Toward Intelligent Prognostics and Health Management for Floating Offshore Wind Turbines

Son Hai Nguyen, Thi Phuong Khanh Nguyen, Kamal Medjaher

Univ. Toulouse, UTTOP, LGP, 47 Av. d'Azereix, 65000 Tarbes, France
son.nguyen@uttop.fr, thi-phuong-khanh.nguyen@uttop.fr, kamal.medjaher@uttop.fr

ABSTRACT

Floating offshore wind turbines (FOWTs) enable the exploitation of deep-water wind resources where conventional fixed-bottom foundations become technically or economically infeasible. While this technology significantly expands the potential of offshore renewable energy, it also introduces new challenges for reliable operation and maintenance due to harsh marine environments, complex aero–hydro–servo–elastic dynamics, and limited operational data availability. Although AI-driven Prognostics and Health Management (PHM) has achieved substantial progress for conventional wind turbines, its application to FOWTs remains relatively limited. This doctoral research proposes an intelligent PHM framework specifically developed for floating wind systems, addressing key challenges related to limited operational data and domain knowledge, heterogeneous and unreliable monitoring data, and dynamic environmental complexity. Domain adaptation combined with knowledge graph construction, multimodal learning for heterogeneous data integration, and physics-informed machine learning for structural dynamic modeling are investigated as complementary methodological contributions. These components are progressively integrated into a unified PHM lifecycle pipeline supporting fault detection, remaining useful life prediction, and maintenance decision support for FOWTs.

1. PROBLEM STATEMENT

The global transition toward low-carbon energy systems is driving rapid expansion of offshore wind energy (Gao et al., 2025), with floating offshore wind turbines (FOWTs) emerging as a key technology for exploiting deep-water wind resources where conventional fixed-bottom foundations are technically or economically infeasible. In particular, FOWTs enable deployment in deep-water regions typically exceeding 60 m in depth, where fixed-bottom structures become increasingly challenging to install and maintain (McMorland et al., 2022). However, realizing this potential requires ensuring that these systems operate reliably and cost-effectively throughout their service life. FOWTs operate under uniquely demanding conditions, including harsh marine environments characterized by strong winds, high waves, and corrosive exposure. In addition, complex aero–hydro–servo–elastic interactions and six-degree-of-freedom platform dynamics introduce significant operational variability (He et al., 2024) that is not present in land-based or fixed-bottom turbines. These conditions complicate monitoring, maintenance planning, and system reliability management. As a result, operation and maintenance (O&M) activities account for up to 30% of the total lifecycle cost of offshore wind farms (McMorland et al., 2022). These challenges highlight the importance of advanced PHM as a promising approach to reduce unplanned downtime and enable condition-based maintenance strategies. However, despite significant advances in AI-driven PHM for conventional wind turbines (Santiago et al., 2024), its application to FOWTs remains limited.

Based on a systematic literature review conducted using Google Scholar and Web of Science, we identified 153 publications related to FOWTs. Through complementary bibliometric and qualitative analyses, we further identified three fundamental challenges that currently hinder the effective deployment of PHM in FOWTs:

- **Challenge 1. Limited operational data & domain knowledge**: As an emerging technology, FOWTs suffer from a critical lack of long-term operational data and documented failure histories. Available datasets remain predominantly simulation-based, with no publicly accessible run-to-failure records under real offshore conditions. This scarcity is further compounded by limited domain knowledge on FOWT-specific failure modes, which differ significantly from those of conventional fixed-bottom turbines due to floating platform dynamics and the harsh marine environment.
- **Challenge 2. Heterogeneous & unreliable data quality**: Effective PHM for FOWTs requires integrating data from multiple heterogeneous sources, including vibration signals, SCADA measurements, inspection images, and maintenance reports. In addition, intermittent off-

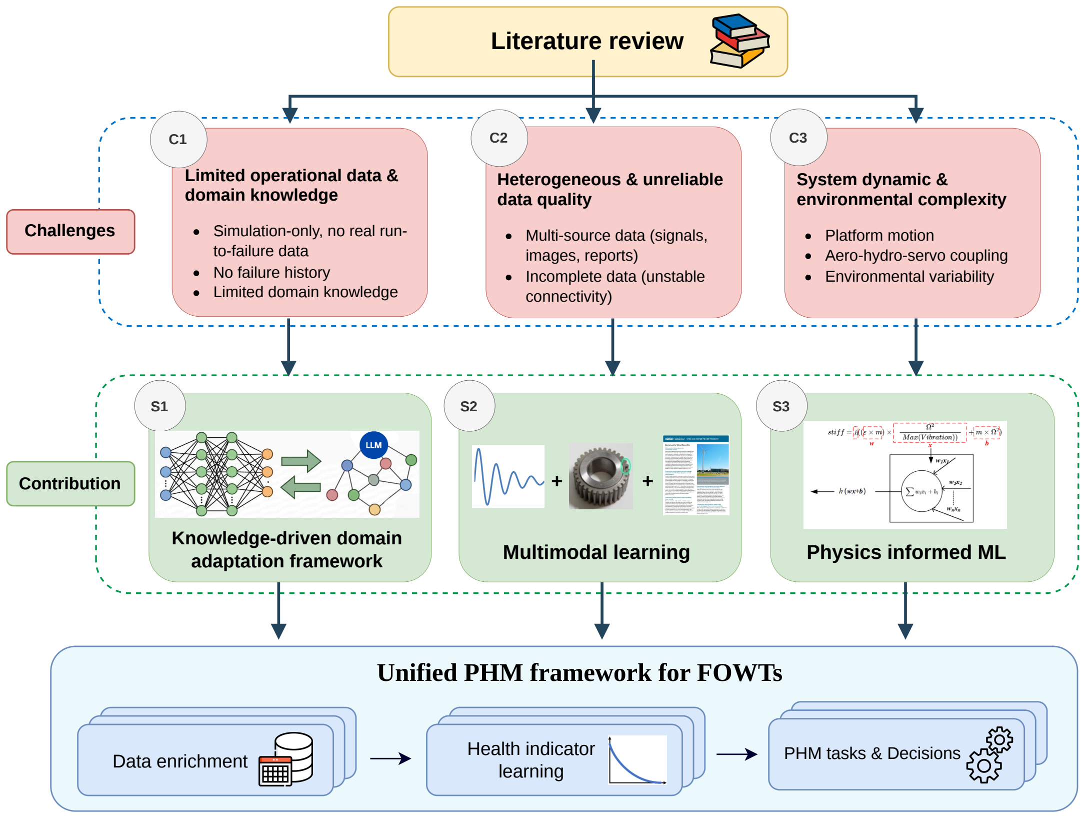

Figure 1. Overview of the proposed research approaches linking the identified challenges to the expected contributions.
C: Challenges; S: Scientific contributions.

shore connectivity leads to frequent data transmission gaps, while prolonged exposure to saltwater and mechanical stress degrades sensor accuracy over time, resulting in noisy, missing, and inconsistent measurements. Managing this data heterogeneity while ensuring sufficient quality and consistency constitutes a central obstacle to developing robust and generalizable predictive models.

- **Challenge 3. System dynamic & environmental complexity**: FOWTs operate under highly dynamic and non-stationary conditions driven by coupled aero-hydro-servo-elastic interactions, six-degree-of-freedom platform motions, and variable metocean environments. Because of these complex dynamics, variations in environmental and operating conditions can obscure early fault signals hidden in sensor data. As a result, detecting degradation and accurately estimating the system's health state is significantly more challenging than in fixed-bottom wind turbine systems.

2. EXPECTED NOVEL CONTRIBUTIONS TO PHM

To address the three challenges outlined above, this PhD research proposes three methodological contributions that are integrated into a unified, end-to-end PHM framework for FOWTs, as illustrated in Figure 1.

Contribution 1: To overcome the scarcity of real FOWT operational data and the lack of documented failure histories (C1), this work proposes a **knowledge-driven domain adaptation framework** that emphasizes formalizing domain knowledge as a key enabler. Large Language Models (LLMs) are used to systematically extract and structure information from technical documents, reports, and literature into a *structured knowledge base* capturing relationships among critical components, fault types, root causes and consequences, environmental influences, inter-component interactions, and relevant physical models. This structured knowledge base supports both data enrichment (e.g., simulation and augmentation) and transfer learning from better-documented fixed-bottom wind turbines, thereby enabling more generalizable and robust PHM models under severe data scarcity.

Contribution 2: To handle the heterogeneity and unreliability of multi-source FOWT data (C2), a **multimodal learning framework** designed to fully exploit both diverse data streams and the structured knowledge derived in Contribution 1. The framework integrates time-series signals, SCADA data, inspection images, and textual maintenance reports into a unified representation, enabling cross-modal learning and knowledge transfer across data types. To cope with practical issues such as missing, noisy, and asynchronous data caused by offshore conditions, robust fusion strategies (e.g., *modality-aware attention,*

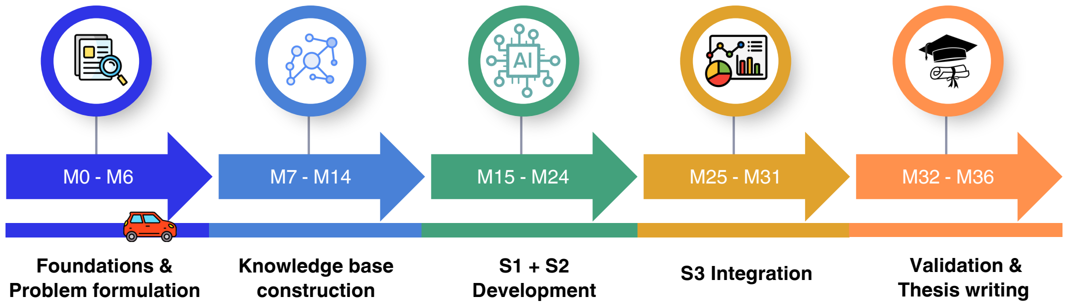

Figure 2. Planned research timeline and milestones over the 36-month doctoral project

uncertainty modeling, and imputation mechanisms) are developed. In addition, the framework leverages *knowledge-guided alignment to enhance transfer learning between modalities and across domains*.

Contribution 3: To address the system dynamic and environmental complexity inherent to FOWT operation (C3), this research develops **physics-informed machine learning models** that explicitly incorporate aero–hydro–servo–elastic dynamics into the learning process. Building upon the knowledge graph and multimodal representations, domain-specific physical laws, constraints, and simplified governing models are embedded to guide learning and regularize model behavior. This integration enables the separation of environmental and operational variability from true degradation signals, reducing spurious correlations introduced by highly non-stationary conditions. Furthermore, the framework supports hybrid modeling strategies that combine data-driven learning with physics-based simulation, helping to bridge the sim-to-real gap. The resulting physics-consistent health indicators are more interpretable, robust, and generalizable, providing reliable inputs for downstream PHM tasks.

3. RESEARCH PLAN

Building upon the research challenges identified in Section 1 and the proposed contributions presented in Section 2, the PhD research is structured into five consecutive phases spanning 36 months, as illustrated in Figure 2. The plan progressively advances from foundational investigations toward the development and validation of an integrated PHM framework for FOWTs.

M0 – M6: Foundations & Problem formulation: The first phase established the scientific foundations of the research. A systematic literature review and bibliometric analysis were conducted to assess the state of the art in PHM, FOWTs, domain adaptation, multimodal learning, and physics-informed machine learning. Available datasets were surveyed and characterized, covering SCADA signals, vibration measurements, inspection images, and maintenance reports. Based on these findings, the three research challenges (C1–C3) were formulated, and a taxonomy of FOWT components, fault modes, and degradation mechanisms was developed to structure the subsequent methodological work. This phase is nearly complete, and a review paper synthesizing its main findings is currently being prepared for journal submission.

M7 – M14: Knowledge base construction (S1): Building on the foundations established in the first phase, this stage focuses on the development of the first research contribution: a structured knowledge base for FOWT PHM. An LLM-assisted pipeline is developed to systematically extract and organize knowledge from technical documents, maintenance reports, and scientific literature. The resulting knowledge base captures component–fault–cause–effect relationships, environmental influences, and inter-component interactions, including relevant physical models. Based on this structured knowledge, data enrichment strategies are designed to compensate for the scarcity of real operational data, leveraging simulation and augmentation techniques guided by domain knowledge.

M15 – M24: Multimodal learning and Domain adaptation (S1+S2): Building upon the knowledge base developed in the previous phase, this phase addresses the challenge of learning from scarce and heterogeneous FOWT data. Because real FOWT datasets are limited and often incomplete across sensing modalities, domain adaptation strategies are employed to leverage relatively abundant labeled data from onshore and fixed-bottom turbine systems, thereby supporting multimodal representation learning in the data-limited FOWT context. On this basis, a multimodal learning framework is developed to integrate heterogeneous monitoring data, including time-series signals, SCADA measurements, inspection images, and textual maintenance reports. The structured knowledge base from S1 guides cross-modal alignment to ensure semantic consistency across modalities, while robust fusion strategies are introduced to handle missing modalities, noisy measurements, and asynchronous data streams. Together, these developments aim to improve generalization across domains and varying data availability conditions.

M25 – M31: Physics-informed ML integration (S3): This stage focuses on integrating physical knowledge of aero-hydro-servo-elastic dynamics into the learning framework. Hybrid approaches are designed to combine data-driven models with physics-based simulations in order to improve robustness and reliability under the complex and non-stationary operating conditions of FOWTs. The structured knowledge base developed in S1 is further leveraged to identify relevant physical constraints and guide model regularization, ensuring that the learned representations remain physically consistent. A key objective of this phase is to disentangle environmental and operational variability from genuine degradation-related patterns, thereby enabling the derivation of physics-consistent health indicators for subsequent PHM analysis.

M32 – M36: Validation and thesis writing: While each preceding phase includes targeted validation of the developed methods and models, this final stage focuses on integrating all contributions into a unified framework. The objective is to assess the overall coherence, consistency, and applicability of the approach rather than to conduct extensive additional validation. This phase concludes with the writing and defense of the doctoral thesis.

REFERENCES

Gao, Q., Ertugrul, N., & Ding, B. (2025). Review and evaluation of offshore wind energy: Resources, markets and technologies. *Int. Mar. Energy J.*, *8*(3), 309–319. doi: 10.36688/imej.8.309-319

He, J., Men, X., Jiao, B., Lin, H., Sun, H., & Lin, X.-M. (2024). Coupled aero-hydrodynamic analysis in floating offshore wind turbines: A review of numerical and experimental methodologies. *Journal of Marine Science and Engineering*, *12*, 2205. doi: 10.3390/jmse12122205

McMorland, J., Collu, M., McMillan, D., & Carroll, J. (2022). Operation and maintenance for floating wind turbines: A review. *Renew. Sustain. Energy Rev.*, *163*, 112499. doi: 10.1016/j.rser.2022.112499

Santiago, R. A. F., Barbosa, N. B., Mergulhão, H. G., Carvalho, T. F., Santos, A. A. B., Medrado, R. C., … Nascimento, E. G. S. (2024). Data-driven models applied to predictive and prescriptive maintenance of wind turbine: A systematic review of approaches based on failure detection, diagnosis, and prognosis. *Energies*, *17*(5), 1010. doi: 10.3390/en17051010