AI-Driven PHM for Floating Offshore Wind Turbines: Review and Main Challenges

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Abstract

Floating Offshore Wind Turbines (FOWTs) offer a transformative solution for capturing wind energy in deep waters, where fixed-bottom installations become economically unfeasible. However, Operations and Maintenance (O&M) costs, which represent up to 30% of total energy costs, remain a major barrier to widespread deployment. The harsh marine environment and limited accessibility demand intelligent and autonomous monitoring systems, making prognostics and health management (PHM) essential for cost-effective FOWTs operations. This paper presents the review of AI-based PHM studies specifically for FOWTs, addressing a significant gap in the existing literature. Particularly, most of existing reviews predominantly focus on offshore operations, digital twin concepts, structural dynamics, or control strategies, none have comprehensively analyzed AI applications tailored to the unique PHM challenges of FOWTs systems. Through a literature review of AI-based PHM studies using the Web of Science and Google Scholar databases, we identify a FOWT-specific monitoring emphasis on structural and station-keeping assets. In addition, we propose a comprehensive end-to-end PHM lifecycle for FOWTs, integrating a hierarchical taxonomy of critical components with a systematic mapping of AI methods to key PHM tasks. By synthesizing the state of the art and identifying critical technological gaps, this work outlines priority research directions essential for enabling reliable, scalable, and autonomous offshore operations.

Keywords: Floating Offshore Wind Turbines, Artificial Intelligence, Prognostics and Health Management, Predictive Maintenance

1. Introduction

The global transition toward renewable energy has accelerated interest in offshore wind as a viable large-scale power source. Among emerging technologies, floating offshore wind turbines (FOWTs) have gained particular attention for their ability to access deep-water sites where conventional fixed-bottom structures are no longer practical. However, the commercial competitiveness of FOWTs is currently constrained by high Operations and Maintenance (O&M) costs (McMorland et al., 2022). The harsh marine environment, characterized by non-stationary strong winds, large waves, and remote offshore locations, significantly limits site accessibility. As a result, maintenance crews face substantially greater challenges in accessing floating wind farms compared to near-shore fixed installations. These conditions render traditional manual maintenance strategies both risky and costly, underscoring the necessity for intelligent and autonomous monitoring solutions. Consequently, the development of advanced PHM (Zio, 2022) systems has evolved from a value-added capability into a critical operational requirement for ensuring the reliability and economic viability of FOWTs.

Over the last decade, PHM has matured into an indispensable discipline in engineering system life-cycle, evolving from traditional time-based maintenance to predictive strategies driven by condition monitoring (Andrew K.S. Jardine, 2006). While physics-based modeling (Otter et al., 2022) has historically provided explainable insights into failure mechanisms, it faces distinct limitations when applied to FOWTs. Unlike fixed-bottom turbines, floating platforms are subject to highly non-linear hydro-aero-servo-elastic coupled dynamics and six-degree-of-freedom motions (He et al., 2024), making precise physical modeling computationally expensive and prone to epistemic uncertainties. Conversely, data-driven approaches leveraging Artificial Intelligence (AI) have demonstrated remarkable efficacy in capturing complex system behaviors directly from multi-source sensor data, offering a pathway to bypass the limitations of simplified physical assumptions (Hirvoas et al., 2025).

Despite the promise of AI, its application to the floating wind sector remains nascent and fragmented. Existing reviews provide useful foundations for AI-enabled PHM in wind energy. (Stetco et al., 2019) reviewed machine learning methods for wind turbine condition monitoring, (Santiago et al., 2024) focused on data-driven predictive and prescriptive maintenance for fault detection, diagnosis, and prognosis. However, these studies mainly address wind turbines as a general asset class, with limited emphasis on the specific PHM challenges of FOWTs. These challenges include distinctive operating conditions, floating-specific critical components, and monitoring requirements that differ from conventional wind turbine systems. To address these challenges, this paper presents the review of AI-based PHM methodologies specifically tailored for FOWTs. The main contributions and structural organization of this study are outlined as follows:

- Through a literature search, we provide statistical insights into the evolution of AI-based PHM for FOWTs from 2000 to 2025. This bibliometric analysis highlights the paradigm shift from traditional heuristics to advanced data-driven strategies and identifies the growing research interest in floating-specific applications.
- We propose a comprehensive, end-to-end PHM life-cycle specialized for FOWTs. This section maps critical FOWTs components to specific AI tasks, establishing a direct correspondence between physical failure modes and algorithmic solutions. Furthermore, we provide a taxonomy of AI paradigms and architectures to elucidate current trends and algorithmic suitability for the marine environment.
- Major technological barriers hindering PHM deployment for FOWTs are identified. Based on these gaps, we propose priority research directions critical to enabling reliable, scalable, and autonomous offshore operations.

The remainder of this paper is organized as follows. Section 2 reviews related works on AI-enabled PHM for offshore wind systems. Section 3 presents an integrated AI-PHM framework tailored to FOWTs. Section 4 discusses current limitations and outlines future research directions. Finally, Section 5 concludes the paper.

2. RELATED WORK

The past decade has witnessed an explosion of research at the intersection of AI and PHM (Nguyen et al., 2022). However, the specific application to FOWTs remains relatively nascent. To contextualize our review, this section first describes our literature research methodology, then analyzes existing studies to identify FOWT-specific monitoring priorities and the research gaps motivating this work.

2.1. Literature research methodology

The literature review process is guided by the PRISMA framework (Page et al., 2021) to ensure transparency and reproducibility. As illustrated in Figure 1, the literature search is conducted using the Web of Science (WoS) core collection and Google Scholar. The search strategy is defined through the logical conjunction of two topic dimensions, restricted to English-language publications. Due to space constraints, only representative keywords are reported below (the full set

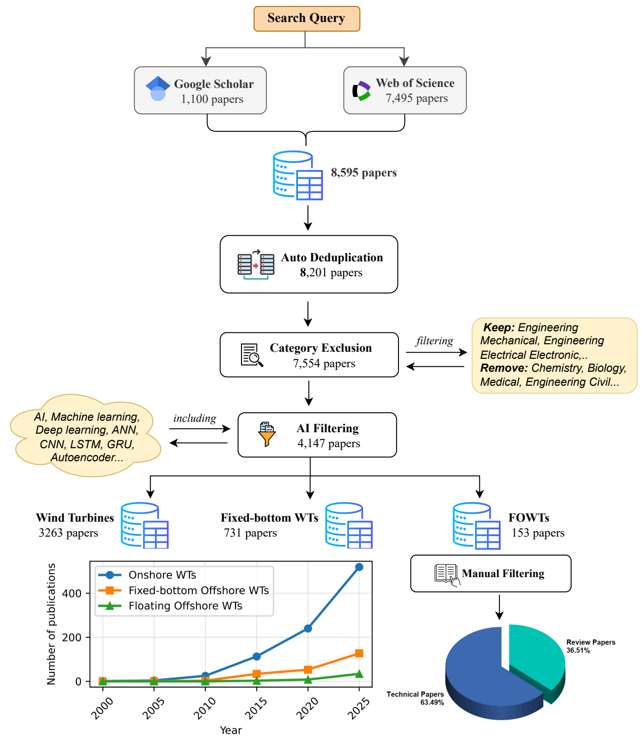

Figure 1. Flowchart of the literature search

of search terms, including additional synonyms and spelling variants, were used in the actual query).

Topic 1 (Domain): "Wind Turbine*" OR "Wind Farm*" OR "Offshore Wind" OR "Floating Wind" OR "FOWTs*" ...

Topic 2 (Research Problem): "Fault detection" OR "Fault diagnosis" OR "Remaining useful life" OR "RUL" OR "Anomaly detection" ...

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TS = (Topic 1 AND Topic 2) AND LA = "ENGLISH"
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The initial search yielded 8,595 publications from both databases. After automated deduplication, a multi-stage screening procedure was applied:

1. *Category exclusion:* Non-technical disciplines (e.g., economics, policy, and ecology) were removed to retain studies in engineering and computer science.
2. *AI-content filtering:* Metadata were screened against a comprehensive dictionary of AI-related keywords covering traditional machine learning, deep learning, and hybrid methods. Subsequently, the retained records were stratified into three distinct domain clusters (onshore, fixed-bottom, and FOWT) using differential search strings. Finally, only the FOWT-specific cluster was subjected to manual full-text validation for the qualitative review.
3. *Manual Screening:* A final manual check was performed to verify relevance. Beyond simple filtering, this process

involved characterizing the core content of each entry, distinguishing between specific algorithmic applications in technical papers and the broader thematic coverage of existing review literature.

This rigorous process results in the formation of a definitive dataset representing the current state of the art in AI-driven PHM for floating offshore wind applications.

2.2. Evolution of FOWTs PHM Research

To contextualize the contributions of this study, we analyze the evolution of PHM research through the lens of recent publication trends, while identifying critical gaps in the existing review literature.

Figure 2 illustrates the temporal evolution of PHM-related

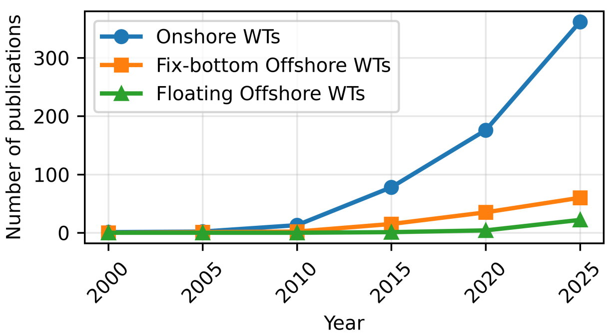

Figure 2. Comparative publication trends by turbine type (2000–2025)

publications across different wind energy sectors. Onshore wind turbines exhibit sustained and accelerating growth in publications, reflecting their technological maturity, extensive global deployment, and long-standing availability of operational data. Fixed-bottom offshore systems show a more moderate but steady increase, consistent with their later commercialization and higher operational complexity compared to onshore installations. In contrast, publications explicitly addressing FOWTs remain sparse until approximately 2020, after which a clear acceleration emerges. This inflection point coincides with the transition of FOWTs from pilot-scale demonstrations to pre-commercial and early commercial projects, increased investment in floating platform technologies, and growing recognition of the critical role of PHM in mitigating high offshore O&M costs. The comparatively low absolute volume of FOWT-related studies further underscores the nascency of the field and highlights the limited transferability of PHM solutions developed for land-based and fixed-bottom systems to floating environments. For instance, (Cuesta et al., 2025) survey general wind turbine maintenance but primarily address mature land-based technologies.

More importantly, a closer examination of the FOWT literature reveals a clear shift in research focus compared to conventional wind turbine PHM studies. As shown in Figure 3, recent FOWTs studies predominantly concentrate on floating-specific assets, particularly *mooring systems* (Grangeat et al., 2025) and *floating platforms* (Chung, Pestana, & Kim, 2021), which collectively represent the dominant share of research interest. Since one study may address multiple components, the total component count can exceed the number of reviewed FOWT papers. In contrast, traditional drivetrain components receive comparatively less attention. This distribution suggests that FOWT PHM studies place stronger emphasis on structural and station-keeping components than on conventional drivetrain components.

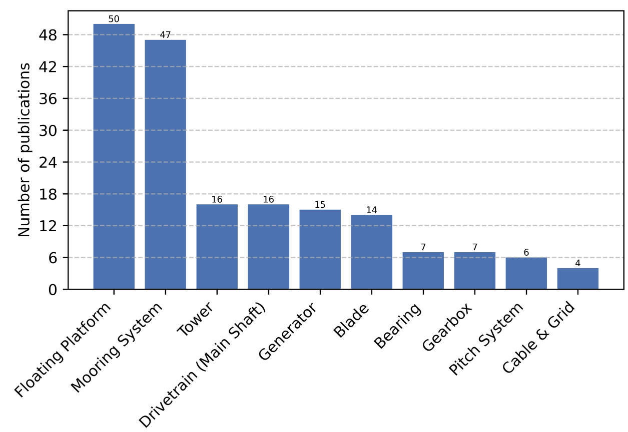

Figure 3. Component-level distribution of FOWTs research

Beyond component-level priorities, the distribution of PHM tasks further reveals an imbalance in the current FOWT research landscape. As shown in Figure 4, the majority of studies focus on fault detection and fault diagnosis, accounting for more than 90% of the surveyed literature. In contrast, prognostics-related tasks, particularly remaining useful life estimation, and maintenance optimization remain significantly underrepresented. This task-level skew indicates that most existing works address early-stage health assessment, reflecting both the relative immaturity of floating offshore wind technology and the limited availability of long-term, run-to-failure operational data required to support prognostics and maintenance optimization across the full PHM life-cycle.

Synthesizing these three statistical dimensions provides insight into the current maturity of AI-driven PHM for FOWTs. The field remains at an early stage of development, having appropriately shifted attention toward floating-specific structural components, yet it is still largely focused on reactive tasks such as anomaly detection and fault diagnosis. While existing studies have clarified *what* should be monitored, most notably mooring systems and platforms, a critical gap persists in *how* to model and predict their long-term degradation. Addressing this gap represents a necessary step toward advancing from

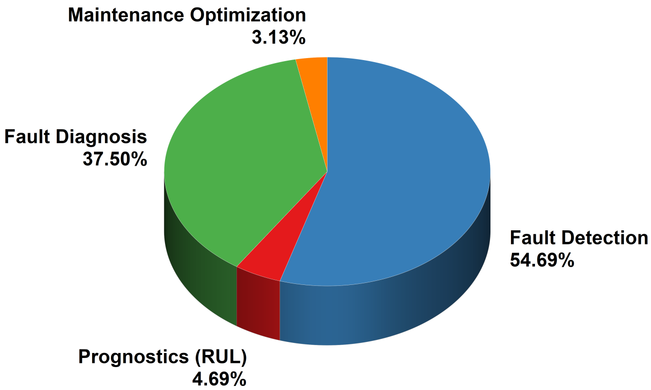

Figure 4. Task-level distribution of PHM research in FOWTs

short-term condition awareness to truly predictive, decision-supportive maintenance strategies for floating offshore wind systems.

3. INTEGRATED AI-PHM FRAMEWORK FOR FOWTS

Figure 5 presents a holistic PHM framework tailored to FOWTs. Aligned with the functional architecture of ISO 13374 and the methodological role of PHM in advanced maintenance defined (Guillén et al., 2016), the framework is conceptualized as a closed-loop life-cycle comprising four interconnected phases:

1. *System characterization*, which establishes the physical baseline through critical component identification, failure mode analysis, and an understanding of FOWT six-degree-of-freedom (6-DOF) dynamics
2. *Condition monitoring*, which enables continuous system surveillance through multi-source data acquisition, signal processing, feature extraction, and health state assessment
3. *Degradation modeling*, which focuses on representing component health evolution, enabling health indicator construction, fault diagnosis, and prognostics
4. *Health management*, which translates analytical outputs into maintenance and operational decisions

While this integrated view is essential for understanding FOWT PHM holistically, the present review focuses on the foundational elements that distinguish floating systems from conventional turbines and directly enable AI-driven analytics. Specifically, the study concentrates on critical component identification in Subsection 3.1 and the AI methodological landscape for PHM in Subsection 3.2. Conversely, phases such as data acquisition, signal processing, and maintenance optimization share substantial commonality with fixed-bottom turbines. Therefore, these aspects are not reviewed exhaustively, allowing the analysis to focus on identifying technological gaps and AI innovations that are specific to FOWTs.

3.1. Monitoring FOWTs critical components

Effective AI-based PHM for FOWTs requires a clear understanding of which assets are monitored and how they fail. (Dao et al., 2019) proposed a common wind turbine taxonomy for reliability data analysis based on a system-subsystem-subassembly structure, while (Catelani et al., 2020) presented a more detailed turbine decomposition to support FMECA-based risk assessment. Building on these hierarchical decomposition principles, this study adapts the taxonomy to FOWTs by incorporating floating support and station-keeping systems, and proposes a three-level taxonomy of FOWT components (Figure 6). The taxonomy is organized into three levels: *system*, *subsystem*, and *components*.

At the system level, the FOWT is viewed as a coupled hydro-aero-servo-elastic system. Unlike fixed-bottom turbines, the floating platform undergoes six-degree-of-freedom (6-DOF) motions, which introduce strong interactions between aerodynamic forces from the rotor and hydrodynamic loads acting on the structure.

Moving to the subsystem level, the taxonomy is divided into two main groups: (1) the *Rotor-Nacelle Assembly (RNA)*, which includes components largely inherited from conventional wind turbines; and (2) the *floating support and mooring system*, which contains safety-critical components unique to FOWT, such as the floating platform and mooring lines.

Finally, the component level further breaks down each subsystem into detailed elements, allowing sensor measurements to be directly associated with localized degradation mechanisms. This hierarchical structure supports effective PHM planning by enabling AI resources to be focused on high-impact, floating-specific vulnerabilities, rather than being applied uniformly across all components. This domain-aware prioritization allows for the selection of AI methodologies that are specifically tailored to the complexity of the identified critical components, as detailed in the following subsection.

3.2. AI enabled PHM for FOWTs

The selection of AI enabled PHM approaches for FOWTs reflects a strategic adaptation to the challenges of the offshore environment rather than a purely computational choice. The literature analysis indicates that this algorithmic landscape is primarily shaped by two fundamental challenges: *data scarcity* and *dynamic complexity*.

From a learning paradigm perspective, Figure 7 shows that supervised learning approaches remain dominant in FOWT PHM studies. This prevalence is primarily driven by data scarcity, which constitutes a fundamental constraint in floating offshore wind applications. In the absence of long-term, run-to-failure operational data from commercial FOWTs, many studies rely on physics-based simulations, numerical models, and controlled experimental setups to generate labeled datasets. As a result, PHM problems are often formulated as

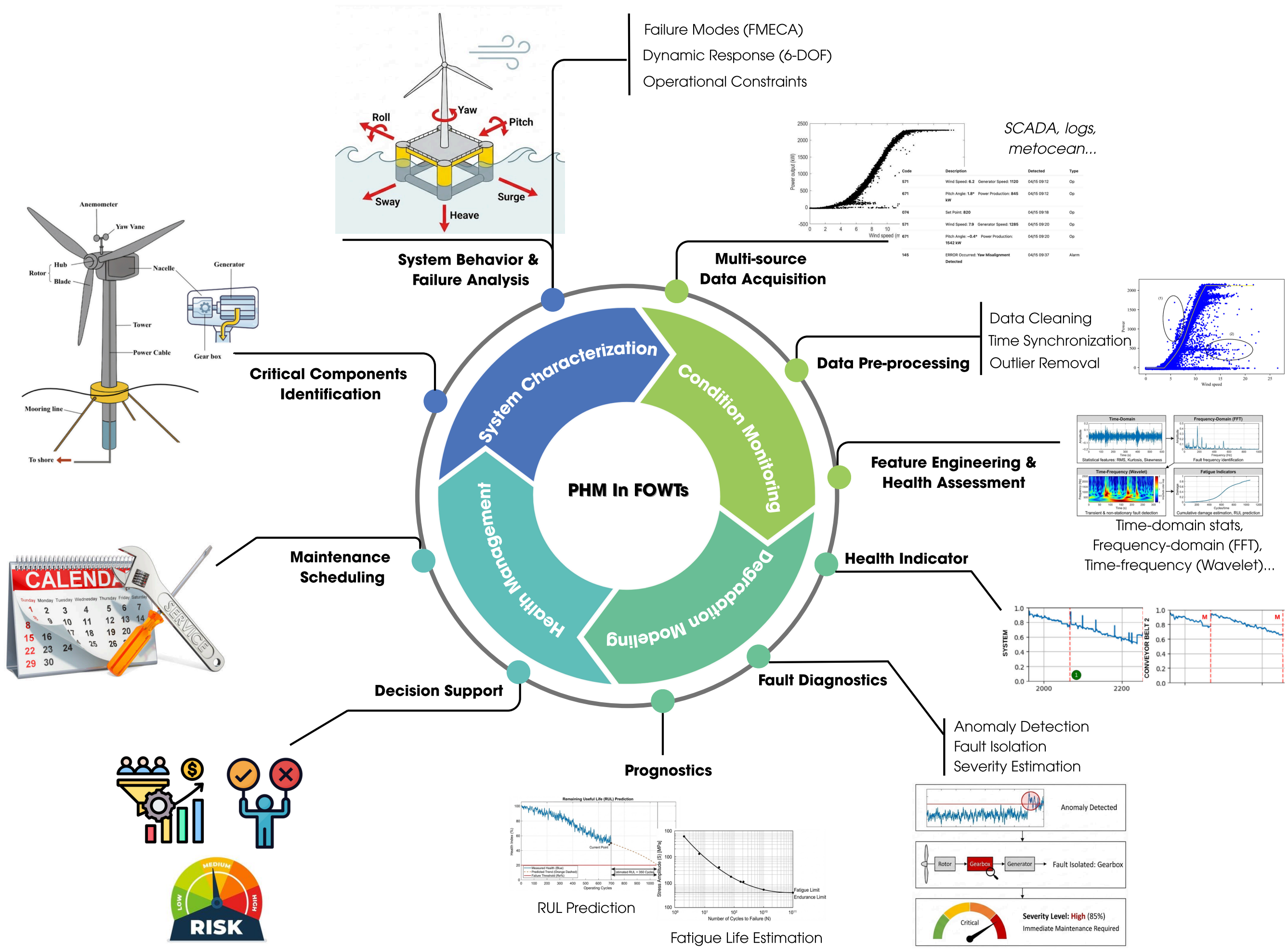

Figure 5. An end-to-end PHM life-cycle framework for FOWTs

supervised classification or regression tasks using synthetic or semi-synthetic labels.

At the same time, Figure 7 also reveals an emerging adoption of unsupervised and transfer learning strategies. This trend reflects attempts to mitigate data scarcity in operational settings, where large volumes of SCADA and structural monitoring data are available but reliable fault annotations are scarce. Unsupervised approaches, such as autoencoders (Berahmand et al., 2024) and generative models including GANs (Sharma et al., 2024), enable the construction of baseline representations of normal behavior, while transfer learning leverages knowledge from mature onshore and fixed-bottom offshore turbines to improve model generalization in floating environments.

Beyond learning paradigms, the choice of model architectures is predominantly governed by the *dynamic complexity* of FOWTs. As illustrated in Figure 8, a stark contrast exists between conventional wind turbines (onshore and fixed-bottom offshore) and floating offshore systems. While conventional wind turbine PHM studies often rely on interpretable statistical models and shallow machine learning approaches, sometimes combined with optimization-based or hybrid frameworks, FOWT studies overwhelmingly adopt deep learning architectures. This architectural shift is primarily driven by the intrinsic dynamic complexity of FOWTs, characterized by high-dimensional and non-stationary signals resulting from strongly coupled aero-hydro-servo-elastic interactions.

Traditional models that depend on handcrafted features and simplified assumptions often struggle to capture these nonlinear dependencies (Bishop, 2006; Worden et al., 2015). In contrast, deep learning frameworks offer superior capability in automated feature representation and end-to-end learning (Liu et al., 2025; Rosafalco et al., 2021). By directly processing raw multi-modal data streams, such architectures are better suited to disentangle environmental variability, such as wave-induced motions, from genuine structural degradation signals, which is essential for robust PHM in stochastic marine environments.

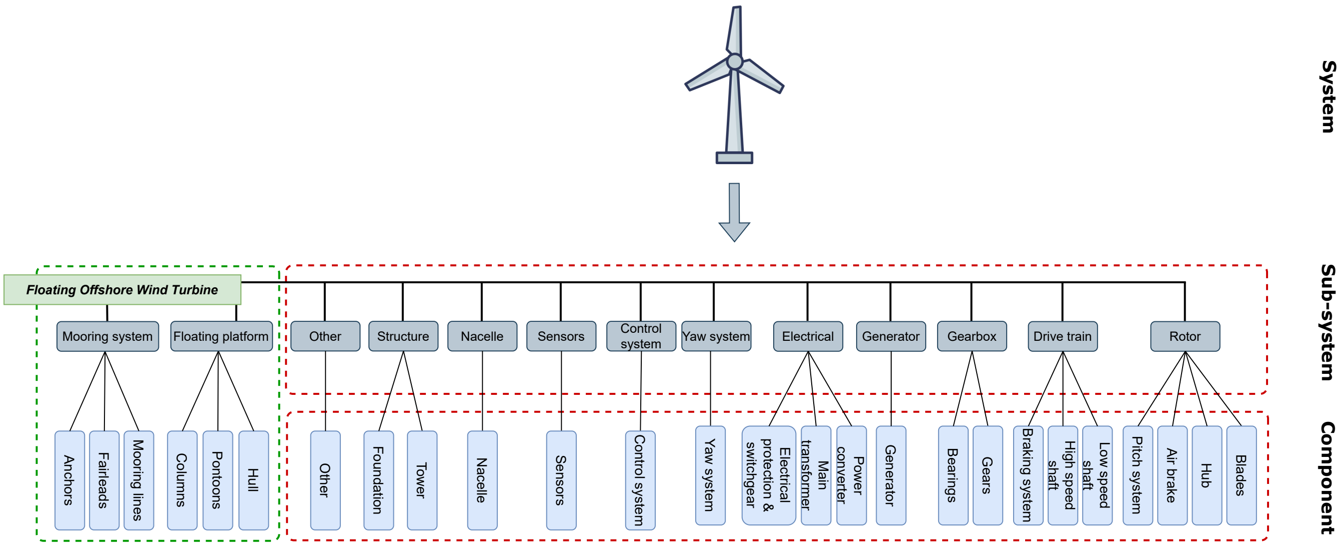

Figure 6. Hierarchical taxonomy of FOWTs critical components

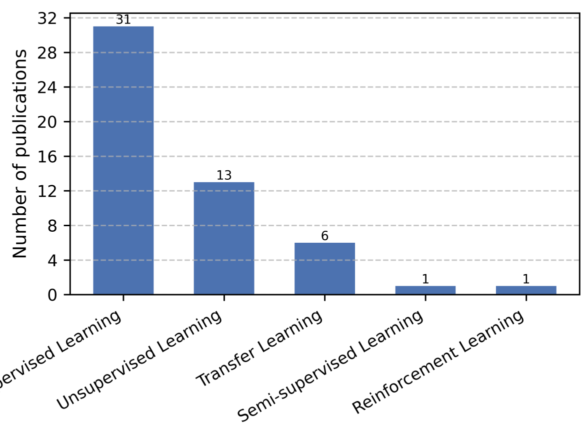

Figure 7. Distribution of AI learning paradigms in FOWTs

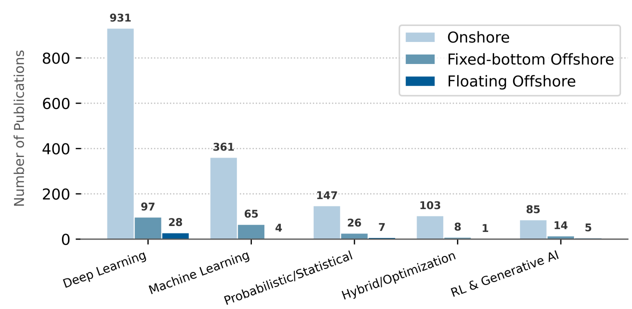

Figure 8. Comparison of AI methodologies: Onshore vs. Fixed-bottom vs. Floating

4. LIMITATIONS AND FUTURE DIRECTIONS

Based on the quantitative analysis in Section 2 and 3, four fundamental limitations impede the transition from theoretical research to industrial deployment:

- **"Data scarcity" paradox:** The lack of representative, failure-specific operational data for floating structures constitutes the primary bottleneck. As a result, most supervised learning approaches rely heavily on simulation data, leading to a persistent "sim-to-real" gap in which models trained on idealized or deterministic simulations fail to generalize to the highly stochastic and coupled marine environment.
- **Immaturity of prognostic capabilities:** The strong emphasis on anomaly detection has resulted in a relative neglect of prognostic tasks. Consequently, most existing PHM systems function as reactive alert mechanisms, providing limited support for long-term degradation forecasting and proactive maintenance decision-making.
- **Environmental robustness and trust:** Harsh marine conditions degrade data quality through biofouling, sensor drift, and intermittent connectivity, while the reliance on opaque, black-box DL models undermines operator trust. As a result, practitioners remain uncertain whether detected anomalies reflect genuine structural degradation or are merely induced by environmental variability, such as wave- and motion-driven responses.
- **Dynamic complexity and model scalability:** FOWT operate as tightly coupled systems in which aerodynamic, hydrodynamic, structural, and control effects interact in complex and often nonlinear ways. Many existing AI-based PHM studies simplify this behavior by analyzing individual components or subsystems in isolation. As a result, these models struggle to represent how loads and degradation propagate across the system under varying

sea states and operating conditions.

To address the above limitations, we outline the following strategic research directions aimed at enabling robust, scalable, and trustworthy AI-based PHM solutions for FOWTs:

- **Domain adaptation and transfer learning:** Given the scarcity of operational FOWT data, mature wind turbine systems provide an important source of transferable knowledge. Domain adaptation and transfer learning can transfer fault signatures and degradation patterns to floating wind applications, while accounting for floating-specific operating conditions. This provides a practical pathway to reduce data scarcity and accelerate AI-PHM deployment in early-stage FOWT projects.
- **Physics-informed and hybrid AI models:** Purely data-driven models remain limited for FOWT PHM because labeled failure data are scarce and operating conditions vary with wind, waves, and platform motion. Physics-informed and hybrid AI models can combine machine learning with physical models, expert knowledge, and domain constraints, such as fatigue accumulation, hydrodynamic loading, and structural dynamics. By constraining learning with governing principles, these approaches can improve the robustness and interpretability of PHM models across the coupled FOWT system.
- **Heterogeneous data fusion and knowledge integration:** FOWT PHM requires combining sensor data with environmental and operational context. Integrating turbine measurements, metocean data, maintenance reports, and inspection records can help distinguish operating-condition effects from true degradation. Large language models can support knowledge extraction from unstructured records, while structured knowledge bases can organize component, fault, cause, and maintenance knowledge for more explainable AI-based PHM.

5. CONCLUSION

This paper presented a review of AI-driven PHM for FOWTs, establishing a unified framework that bridges physical system characterization with data-driven analytics. The analysis highlights a clear shift in the research focus from conventional drivetrain monitoring toward structure-centric surveillance of safety-critical floating components. However, despite this shift, current approaches remain predominantly reactive, largely constrained by limited availability of representative operational and failure data, which has led to a strong emphasis on anomaly detection and a relative lack of prognostic capabilities. In addition, the widespread use of opaque DL models poses challenges in terms of interpretability and operational trust in harsh marine environments. To address these limitations, future research should prioritize *Domain Adaptation* to leverage knowledge from mature fixed-bottom fleets and *Physics-Informed Machine Learning* to ensure robust, interpretable predictions. Ultimately, integrating these technologies can support more autonomous, robust, and trustworthy PHM systems for future floating offshore wind farms.

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