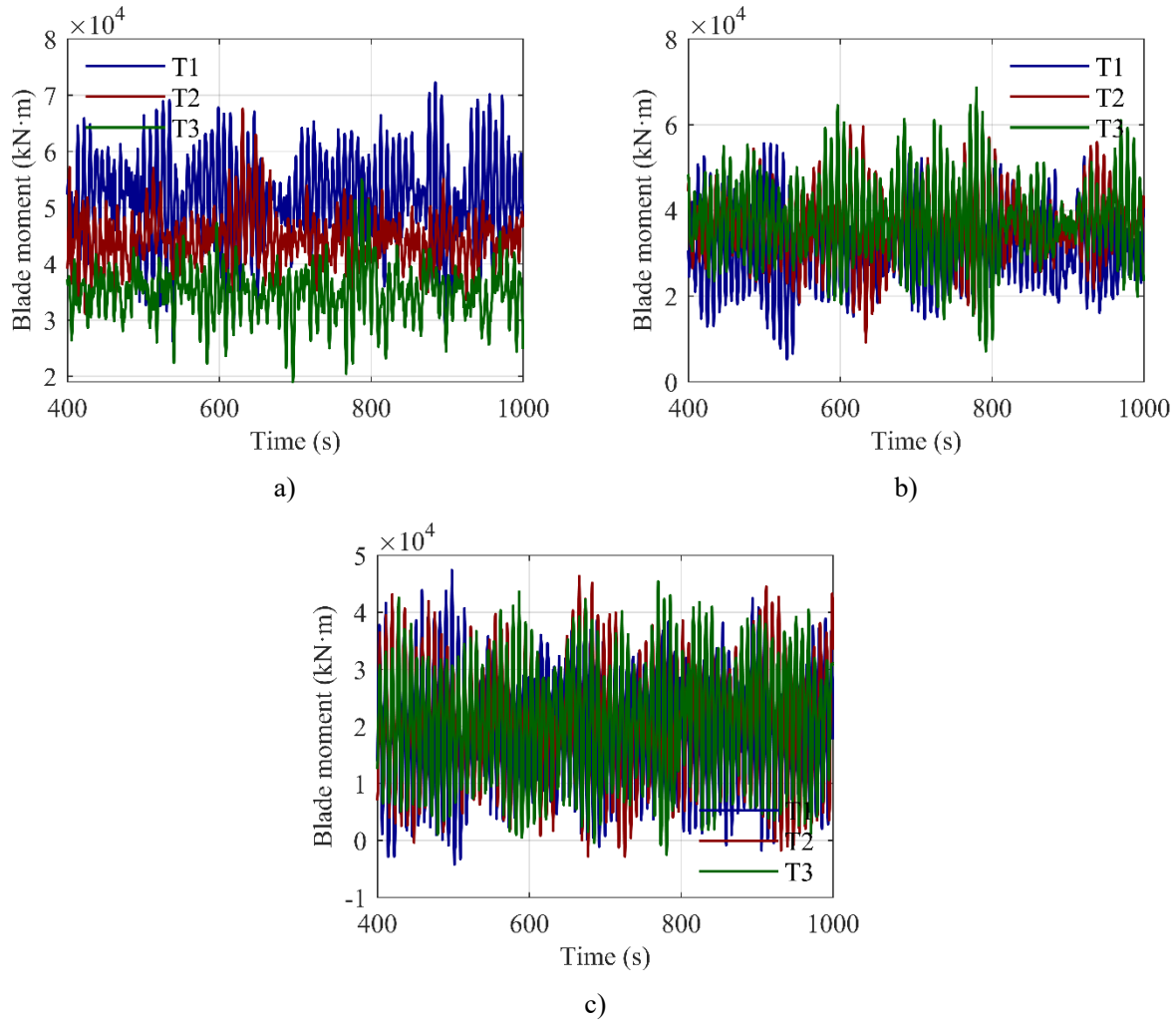


Figure 7-9 Dynamic response of turbines at different locations in the wind farm under typical wind speeds. a) 11 m/s; b) 15 m/s; c) 21 m/s.

As discussed in [Section 3.5](#), the dynamic state of the turbine is significantly improved following the implementation of a real-time de-rating strategy. However, when analyzing the performance at the wind farm scale, inter-turbine interactions, particularly the redistribution of aerodynamic loading further influence the dynamic response of individual turbines. As derived in [Section 7.2](#), de-rating the upstream turbine may reduce the wake effects, thereby enhancing the wind speed available to downstream turbines. [Figure 7-10](#) illustrates the wind speed distribution at downstream turbines when the upstream turbine operates under either conventional control or de-rating control strategies. The results reveal that, before the wind speed reaches the de-rating threshold, the wind speed distribution experienced by the downstream turbines is similar under both control strategies. However, as the wind speed approaches the rated wind speed, the de-rating strategy applied at the upstream turbine leads to a significantly higher wind speed at the downstream turbines compared to the reference control scenario. This demonstrates that de-rating control can improve the wind speed recovery in the wake region, which is beneficial for enhancing the performance of downstream turbines. Nevertheless, this beneficial effect diminishes as the inflow wind speed increases. At higher wind speeds, the relative improvement in wake recovery from de-rating control becomes less pronounced, indicating that the influence of wake effects diminishes with stronger upstream inflows.

In summary, the de-rating method not only delays the corrosion-fatigue degradation of upstream turbines but also enhances the wind speed available to downstream turbines by improving the wake recovery characteristics. However, a comprehensive cost-benefit analysis of

this strategy, in terms of both performance degradation delay and overall energy production enhancement at the wind farm level, requires further discussion and evaluation.

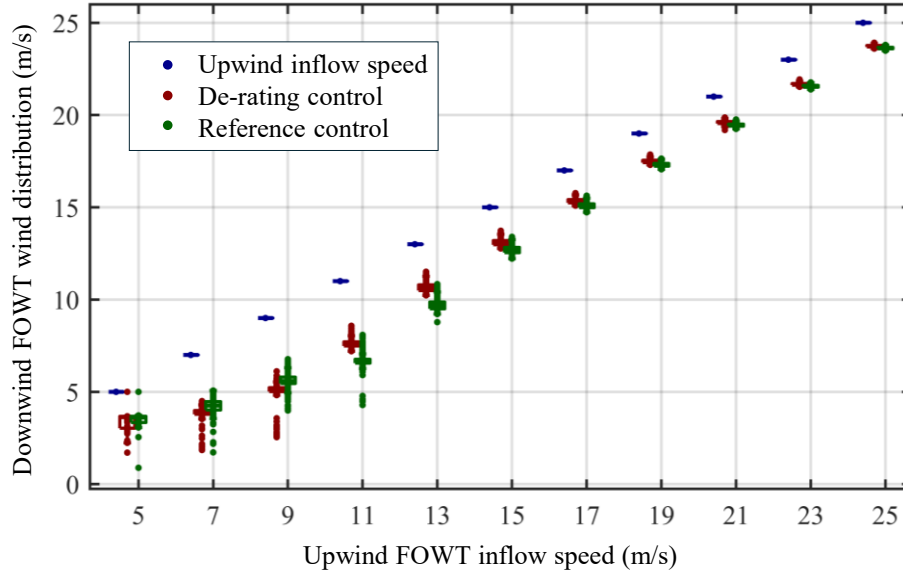


Figure 7-10 Impact of de-rating strategy on downwind turbines in wind farm analysis.

7.5.3 OppOM application on the wind farm level

Figure 7-11 demonstrates the application of the proposed OppOM strategy at the wind farm scale, with operations analyzed on a monthly basis across a 25-year period, totaling 300 time units. The results clearly illustrate that de-rating is frequently employed as an effective method to delay FOWT degradation at the wind farm level. The three turbines each underwent 44, 41, and 40 instances of de-rating, respectively. In comparison, only 34 offshore maintenance missions were required, with an average of one maintenance trip every 8.8 months. This significantly reduces the frequency of offshore operations, alleviating the O&M pressure typically associated with offshore wind farms. It is noteworthy that, compared to the other turbines, WT3 required fewer maintenance trips in the early stages of its service life, relying mainly on a small number of de-rating actions and repairs to the tower and mooring system. This outcome is primarily due to the fact that the

wake effect strongly influences the wind speed distribution around the upper structures, while the lower sections, especially the foundation, are more affected by wave impacts. As a result, the loading conditions of WT3 are more similar to those of the upstream turbines (WT1 and WT2), which experience greater wind speed reduction due to wake interference.

In contrast, the OppOM strategy applied to a single FOWT, as discussed in Section 6.5, requires a slightly higher maintenance frequency, about one intervention every 10.3 months. This is slightly higher than the wind farm-level OppOM, demonstrating that turbine maintenance consumption is not a simple linear relationship. Notably, the opportunistic-based approach allows multiple turbines to share maintenance costs during each maintenance trigger. As a result, after each offshore trip, multiple turbines can undergo simultaneous maintenance tasks, optimizing resource utilization and reducing overall operational costs.

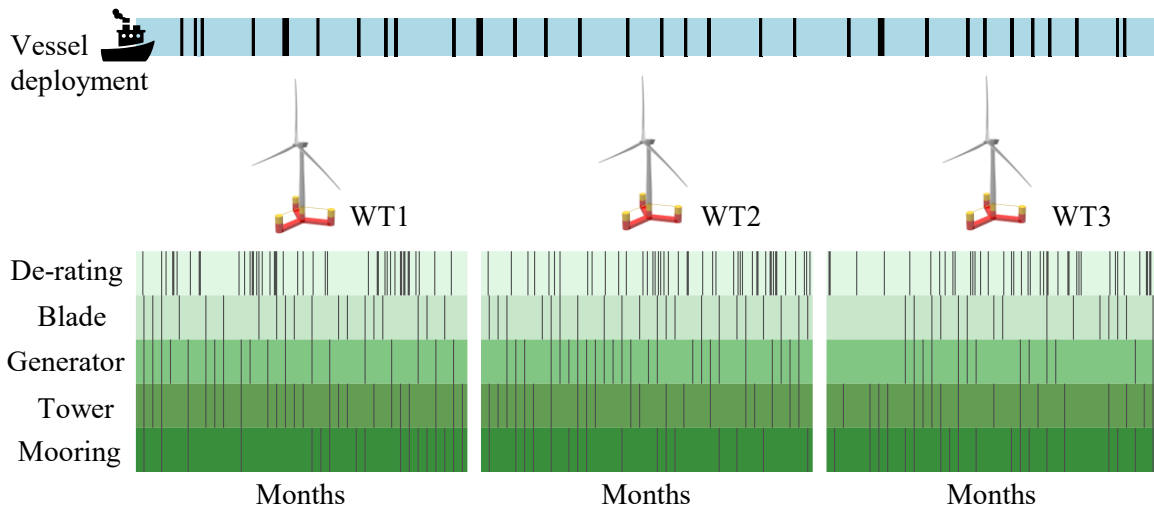


Figure 7-11 Application of OppOM in wind farm-level operation and maintenance.

Furthermore, from the perspective of the wind farm's average reliability index, it is evident that the implementation of OppOM effectively ensures that the wind farm remains in a structurally safe operational state. The introduction of de-rating plays a key role in mitigating the absence of repairs, ensuring a gradual degradation of the structure over time. By strategically scheduling de-

rating actions, the system can maintain optimal operational performance even in the absence of frequent repair interventions. This approach also guarantees that each offshore maintenance mission addresses multiple components, significantly reducing the overall maintenance costs and improving operational efficiency.

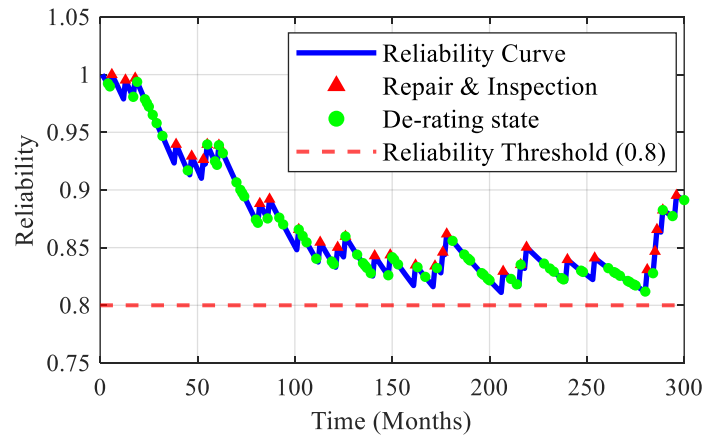


Figure 7-12 Development of wind farm reliability under the OppOM strategy.

Figure 7-13 presents the reliability distribution of the wind turbines across their entire lifecycle. The results show that all three turbines consistently remain in a safe operational state, with reliability indices consistently above the 0.8 threshold. The average reliability index for the wind farm is 0.87, demonstrating that the OppOM strategy effectively ensures the long-term operational safety of the offshore wind farm. This highlights the capability of the proposed maintenance strategy to sustain structural integrity and operational performance over the entire lifecycle, even under the challenging conditions of offshore wind energy production.

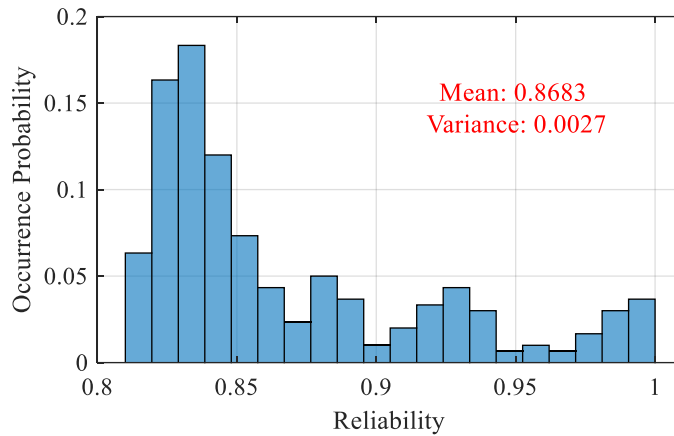


Figure 7-13 Reliability distribution of the FOWTs over their entire lifecycle.

Figure 7-14 shows the energy production development of the wind farm under the OppOM strategy. It can be observed that all three FOWTs in the wind farm maintain stable power generation, with no significant differences between the turbines. This demonstrates that the combined de-rating approach effectively mitigates the negative impact of wake effects, as downstream turbines' power generation is not severely reduced. Additionally, the overall power production of the wind farm remains stable around an average of 172,435.2 MWh, ensuring the consistent performance of the plant.

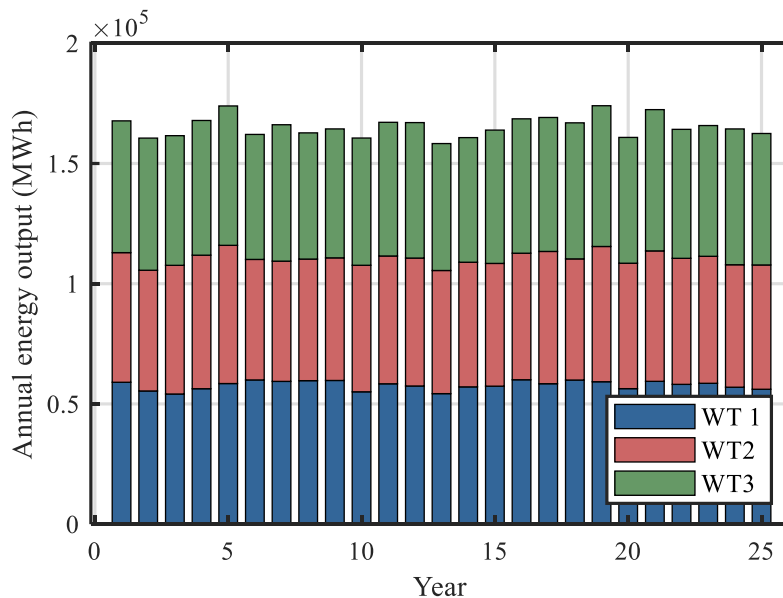


Figure 7-14 Annual variation in wind farm energy production.

Furthermore, to illustrate the integrated distribution of various performance indicators, Figure 7-15 shows the distribution of metrics at the wind farm level under different maintenance strategies. It is evident that the application of OppOM at the wind farm level offers more pronounced advantages compared to single-turbine analysis. The overall performance index is 0.82, higher than OppM (0.80) and CBM (0.76). In terms of health, the differences between the three strategies are relatively small. However, in terms of energy production, OppOM shows a significant advantage. Over the 25-year service period, the total energy produced reaches 4,323,380.9 MWh, surpassing OppM (4,417,181.4 MWh) and CBM (4,019,515.3 MWh). This is due to the intervention of de-rating, which not only significantly reduces downtime but, as discussed in Section 6.2, improves the wind speed at downstream turbines, optimizing overall energy production. Furthermore, due to this optimization in energy output, OppOM also achieves the highest carbon reduction, totaling 2,245,112.2 t, while maintaining the lowest lifecycle costs.

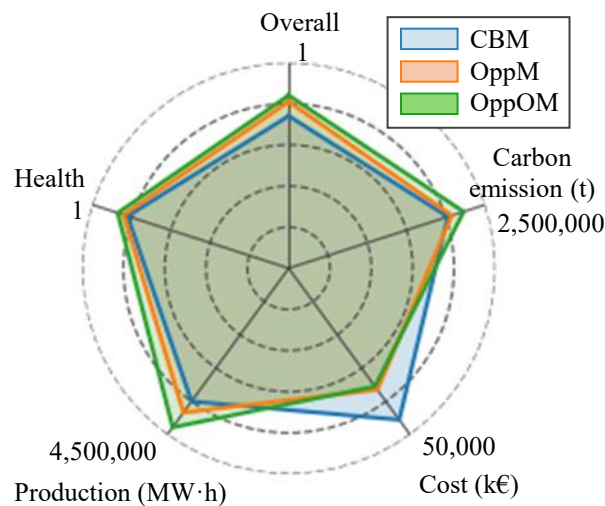


Figure 7-15 Multi-attribute distribution of the wind farm under the OppOM.

7.5.4 Impact of climate change

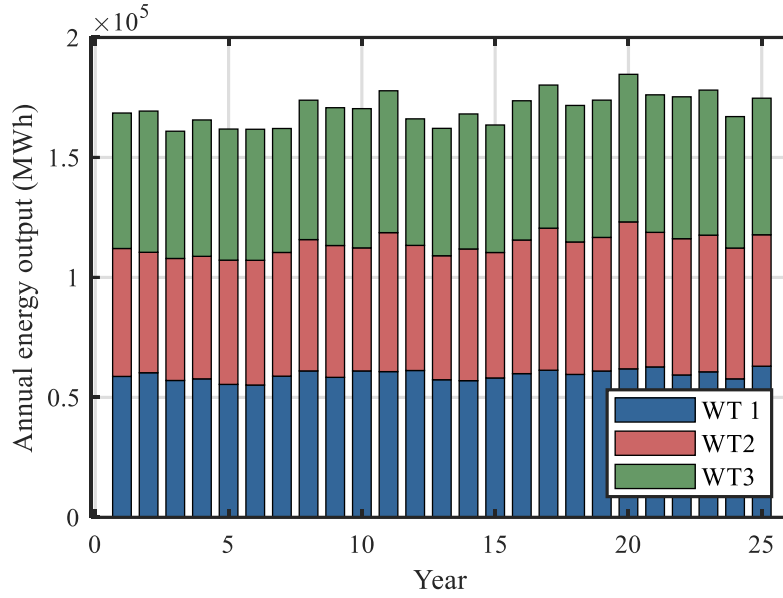
Climate change has a dual impact on the performance of FOWTs. On the positive side, increased

wind speeds can significantly enhance power generation (Zhang et al., 2025)(Jiaxin Zhang et al., 2025). To systematically evaluate the effect of varying climate change scenarios on the durability and reliability of FOWTs, this study incorporates three distinct climate change cases, each representing different levels of environmental severity, as introduced in Sections 7.3, as shown in Table 7-2. It is important to note, based on the analysis in Sections 7.3, that wave height and wind speed are linearly correlated. Therefore, this analysis focuses on varying wind speed levels, with wave heights calculated using Figure 7-3.

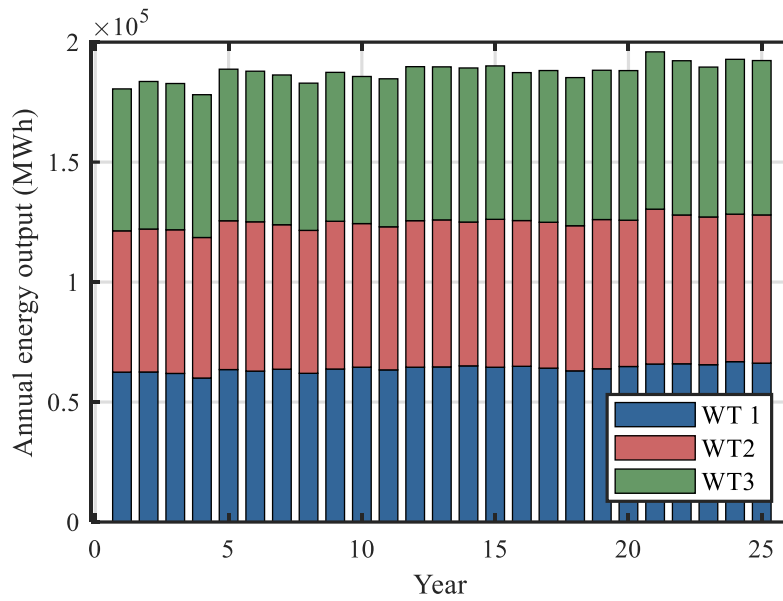
Table 7-2 Environmental parameters of investigated climate change scenarios.

	Wind speed	Temperature
Scenario 1	W1	T1
Scenario 2	W2	T2
Scenario 3	W3	T3

This chapter fully considers the impact of climate change on the O&M of structures, specifically examining the effects of varying wind-wave conditions and corrosion environments. Under the climate change scenario, the variation in total annual energy production across the three turbines in the wind farm is shown in Figure 7-16. Figure 7-16 Annual variation in wind farm energy production under climate change. a) Scenario 2; b) Scenario 3.. It is clear that climate change significantly affects the farm's energy production. As discussed in Section 7.5.3, when climate change is not considered (Scenario 1), the total energy output of the offshore wind farm is 4,323,380.9 MWh. However, under low-level climate change conditions, the total production increases to 4,375,785.2 MWh, reflecting a 1.21% increase. For high-level climate change scenarios, the increase is even more substantial, with production rising by 4.17% to reach 4,503,665.8 MWh. However, this increase in energy production often comes at the cost of safety, leading to greater O&M pressures, which in turn affects the overall lifecycle performance attributes.



a)



b)

Figure 7-16 Annual variation in wind farm energy production under climate change. a) Scenario 2; b) Scenario 3.

Furthermore, Figure 7-17 illustrates the maintenance scheduling under different levels of climate change. It can be observed that high-level climate change leads to a significant increase in both maintenance frequency and de-rating actions. In comparison, the increase in maintenance

frequency is relatively small, with the number of interventions in the three scenarios being 34, 39, and 44, respectively. However, the number of de-rating events shows a more pronounced increase, rising by 26 and 73 instances under low and high-level climate change conditions, respectively. This highlights that, in wind farm O&M management, de-rating provides a more cost-effective approach. Faced with the challenges of climate change, using non-contact frequency regulation (de-rating) instead of direct maintenance actions offers a significantly higher overall benefit.

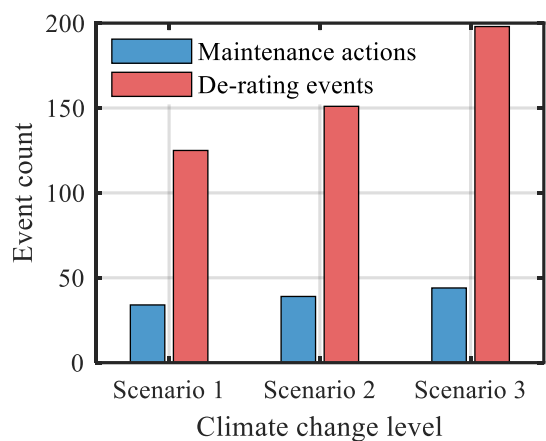


Figure 7-17 Number of maintenance actions under different levels of climate change.

Figure 7-18 compares the distribution of various performance metrics under different levels of climate change. It is evident that the application of the OppOM strategy in wind farm management ensures that the farm maintains high overall performance. In terms of structural safety, due to the real-time management enabled by OppOM, climate change does not cause significant disruption, with the farm's safety index remaining above 0.85 throughout the operational period. Regarding costs, while high-level climate change leads to more maintenance actions and increased de-rating periods, resulting in higher operational expenses, the overall economic impact remains positive when considering the increased energy production driven by climate change.

Similarly, in terms of carbon emissions, while more maintenance actions under climate change result in additional emissions, the increased energy output contributes to higher carbon

offsetting. As a result, the overall emission reduction capability of the turbines continues to grow, reaching 2,271,191.1 tons in Scenario 2 and 2,302,492.5 tons in Scenario 3.

Overall, although climate change imposes a dual impact on the performance of FOWTs (Zhang et al., 2025), the application of the OppOM strategy, with its well-planned maintenance layout, ensures that turbines can still deliver a high cost-benefit improvement in the face of climate change.

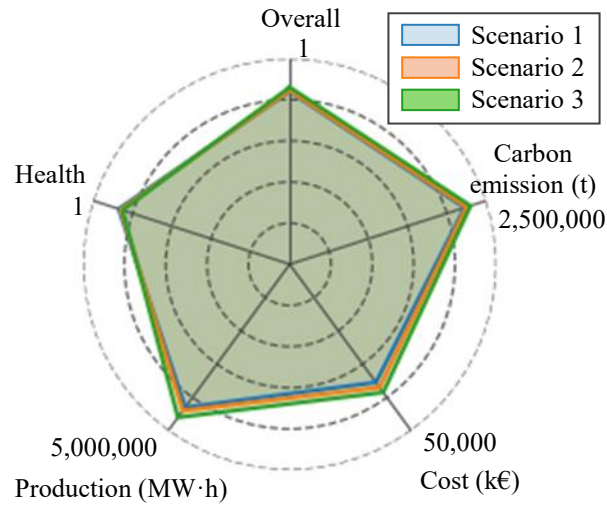


Figure 7-18 Multi-attribute distribution of the wind farm under the OppOM in different climate change scenarios

7.6 Summary

This chapter addresses the complexities of offshore wind farm O&M management under climate change scenarios, proposing an integrated framework that combines wake effect dynamic compensation with OppOM. By coupling climate scenario forecasting, turbine dynamic coupling models, and cost-benefit analysis, the framework achieves coordinated optimization of structural safety, energy production efficiency, and lifecycle costs at the wind farm level. The specific conclusions are as follows:

- (1) Upstream turbine wake significantly reduces downstream wind speeds. As the inflow wind speed increases from 11 m/s to 21 m/s, the average wind speed at downstream turbines T2 and T3 decreases by 30.6% and 35.3%, respectively, falling to 6.5% and 7.3%. Concurrently, the blade loading at downstream turbines also decreases. This demonstrates that wind farm-level analysis must account for dynamic wake models to accurately predict the coupling effects between turbines.
- (2) At near-rated wind speeds, the upstream de-rating strategy increases downstream wind speed by 12-15%, while reducing the offshore maintenance frequency to 8.8 months per trip (a 15% improvement in efficiency compared to single-turbine O&M). This approach balances upstream fatigue degradation with downstream energy gains, confirming the critical role of dynamic power regulation in wind farm collaborative management.
- (3) Under high-level climate change scenarios, wind resource intensity increases the total energy production of the wind farm by 4.17% (reaching 4,503,665.8 MWh), with carbon emissions reduction rising to 2,302,492.5 tons. However, the frequency of extreme climate events accelerates structural corrosion, leading to a 29.4% increase in offshore maintenance missions (from 34 to 44 trips), and de-rating interventions increase by 73 instances. This highlights that climate change affects the wind farm through a dual path of wind resource gain and structural damage acceleration, necessitating dynamic strategies to balance short-term gains with long-term risks.
- (4) The OppOM strategy mitigates the wake effect by de-rating the upstream turbines, increasing the wind speed at downstream turbines by 12-15%, driving the total energy production to 4,323,380.9 MWh (a 7.6% increase over the traditional CBM strategy). Additionally, shared maintenance windows reduce the repair demand for downstream

turbines (e.g., WT3) by 20-30%, allowing multiple turbine tasks to be completed during each offshore maintenance trip. Over the 25-year period, offshore maintenance costs decrease by 18.2%, demonstrating the core value of wind farm-level collaboration in overcoming the "wake loss–maintenance silo" challenge.

- (5) Dynamic de-rating thresholds are adjusted based on real-time climate predictions, with power output controlled accordingly. Combined with collaborative O&M trigger rules (e.g., cumulative damage exceeding thresholds or energy production fluctuations >5%), the wind farm maintains an annual average reliability index of 0.87 and carbon emission intensity of 0.52 t/MWh even under extreme climate conditions. Compared to traditional strategies, the OppOM strategy improves the overall performance index by 7.9% (reaching 0.82) and reduces lifecycle costs by 12.5%, providing an integrated solution for “safety management, maximum profit, and carbon neutrality” in climate-resilient wind farms.

CHAPTER 8

Conclusions and Future works

8.1 *Conclusions*

This thesis presents an integrated digital twin framework for deep-sea FOWTs, combining high-fidelity multi-physics simulations, physics-informed machine learning, and reinforcement learning-driven Opportunistic Operation and Maintenance (OppOM). The front-end uses OpenFAST to accurately capture wind, wave, and control-coupled loads with localized stress, the middle layer employs PIML for fast, real-time simulation of dynamic responses, and the back-end integrates DBN, POMDP, and A3C for adaptive decision-making in the four-dimensional space of health, capacity, cost, and carbon emissions. Validated through 25-year lifecycle simulations, the approach enhances turbine reliability, improves wind farm annual energy output, and increases carbon reduction, offering a new paradigm for safe, economical, and low-carbon operation and maintenance of future deep-sea, large-capacity FOWTs. The key conclusions are as follows:

- (1) OpenFAST was used to develop a unified multi-physics model that integrates wind, wave loads, control logic, and structural dynamics, along with a module for extracting local stress responses. This model enables detailed tracking of stress responses for the four main subsystems: blades, generators, towers, and mooring systems. Results show that the generator and tower are highly sensitive to control parameters near rated wind speeds, while blade response increases monotonically with wind speed, and mooring is primarily wave-driven.

Under pre-emptive de-rating conditions, stress distributions are significantly narrowed, with peak values decreasing by 8-15%, providing a physical basis for lifespan extension.

(2) Building on multi-physics loads, the thesis introduces a probabilistic corrosion-fatigue (PCF) risk framework that reveals heterogeneous degradation paths, such as blades/generators reaching critical state in 15 years, tower accelerating after 19 years, and mooring system degradation accelerating after 16 years. Importance sampling for PCF calculations shows that high-strength bolts in offshore environments have a characteristic lifespan of only 30% of their onshore counterparts, becoming the system's weak point. Replacing the reference controller CS1 with CS3 (9 m/s cut-in wind speed) improves corrosion-fatigue reliability by 46.2%, while the total energy loss is just 9%, verifying the critical role of control parameter optimization in balancing safety and performance.

(3) To meet the need for long-term, high-precision load-response predictions, the thesis develops a PIML method that integrates resonance mechanisms. The model uses a sliding window with STFT to extract local dominant frequencies and incorporates resonance amplification effects into the loss function. The model achieved $R^2 \geq 0.95$ in single-degree-of-freedom systems, vehicle-bridge coupling, and 60-floor high-rise real-world data. Applied to the 15 MW FOWT, the model demonstrated excellent predictive accuracy, with R^2 values of 0.954, 0.963, 0.966, and 0.947 for 5 m/s, 10.6 m/s, 20 m/s, and shutdown (30 m/s) wind speeds, respectively. Compared to physical modeling, inference time was reduced to seconds, providing the potential for real-time health assessment and decision-making.

(4) With support from reliability evolution and high-speed predictors, the thesis proposes a DBN-POMDP-A3C OppOM framework. The daily degradation of four turbine components is updated through a hybrid DBN, with partially observable meteorological and monitoring

signals described via POMDP. The A3C reinforcement learning algorithm iteratively generates actions in parallel environments. The reward function integrates multi-attribute utility (MAU) for health, capacity, cost, and carbon emissions. In a 25-year North Sea lifecycle simulation with standard weather windows and accessibility constraints, the OppOM strategy extended the average offshore mission interval from 6.5 months to 8.8 months, improving the composite utility index from 0.76 to 0.82.

(5) The OppOM strategy demonstrates optimal overall performance. Its average safety index over the service period reaches 0.87, significantly higher than OppM (0.84) and CBM (0.82), indicating more effective maintenance and operational safety. Although OppOM involves some power loss during de-rating, it successfully reduces stresses during high-load periods, delays degradation of key components, and minimizes downtime during maintenance. Over 25 years, the total energy produced reaches 1,661,121.5 MWh, surpassing OppM's 1,647,823.3 MWh and CBM's 1,480,231.7 MWh. Additionally, with fewer offshore repairs and optimized energy production, OppOM achieves the lowest lifecycle costs while reducing carbon emissions by 853,541.1 tons CO₂.

(6) The OppOM strategy was further extended to a three-turbine semi-submersible wind farm, coupling wake models with climate change scenarios. De-rating of the upstream turbines by 10%-15% improves the downstream wind speed by 12%-15%, leading to a 7.6% increase in overall annual energy production. Offshore maintenance costs decrease by 18.2% over 25 years. In high-level climate scenarios, where warming increases wind speeds but extreme events also increase, OppOM maintains an annual reliability of ≥ 0.85 , and the total carbon reduction reaches 2.30 Mt CO₂, demonstrating the strategy's robustness and scalability under climate change.

In conclusion, this research establishes an end-to-end digital twin loop for deep-sea, large-capacity floating wind turbines, integrating high-fidelity multi-physics simulations → physics-informed AI rapid prediction → reinforcement learning-driven OppOM decision-making. This framework offers a comprehensive path for lifecycle management that balances safety, economic viability, and low carbon emissions, providing a solid methodological foundation for scaling applications in larger wind farms and other marine engineering projects in the future.

8.2 Suggestions for future works

Although significant methods and interesting conclusions have been achieved, future work can further enhance and optimize the current approaches by integrating real-time data and varying turbine configurations. Future research can deepen along four main lines:

- (1) Building a real-time digital twin platform that integrates cloud, edge, and terminal systems. This platform would synchronize physical turbines with high-fidelity models in extreme marine conditions, ensuring seamless coexistence. By leveraging distributed sensors at the edge, and containerized OpenFAST clusters with streaming databases at the cloud side, this system would enable real-time synchronization of scene, climate, and market data. Event-driven synchronization and model partition update mechanisms between edge, cloud, and terminal would ensure consistency of physical-model-data across 25-year asset lifecycles. This system will shift digital twins from "offline analysis" to "online coexistence," laying the foundation for future automation and unmanned operations in wind farms.
- (2) The current representation of composite blades as equivalent isotropic continua should be replaced by laminate-level models that capture ply orientation, stacking sequence, and progressive damage mechanisms. Composite-specific failure criteria will be incorporated to

provide more accurate predictions of blade reliability under coupled aero-hydro loads.

(3) Future research should extend the modeling framework to incorporate extreme events such as typhoons, hurricanes, and severe storm surges. These scenarios involve sudden wind direction changes, steep and breaking waves, and impulsive hydrodynamic loads, which may generate short-duration extreme stresses and accelerate fatigue damage. Particular attention should be given to capturing shock-type loading on blades, towers, and mooring systems, as well as to evaluating potential local failures such as joint loosening, bolt fracture, or tower buckling. Probabilistic rare-event simulation techniques and coupled nonlinear models will be required to adequately characterize these phenomena. In addition, the influence of extreme events on operation and maintenance strategies should be investigated. Post-event inspections, targeted structural health monitoring, and preventive replacement of critical components may need to be defined as additional maintenance triggers following typhoon passages.

(4) Integrating large language models (LLMs) to transform operational logs, sensor data, and simulation results into machine-readable knowledge graphs. LLMs like GPT and deepseek can be used for semantic encoding and chained reasoning of heterogeneous data. On the frontend, LLMs can work in tandem with time-series models to generate alarm summaries, failure explanations, and work order creation. On the middle layer, high-dimensional time-series features outputted by PIML can be mapped to natural language knowledge graphs for training strategy interpreters. On the backend, LLMs act as strategy reviewers, auditing action sequences generated by A3C for safety, compliance, and carbon emissions, thereby closing the "human-machine-intelligence" loop.

(5) Expanding the OppOM strategy to a distributed multi-agent collaborative optimization framework for large-scale wind farms and multi-energy units. While the current OppOM

strategy focuses on a three-turbine pilot wind farm, future work could scale this approach to handle hundreds of floating turbines, multiple wind farm zones, and flexible DC transmission systems. Each turbine, substation, or energy storage unit would act as an intelligent agent, ensuring self-consistent local states, actions, and rewards, and sharing embeddings via graph neural networks or federated reinforcement learning. The strategy would also integrate price, frequency, and capacity compensation signals to balance turbine lifetime-intra farm coordination-regional power tracking-market revenues.

Appendix

A1. Equivalent fatigue load for FOWTs

The calculation of the Equivalent Fatigue Load (EFL) for wind turbines simplifies the complex load sequence into a constant-amplitude equivalent load, allowing for a more straightforward estimation of fatigue life. This method is based on Miner's cumulative damage theory, where the goal is to ensure that the fatigue damage caused by the actual load spectrum is equivalent to that caused by the equivalent load. The EFL can be computed using the following equation:

$$L_{eq} = \left(\frac{\sum_{i=1}^n (L_i^m \cdot N_i)}{\sum_{i=1}^n N_i} \right)^{\frac{1}{m}} \quad (A1.1)$$

where L_i^m represents the i th load amplitude, N_i denotes the corresponding number of load cycles, n is the total number of load steps, and m is the slope of the S-N curve, which is determined experimentally based on the fatigue characteristics of the material.

A2. PDFM-driven TDRA

To conduct TDRA by PDFM, the initial step is to numerically solve GDEE via adopting the total variation diminishing-based finite difference method (TVD-FDM) (Li et al., 2012). For the numerical calculation, a discrete function $z(t)$ and its derivative function $\dot{z}(t)$ are generated for each representative point θ_{rp} , respectively:

$$z(t) = Z(\theta, k \cdot \Delta t), \quad k = 0, 1, 2, \dots, n_t \quad (A2.1)$$

$$\dot{z}(t) = \begin{cases} \left[Z(\theta_p, (k+1) \cdot \Delta t) - Z(\theta_p, k \cdot \Delta t) \right] / \Delta t, k = 0 \\ \left[Z(\theta_p, (k+1) \cdot \Delta t) - Z(\theta_p, (k-1) \cdot \Delta t) \right] / (2 \cdot \Delta t), k = 1, \dots, n_t - 1 \\ \left[Z(\theta_p, k \cdot \Delta t) - Z(\theta_p, (k-1) \cdot \Delta t) \right] / \Delta t, k = n_t \end{cases} \quad (\text{A2.2})$$

where Δt is the time step and n_t is the number of time steps corresponding to Δt .

Given the sudden changes in the performance function and their computational challenges for the TVD-FDM-based GDEE, the ‘two-step translation’ method (H.-Y. Guo et al., 2020) is employed. The first translation involves constructing a virtual performance function $\tilde{z}(t)$:

$$\tilde{z}(t) = z(t) + \Delta z_s = z(t) + \left| 2z(m_{\text{cr},s} \cdot \Delta t) - z((m_{\text{cr},s} - 1) \cdot \Delta t) - z((m_{\text{cr},s} + 1) \cdot \Delta t) \right| \quad (\text{A2.3})$$

where Δz_s denotes the translation distance at the s -th critical time instant $t_{\text{cr},s}$.

Then, the GDEE of $\tilde{Y}(t)$ can be formulated and solved via TVD-FDM, yielding the joint PDF of $\tilde{z}(t)$ and $\boldsymbol{\Theta}$, $p_{\tilde{z}\boldsymbol{\Theta}}(\tilde{z}, \boldsymbol{\theta}, t)$. The second translation is then applied to obtain $p_{z\boldsymbol{\Theta}}(z, \boldsymbol{\theta}, t)$:

$$p_{z\boldsymbol{\Theta}}(z, \boldsymbol{\theta}, t) = p_{\tilde{z}\boldsymbol{\Theta}} \left(z + \sum_{s=1}^{n_{\text{cr}}} \Delta z_s \cdot H(t - t_{\text{cr},s}), \boldsymbol{\theta}, t \right) \quad (\text{A2.4})$$

where n_{cr} is the number of critical time instants; and $H(x)$ is the Heaviside function and equals 1 when $x \geq 0$ and 0 when $x < 0$.

By incorporating the $p_{z\boldsymbol{\Theta}}(z, \boldsymbol{\theta}, t)$ of all representative points, $p_z(z, t)$ is expressed as:

$$p_z(z, t) = \int_{D_{\boldsymbol{\Theta}}} p_{\tilde{z}\boldsymbol{\Theta}} \left(z + \sum_{s=1}^{n_{\text{cr}}} \Delta z_s \cdot H(t - t_{\text{cr},s}), \boldsymbol{\theta}, t \right) d\boldsymbol{\theta} \quad (\text{A2.5})$$

Finally, the failure probability $p_f(t)$ is calculated by integrating $p_f(y, t)$.

A3. GA-based optimization

For the optimization problem addressed in this study, the Genetic Algorithm (GA) is employed as the solution method (Lee & Kim, 2007; Tao et al., 2023). GA is a robust metaheuristic algorithm

inspired by the process of natural selection, which is particularly suitable for solving complex, non-linear, and multi-objective optimization problems like the one proposed in this study. The GA parameters are set as follows: Population size 5000; Crossover probability 0.8; Mutation probability 0.2; Stopping criterion: 1000 generations.

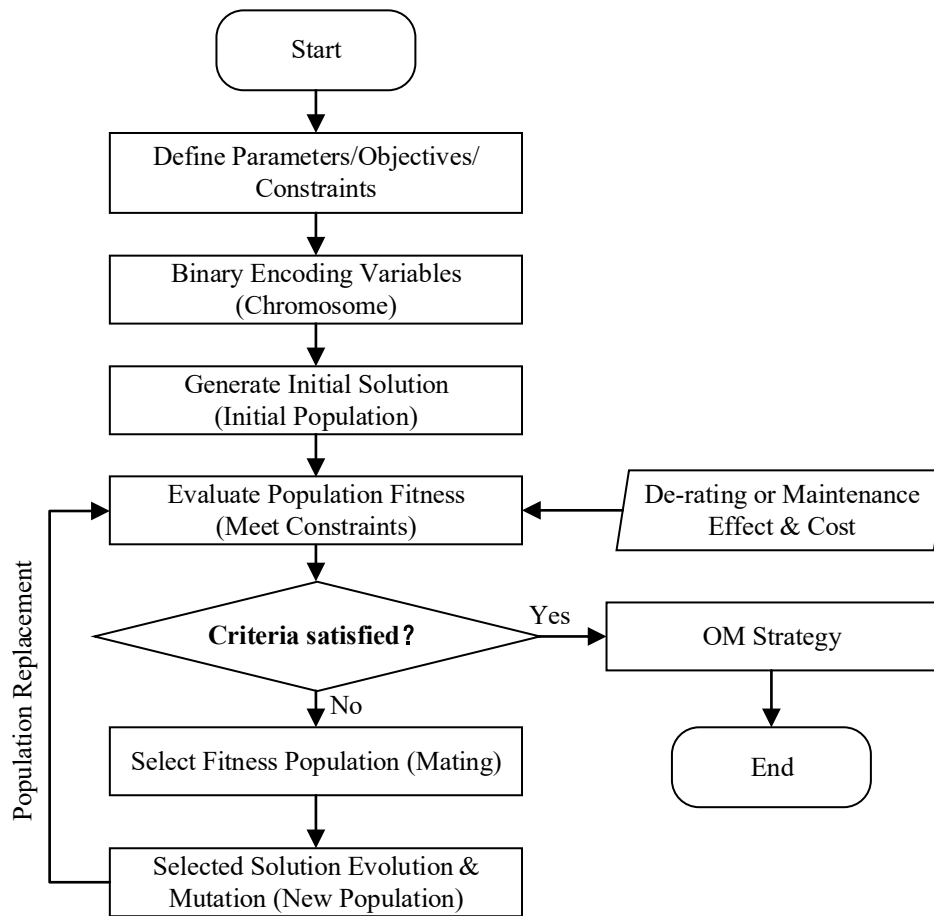


Figure A3-8-1 GA flowchart in OM optimization

In the GA framework, a chromosome in the planning module represents a candidate maintenance plan. The decision variables encoded in the chromosome correspond to the action years and action types, such as maintenance or de-rating operations (Tao et al., 2023). Each genome within the chromosome is a decimal number between 0 and 1, representing specific aspects of the maintenance or de-rating strategy. For instance, the genomes corresponding to

maintenance or de-rating years determine the specific year in which each maintenance action or de-rating adjustment is executed. These genomes are mapped to actual years or actions during the decoding process ([Lee & Kim, 2007](#)). The GA evolves this population of candidate solutions through selection, crossover, and mutation operations.

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