STRUCTURAL HEALTH MONITORING OF WIND TURBINE BLADES USING VIBRATION-BASED DAMAGE DETECTION AND MACHINE LEARNING

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Abstract

Wind turbine blades are subjected to complex, time-varying aerodynamic and gravitational loads over 20-year design lives, making early damage detection essential to prevent catastrophic failure and reduce operation-and-maintenance (O&M) costs, which represent 20–35% of levelised cost of energy (LCOE) for onshore wind. This thesis develops and validates a vibration-based structural health monitoring (SHM) framework for a 45-metre GFRP wind turbine blade, combining high-fidelity finite element (FE) modelling with machine learning classification of damage scenarios. A full-scale FE model of the blade (ANSYS Mechanical, 180,000 shell elements) was validated against experimental modal analysis (EMA) data from a 1:10 scale laboratory specimen; first five natural frequencies matched within 3.2%. Damage scenarios (delamination at 25% and 60% span, trailing-edge debonding, leading-edge erosion) were simulated by selectively reducing element stiffness. Modal strain energy (MSE) damage indicators were extracted from the FE database of 1800 damage cases. A Random Forest (RF) classifier trained on MSE features achieved 96.8% damage detection accuracy and 91.3% location accuracy (5-class) in cross-validation. Deployment on a 5-node wireless sensor network (MEMS accelerometers, 1000 Hz sampling) on the physical specimen confirmed real-world detection of 40 mm × 40 mm artificial delaminations with 93% accuracy, validating the computational framework for field implementation.

Keywords: structural health monitoring; wind turbine blade; vibration-based damage detection; modal strain energy; random forest; machine learning; GFRP; delamination

1. Introduction

Global installed wind capacity surpassed 1 TW in 2023, with blades becoming progressively larger (≥90 m tip-to-tip for offshore platforms) to capture greater energy at lower wind speeds. Glass-fibre-reinforced polymer (GFRP) composite blades are subject to fatigue-induced delamination, trailing-edge adhesive joint failures, and leading-edge erosion from rain and particulate impact. Undetected damage can propagate to catastrophic blade separation, causing turbine loss and ground hazard. Current inspection methods (rope-access visual or drone imaging) are intermittent, expensive (~€15,000 per inspection), and unable to detect sub-surface delaminations [1].

Vibration-based SHM exploits the principle that structural damage alters local stiffness and hence modal parameters (natural frequencies, mode shapes, damping). By continuously monitoring these parameters, damage onset can be detected automatically between scheduled maintenance intervals. The integration of machine learning classifiers enables discrimination of damage type, location, and severity from high-dimensional feature sets—a capability not achievable with classical threshold-based methods [2].

2. Finite Element Modelling

The blade geometry was defined from a NACA 63-618 profile at root and DU 91-W2-250 at tip, with a 45 m span. The FE model used layered shell elements (SHELL281 in ANSYS) with a 15-layer GFRP lay-up schedule ($[0^\circ/\pm 45^\circ]_s$ at spar caps, $[0^\circ/90^\circ]$ at leading/trailing edge panels). Material properties: $E_1 = 38$ GPa, $E_2 = 9$ GPa, $G_{12} = 3.6$ GPa, $\nu_{12} = 0.29$, $\rho = 1860$ kg/m^3. The model comprised 180,420 elements and was validated against experimental modal analysis of a 4.5 m scale specimen; frequency errors < 3.2% for modes 1–5.

3. Damage Simulation and Feature Extraction

Eighteen damage scenarios were defined across four damage types and three severity levels. Each scenario was realised by reducing the in-plane stiffness E_1 and E_2 of affected elements by 20%, 50%, or 80%, representing early, moderate, and severe damage respectively. Modal strain energy (MSE) damage index for element j:

$MSE_j = (\varphi_i^T K_j \varphi_i / \varphi_i^T K \varphi_i) / (\varphi_0^T K_{j0} \varphi_0 / \varphi_0^T K_0 \varphi_0)$ where φ is the mode shape vector and subscript 0 denotes the healthy baseline. 1800 damage cases were generated via Latin Hypercube Sampling of stiffness reduction magnitudes.

4. Machine Learning Classification

MSE indices from the first five modes (5 modes × 6 sensor locations = 30 features) were input to a Random Forest classifier with 500 trees (scikit-learn, Python 3.11). Hyperparameters tuned by 5-fold cross-validation: max_depth = 12, min_samples_leaf = 4. Training/test split: 80/20. Results: damage detection accuracy 96.8%, damage location accuracy (5 spatial zones) 91.3%, damage severity classification (3 classes) 88.1%. Feature importance analysis identified the 60%-span MSE features from modes 2 and 3 as most discriminative, consistent with the bending-dominated dynamic response of slender blades.

5. Experimental Validation

Five MEMS accelerometers (PCB 333B40, ±50 g, 0.5–1000 Hz) were bonded at 0%, 25%, 50%, 75%, and 100% span on the 4.5 m scale specimen. Ambient vibration (fan excitation, broadband 1–100 Hz) served as the operational input. Stochastic Subspace Identification (SSI-COV) was used to extract operational modal parameters in real time. Artificial delaminations (40×40 mm area, 2 mm depth) were introduced at three locations using a Teflon insert. The RF classifier detected all three delaminations with 93% accuracy across 60 test conditions, confirming real-world viability.

6. Conclusions

- A validated 180k-element FE model of a 45 m GFRP wind turbine blade captures the first five natural frequencies within 3.2% of experimental values.
- Modal strain energy indices computed from simulated mode shapes provide robust damage-sensitive features discriminating delamination, trailing-edge debond, and leading-edge erosion scenarios.
- A Random Forest classifier achieves 96.8% damage detection and 91.3% location accuracy on the 1800-case simulated database.
- Physical validation on a 1:10 scale specimen with MEMS sensors confirms 93% detection accuracy for 40×40 mm artificial delaminations under ambient vibration excitation.
- The proposed SHM framework is suitable for continuous online monitoring, reducing blade inspection costs by an estimated 60% relative to rope-access campaigns.

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