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A Domain-Adaptive Framework for Damage Detection of Offshore Wind Turbine Jacket Substructures using Machine Learning

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Implementing effective Structural Health Monitoring (SHM) for offshore wind turbine jacket substructures is critical for minimizing Operations and Maintenance (O&M) costs, yet it remains challenging due to the scarcity of real-world fault data and the difficulty of detecting incipient damage. To address this, a high-fidelity coupled simulation framework integrating OpenFAST and Abaqus was established, generating a comprehensive database covering 17 structural health states, including complex cross-level damage scenarios. The study evaluates different feature engineering strategies across machine learning and deep learning models. Results indicate that Extreme Gradient Boosting (XGBoost), utilizing a hierarchical classification strategy and raw time-domain signals under wind-only loading conditions, achieved a robust 100% accuracy, establishing a strong baseline. In contrast, deep learning approaches, including LSTM and ResNet, demonstrated the advantage of automated feature extraction, effectively capturing temporal dependencies and stiffness-induced spectral shifts respectively. However, under complex environmental loading, these architectures exhibited higher sensitivity to data scale and signal dominance (e.g., damage masking), highlighting the challenges of end-to-end learning in mixed-fault scenarios. Finally, to mitigate data scarcity for early-stage faults, a hybrid Semi-Supervised Domain Adaptation (SSDA) strategy integrating DANN with Maximum Mean Discrepancy (MMD) was investigated. This approach successfully facilitated knowledge transfer from severe to incipient damage scenarios, improving accuracy from 45% to 56%, demonstrating the preliminary feasibility of adversarial learning in enhancing the detectability of subtle structural degradation where labeled data is limited.

Keywords: Structural health monitoring, offshore wind turbine, jacket substructure, machine learning, deep learning, domain adaptation, semi-supervised learning.

1. Introduction

Taiwan's offshore wind development is rapidly transitioning towards deeper waters (depths > 40m), where jacket foundations are preferred for their structural stability (GWEC 2023; 4COffshore 2020). However, the harsh marine environment imposes high Operations and Maintenance (O&M) costs, which can account for a substantial portion of the Levelized Cost of Energy (LCOE) (Zhu 2021; Black et al. 2021). A major challenge in SHM is the variability of Operational and Environmental Conditions (OECs), such as fluctuating wind and waves, which often mask damage signatures and lead to false alarms (Weijtjens et al. 2017; Oliveira et al. 2018). Previous research has extensively explored data-driven approaches for OWT fault diagnosis. For instance, Hoxha et al. (2020) and Feijóo et al. (2021) demonstrated the efficacy of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks in classifying damage based on vibration signals. Building on these advancements, Residual Networks (ResNet) have further demonstrated exceptional capability in extracting subtle damage features from high-dimensional data, achieving high accuracy under stable conditions (He et al. 2016). However, standard supervised learning models often struggle with "domain shift"—a performance degradation that occurs when the environmental distribution of the testing data differs from that of the training data (Ganin et al. 2016).

To address these challenges, this study proposes a comprehensive diagnosis framework driven by high-fidelity simulation data. First, a coupled simulation utilizing OpenFAST and Abaqus is established to generate a large-scale dataset covering 17 structural health states under comprehensive environmental scenarios (Jonkman et al. 2009; Van Gerven 2011). This extensive database serves as the foundation for rigorously evaluating the performance of supervised learning models in extracting discriminative features for incipient damage detection. Additionally, to preliminarily investigate robust performance under domain shift, a Semi-Supervised Domain Adaptation (SSDA) strategy integrating Domain-Adversarial Neural Networks (DANN) with Maximum Mean Discrepancy (MMD) is briefly explored to assess the feasibility of learning domain-invariant features by minimizing distributional discrepancies (Gretton et al. 2012). This study adopts a two-stage research strategy. First, a comprehensive evaluation of supervised learning baselines is conducted under controlled conditions to establish diagnostic benchmarks and identify key challenges such as damage masking. Building upon these findings, a preliminary domain adaptation strategy is then explored to address the identified limitations of data scarcity for incipient faults.

2. Methodology

This study employs a simulation-based approach to generate a high-fidelity dataset for training and testing the proposed diagnosis models. The framework consists of a coupled aero-hydro-servo-elastic simulation and a deep learning-based diagnosis system.

2.1. *Coupled Simulation Framework*

To rigorously evaluate the structural performance under realistic operational conditions, a high-fidelity coupled simulation framework is established, integrating the aero-hydro-servo-elastic capabilities of OpenFAST with the advanced finite element analysis (FEA) of Abaqus.

2.1.1. *Numerical Model Configuration*

The structural model represents the NREL 5MW baseline wind turbine (Jonkman et al. 2009) supported by an OC4 jacket substructure (Popko et al. 2012) in a water depth of 50 meters. The modeling process in Abaqus involves the following key technical specifications:

- Element Type: The jacket substructure, including legs and braces, is modeled using 2-node linear beam elements (B31) to efficiently capture the global structural stiffness and dynamic response.
- Structural Assembly: The transition piece (TP) is modeled as a rigid body using kinematic couplings to transfer loads from the tower base to the jacket legs, ensuring correct load path distribution.
- Mass Distribution: Non-structural masses, such as the nacelle and rotor assembly, are simplified as lumped masses with defined rotary inertia applied at the tower top.

2.1.2. *Load Calculation and Coupling Interface*

A Python-based automated interface was developed to facilitate one-way coupling between OpenFAST (Jonkman and Buhl 2005) and Abaqus. The simulation procedure begins with the calculation of aerodynamic and hydrodynamic loading. OpenFAST is employed to simulate the time-history loads, utilizing the AeroDyn and HydroDyn modules to calculate the aerodynamic forces on the rotor and the hydrodynamic wave forces on the substructure, respectively. The turbulent wind fields are generated by TurbSim using the Kaimal spectrum, while the irregular waves are simulated using the JONSWAP spectrum.

Subsequently, the interface extracts the aggregated environmental loads—comprising both aerodynamic and hydrodynamic components—as time-series forces and moments (6 DOFs) at the tower base interface. In the Abaqus FE model, these global loads are applied as concentrated point loads to a defined Reference Point (RP) located at the geometric center of the transition piece. A kinematic coupling constraint is utilized to rigidly distribute these concentrated loads from the RP to the surrounding interface nodes of the jacket structure. Finally, a transient dynamic analysis is conducted using a dynamic implicit solver to compute the global structural response. This approach effectively captures the coupled dynamic effects of wind and wave excitations while ensuring computational efficiency for generating the large-scale dataset required for deep learning. It should be noted that the current framework employs one-way coupling, where the structural response does not feed back into the aerodynamic and hydrodynamic load calculations. While this simplification is computationally efficient, it may underestimate load redistributions in severely damaged states, and future work could investigate two-way coupling to improve fidelity.

2.2. *Damage Scenarios and Dataset Generation*

To construct a comprehensive database for validating the SHM algorithms, this study simulates a variety of structural damage scenarios by reducing the Young's modulus (E) of specific members. Based on the structural stress distribution and environmental exposure, damage is introduced across three critical levels: Level 1 (bottom section, fatigue-prone), Level 2 (intermediate section), and Level 3 (splash zone, corrosion-prone). The schematic of the structure and the designated damage locations is illustrated in Fig. 1. To capture the complexity of real-world degradation, a total of 17 structural health states are defined and categorized into three groups:

- Healthy State (Class 1): The baseline structure with nominal material properties (E = 210 GPa).
- Single-Level Damage (Classes 2–13): These scenarios simulate damage occurring at a single location across the three levels (covering 3 X-joints and 3 K-joints) with two severity levels (5% and 20%).
- Cross-Level Damage (Classes 14–17): To investigate the capability of detecting multi-site damage, simultaneous severe damage (20% reduction) is introduced at both Level 1 (K-joint) and Level 3 (X-joint).

The systematic design of these 17 health states, especially the inclusion of cross-level damage scenarios, allows for a rigorous evaluation of the diagnosis framework's capability to disentangle complex, coupled damage signatures relative to single-site failures.

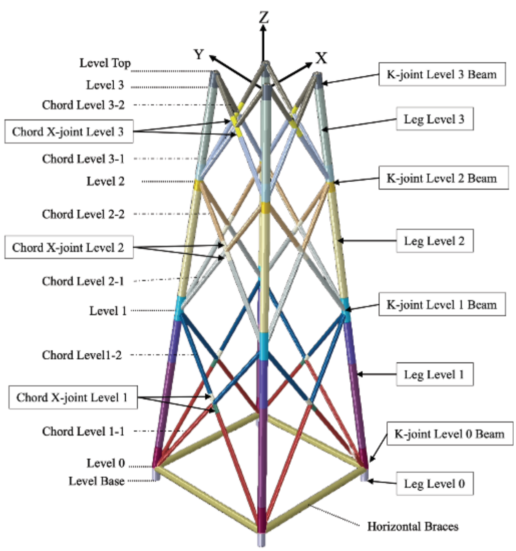

Fig. 1. Abaqus finite element model and sensor locations

2.3. *Data Preprocessing and Diagnosis Framework*

The proposed diagnosis framework is structured into two primary phases: data preprocessing and damage classification. Within this architecture, the study rigorously evaluates a suite of supervised learning algorithms alongside the domain adaptation strategy. To optimize performance across these diverse model architectures, raw acceleration data is transformed into distinct feature representations tailored to specific input requirements.

2.3.1. *Feature Engineering Strategy*

Feature extraction is customized to align with the distinct requirements of the model architectures. Normalized 1D time-series signals serve as inputs for XGBoost, LSTM, and CNN. Abdeljaber et al. (2017) highlighted that this approach preserves the full temporal resolution of the raw waveforms, enabling the extraction of subtle hierarchical features without the information loss associated with manual aggregation. Conversely, for ResNet, data is transformed into Power Spectral Density (PSD). As proposed by Jiang et al. (2018), this representation highlights energy distributions across frequencies, effectively capturing stiffness-induced spectral shifts while mitigating phase noise.

2.3.2. *Baseline Supervised Learning Models*

To establish a robust baseline and evaluate the proposed framework, four widely used supervised learning algorithms are implemented. The diagnosis begins with Extreme Gradient Boosting (XGBoost), an optimized distributed gradient boosting library designed for high efficiency and flexibility (Chen 2016). Contrary to conventional approaches that rely on extracted statistical features, this study utilizes raw time-domain acceleration signals directly as inputs to preserve the full temporal resolution of the vibration data. Furthermore, as illustrated in Fig. 2, a hierarchical classification strategy is employed to decompose the complex diagnosis task into three sequential sub-problems: (1) Localization (identifying the damaged level), (2) Joint Type Identification (distinguishing between X-joint and K-joint), and (3) Severity Estimation (determining the extent of stiffness reduction)

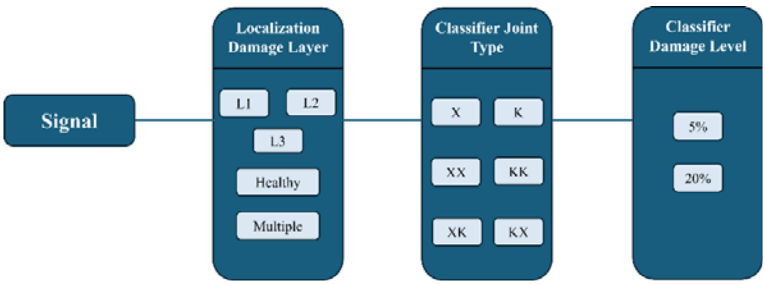

Fig. 2. The proposed hierarchical classification framework for damage diagnosis.

To capture temporal dynamics, Long Short-Term Memory (LSTM) networks are employed. Their gating mechanisms enable the model to learn long-term dependencies and sequential patterns directly from time-series inputs, overcoming the vanishing gradient problem of standard Recurrent Neural Networks (RNNs). For automatic feature extraction, a 1D-Convolutional Neural Network (CNN) is utilized as a comparative baseline, processing the multi-channel acceleration time-series directly through convolutional and max-pooling layers. However, this end-to-end approach generally requires larger balanced datasets to match the efficiency of XGBoost.

Finally, Residual Networks (ResNet) are implemented for deep feature extraction. By introducing skip connections within residual blocks, ResNet mitigates the vanishing gradient problem and enables significantly deeper architectures capable of capturing complex non-linear patterns. This deep hierarchical representation is particularly critical for distinguishing the minute structural variations associated with incipient damage

2.3.3. *Semi-Supervised Domain Adaptation Strategy*

To mitigate the performance degradation caused by domain shifts, this study implements a Semi-Supervised Domain Adaptation (SSDA) strategy. The proposed architecture integrates two complementary mechanisms: Domain-Adversarial Neural Networks (DANN) and Maximum Mean Discrepancy (MMD). First, following Ganin et al. (2016), the DANN component extends the feature extractor (e.g., ResNet) by adding a domain classifier connected via a Gradient Reversal Layer (GRL) to induce domain confusion. To further enhance alignment, MMD is employed as a regularization term to explicitly minimize the distributional discrepancy between source and target feature representations in a reproducing kernel Hilbert space (Gretton et al. 2012). By synergizing adversarial learning with statistical moment matching in an SSDA setting, the model is trained to learn features that are not only discriminative for damage classification but also invariant to domain differences, leveraging both the abundant labeled source data and the limited labeled target data.

Case Study: Severity Adaptation The experimental validation focuses on a Severity Adaptation scenario. This case addresses the challenge of detecting incipient damage by transferring knowledge from labeled severe damage data (Source Domain) to identify minor stiffness reductions (Target Domain), simulating a real-world context where early-stage fault data is inherently scarce.

3.Results

This section presents the classification performance of the proposed framework. Prior to establishing the final baseline, an initial investigation was conducted using Long Short-Term Memory (LSTM) networks to assess the learnability of temporal dependencies. This preliminary analysis revealed a critical physical insight regarding "damage masking": in complex mixed-damage scenarios, the subtle vibration signatures of incipient faults were frequently overshadowed by the dominant structural response of severe damage, leading to misclassification. Guided by this observation, the subsequent evaluation shifts focus to a hierarchical classification strategy utilizing Extreme Gradient Boosting (XGBoost) and raw signal inputs, which demonstrated superior capability in disentangling these coupled features.

In this study, we identify two distinct masking phenomena: (1) Spectral masking, where high-energy wave-frequency components in the PSD overlap with and obscure the subtle spectral shifts caused by incipient damage; and (2) Structural masking (or damage masking in mixed-fault scenarios), where the dominant vibration response of severe damage overshadows the subtle signatures of co-existing minor faults in the time domain, leading to misclassification.

3.1. *Time-Domain Baseline Evaluation (XGBoost)*

Adopting the proposed hierarchical three-stage classification strategy, the XGBoost model was evaluated. It is important to note that for this baseline establishment, the input data consisted of raw time-domain acceleration signals generated under pure wind loading conditions, isolating the structural response from hydrodynamic interference. This structured approach effectively decomposes the complex multi-class problem, allowing the model to achieve an overall classification accuracy of 100% across the 17 health states. As demonstrated by the confusion matrix in Fig. 3, the model exhibits a perfect diagonal alignment with no misclassifications. This result confirms the exceptional robustness of XGBoost in handling class imbalance and limited sample sizes, proving that raw time-domain features—when free from wave noise masking—contain sufficient information to distinguish even the most complex cross-level damage scenarios.

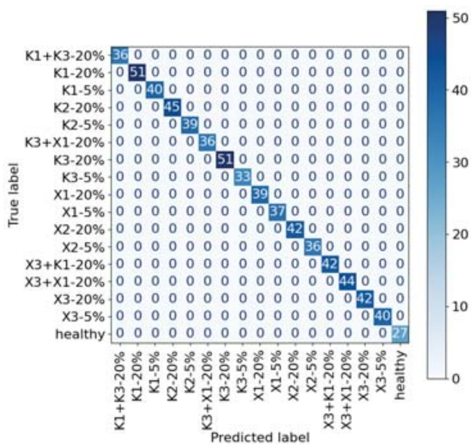

Fig. 3. Confusion matrix of the XGBoost model.

It is important to note that the XGBoost baseline was evaluated under wind-only loading conditions, while the ResNet model was tested under combined wind and wave loading. Consequently, the direct comparison of their absolute accuracy values should be interpreted with caution, as the latter condition introduces significant additional noise. A rigorous comparison would require evaluating both models under identical environmental settings.

3.2. *Spectral Feature Analysis (ResNet)*

Following the baseline establishment, deep learning approaches were evaluated to assess their capability in automated feature extraction. Initial experiments utilizing 1D-Convolutional Neural Networks (CNN) on raw time-domain signals yielded suboptimal performance compared to the tree-based baseline. The standard CNN architecture struggled to establish sharp decision boundaries for the hierarchical categorization of subtle damage, often confusing adjacent severity levels. To overcome this limitation and enhance feature distinctiveness, the strategy shifted from the time domain to the frequency domain. The raw signals were transformed into Power Spectral Density (PSD) maps to highlight energy distributions, and a Residual Network (ResNet) was employed to capture stiffness-induced spectral shifts. To further evaluate robustness under more rigorous constraints, this deep learning assessment was conducted under a complex environmental setting involving combined wind and wave loading. This introduces significant hydrodynamic interference, presenting a challenging scenario for identifying damage features amidst environmental noise.

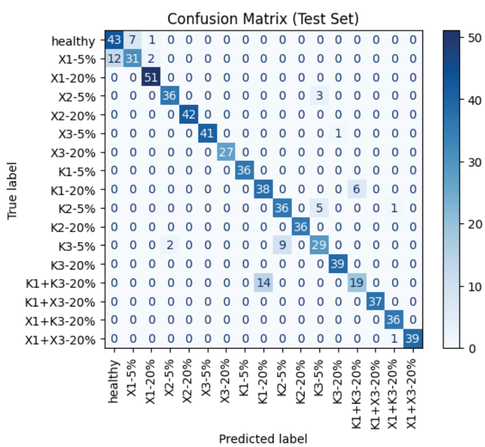

Fig. 4. Confusion matrix of the ResNet model.

Additionally, to mitigate overfitting and improve generalization against this noise, label smoothing regularization was applied during the training process. Under these conditions, the ResNet model achieved a commendable overall classification accuracy of 90%. While the model successfully identified major structural faults, the confusion matrix (Fig. 4) indicates that the high-energy wave frequency components often overlap with the vibration signatures of incipient damage. This "spectral masking" effect validates that even with regularization techniques, the presence of hydrodynamic noise remains a limiting factor for detecting early-stage faults compared to the noise-free baseline.

3.3. *Feasibility of Domain Adaptation for Incipient Faults*

Finally, the proposed Semi-Supervised Domain Adaptation (SSDA) strategy was evaluated to address the challenge of data scarcity for early-stage faults. Consistent with the deep learning analysis in Section 3.2, this framework employs the ResNet architecture as the shared feature extractor, utilizing PSD maps as inputs to capture spectral energy distributions. The experimental validation focuses on a specific severity adaptation scenario: transferring knowledge from a source domain characterized by distinct damage (20% stiffness reduction) to a target domain of incipient faults (5% stiffness reduction).

The difficulty of this transfer task is highlighted by the baseline model's low accuracy of 45% when directly applied to the target domain, indicating a substantial distributional discrepancy between the high-severity and low-severity features. Initial implementation of the standard DANN architecture yielded only marginal improvements. However, by integrating Maximum Mean Discrepancy (MMD) to explicitly align the statistical moments of the feature distributions, the hybrid model achieved a notable relative improvement, raising the accuracy from 45% to 56%. This 11 percentage-point increase confirms the effectiveness of combining adversarial learning with MMD for distributional alignment, and provides a promising foundation for further optimization. These results demonstrate the feasibility of the proposed SSDA strategy, offering a baseline for future research in identifying incipient faults where labelled data is limited.

4. Discussion

The experimental results highlight a distinct trade-off between model complexity and feature engineering strategies. The superior performance of the XGBoost baseline, achieving 100% accuracy, validates the effectiveness of the proposed hierarchical classification strategy. By decomposing the complex multi-class diagnosis into manageable sub-tasks (Localization, Joint Type, and Severity), the gradient boosting algorithm effectively sharpens decision boundaries at each stage. Furthermore, the utilization of raw time-domain signals proved advantageous over frequency-domain transformations. This suggests that the tree-based model can efficiently exploit transient vibration characteristics and impact-induced non-linearities, which are crucial for distinguishing subtle damage states but are often smoothed out in statistical or spectral representations.

In contrast, the analysis of deep learning models reveals specific physical limitations associated with data representation and environmental noise. For the ResNet model operating in the frequency domain, a critical "spectral masking" effect was observed. While effective for detecting severe faults, the model struggled to distinguish healthy states from incipient damage, indicating that high-energy wave frequency components often overshadow the subtle spectral shifts caused by minor stiffness reductions. Additionally, the transformation to Power Spectral Density (PSD) discards phase information, leading to ambiguity between symmetric or structurally similar locations, where damage induces nearly identical global energy changes. Conversely, the LSTM network, while preserving temporal information, faced challenges in disentangling coupled signatures in mixed-damage scenarios, often misclassifying them as healthy due to the dominance of the primary structural response. These findings underscore that deep learning architectures exhibit a higher dependency on data scale and are more susceptible to "structural noise" compared to the hierarchical tree-based approach.

Finally, addressing the challenge of data scarcity, the SSDA strategy demonstrated the feasibility of knowledge transfer. Although the quantitative improvement was modest, the integration of DANN and MMD successfully aligned feature distributions between severe damage (source) and incipient damage (target) scenarios. This confirms that adversarial learning combined with statistical alignment offers a promising pathway for identifying early-stage faults where labeled data is inherently rare, potentially bridging the domain gap that limits standard supervised learning.

5. Conclusion

This study proposes a comprehensive framework for the structural health monitoring of jacket-type offshore wind turbines, integrating high-fidelity coupled simulations with advanced diagnosis models. A database covering 17 structural health states was established using OpenFAST and Abaqus to validate the methodology. The key conclusions are as follows:

- Superiority of Hierarchical XGBoost on Raw Signals: Contrary to traditional methods relying on statistical features or frequency transformations, this study confirms that the direct utilization of raw time-domain acceleration signals yields the most robust performance. The XGBoost model, employing a hierarchical classification strategy, achieved 100% accuracy. This validates that decomposing the complex diagnosis task into sub-stages (Localization, Joint Type, Severity) allows the gradient boosting algorithm to effectively capture transient vibration signatures, establishing it as a highly efficient baseline for jacket structure diagnostics.
- Deep Learning Limitations and Masking Effects: While deep learning architectures (ResNet and LSTM) demonstrated competence, they revealed critical physical limitations under environmental complexity. The frequency-domain ResNet suffered from "spectral masking," where high-energy wave noise overshadowed the subtle spectral shifts of incipient damage. Similarly, the LSTM network exhibited a "structural masking" phenomenon in mixed-damage scenarios, misclassifying coupled low-severity faults due to the dominance of the primary damage response. These findings underscore that without massive datasets, end-to-end deep learning struggles to disentangle signal-to-noise conflicts in realistic marine environments.
- Feasibility of Domain Adaptation: To address the scarcity of labeled data for early-

stage faults, a Semi-Supervised Domain Adaptation (SSDA) strategy was evaluated. The integration of DANN with Maximum Mean Discrepancy (MMD) successfully facilitated knowledge transfer from severe damage scenarios (source) to incipient damage cases (target). The resulting 11% improvement in accuracy demonstrates the feasibility of aligning feature distributions across severity levels, offering a promising pathway to enhance detection sensitivity where direct training data is unavailable.

Future work will focus on the following aspects: (1) evaluating the proposed framework under combined wind and wave loading conditions for all models to enable fair comparisons; (2) investigating optimal sensor placement strategies using sensitivity analysis; (3) enhancing the SSDA framework with advanced techniques such as contrastive learning or curriculum learning to improve incipient fault detection beyond the current level of accuracy; (4) validating the simulation-based framework against field measurement data from operational offshore wind farms; and (5) exploring the scalability of the hierarchical classification strategy to other substructure types.

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