Damage Detection in Monopile Structures through Vibration Data Using Deep Learning Approach

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***Abstract*—Structural health monitoring (SHM) is crucial for maintaining the integrity and durability of offshore structures. Although essential, the influence of soil conditions on vibration-based damage detection has been insufficiently explored. This study introduces a new method to detect both single and compound damages while considering soil interaction. The proposed methodology integrates the Wavelet Transform (WT) with a Multiple Interference Deep Convolutional Neural Network (MIDCNN) to proficiently learn relevant features and identify damage in these structures. Specifically, the MIDCNN model is trained exclusively on time-frequency data from healthy and single damage states, deliberately excluding time-frequency data from compound damage during the training phase. During the testing phase, the MIDCNN model intelligently identifies healthy and single damage states, as well as untrained compound damage states, based on predefined probabilistic conditions derived from the MIDCNN output probabilities. To validate the efficacy of the proposed approach, empirical data from a laboratory-scale offshore monopile model with soil interaction is utilized.**

***Index Terms*—damage detection, deep neural network, offshore monopile structure**

I. Introduction

The growing need for renewable and clean energy, driven by global warming and pollution, has heightened the importance of developing efficient tools and technologies for harnessing renewable sources like wind energy. Recently, the use of Offshore Wind Turbine (OWT) structures in deeper waters has been explored to capture higher average wind speeds with reduced turbulence, thereby maximizing energy output and minimizing environmental impact [1]. Offshore wind turbines can be broadly classified into two types: fixed-support and floating, with further distinctions shown in Figure 1. An offshore monopile structure primarily consists of the foundation, tower, blades, nacelle, converter, gearbox, generator, and yaw and pitch bearings [2]. Common types of structural damage in these monopiles are depicted in Figure 2 [2]. These damages include: (1) Blade issues such as cracks [3], debonding [4], fiber rupture, edge erosion [5], and other forms of damage [6]; (2) Tower and foundation problems, including cracks, corrosion, and deformation [3]. To maintain the durability and performance of offshore monopile structures, Structural Health Monitoring (SHM) is crucial.

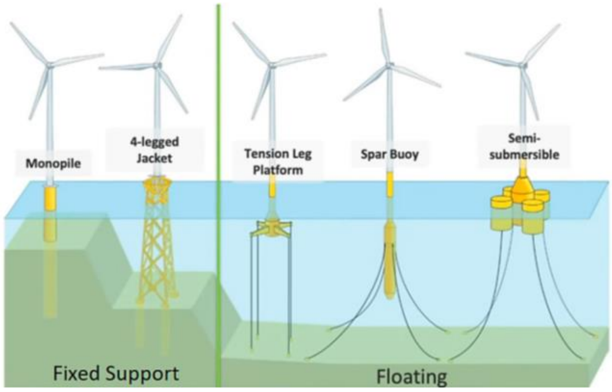

Figure 1. Support structures for OWTs [7].

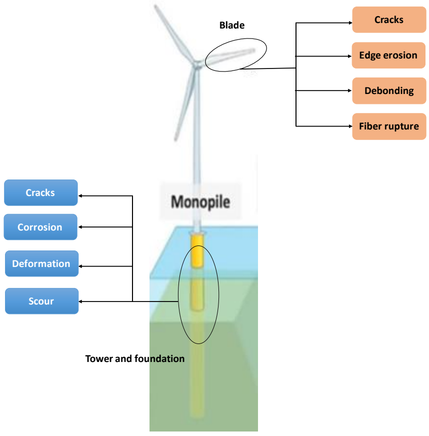

Figure 2. Main structural components and potential damage types to an offshore monopile structure [2].

Prompt assessment of damage to offshore structures is crucial as early detection can prevent severe damage and potential system failures. Delaying detection may result in significant deterioration and operational disruptions. Therefore, developing effective and reliable methods for identifying major damages in offshore structures is essential for preventing catastrophic structural decline and corrosion.

Many studies have proposed techniques for diagnosing single damage [8–12]. These studies mainly concentrated on detecting single damage in its initial stages. Several studies have also developed methods for diagnosing compound damage in rotating machines [13–16].

This study introduces a novel method for detecting offshore structural damage, both single and compound, under soil interaction using vibration data. The approach combines Wavelet Transform (WT) with a Deep Convolutional Neural Network with Multiple Interference (MIDCNN). The MIDCNN is trained exclusively on datasets of healthy states and single damages to model compound damage as patterns formed by these single damages. During testing, the MIDCNN can identify healthy and single damage states and also detect untrained compound damage based on features linked to the healthy state and single damages, using probabilities derived from the MIDCNN output.

II. Materials and Methods

The laboratory-scale offshore monopile model's experimental setup includes several key components for the investigation. These components are a steel pile, a soil box, a National Instrument cDAQ-9172 data acquisition system, a B&K 4809 shaker, seven ENDEVCO 61C12 accelerometers, a PCB 208C03 force transducer, a B&K 2706 power amplifier, signal transfer cables, a tamper, a compactor, and a computer. For offshore wind turbines with capacities below 5 MW, the pile specifications are a diameter of 4.5 m, a buried depth of 30 m, a length of 82.5 m, and a thickness of 0.15 m, aligning with engineering requirements [17]. This study employed a geometric scale of 1:75 based on the engineering prototype and Froude's law [18], A schematic of the laboratory-scale offshore monopile model is provided in Figure 3.

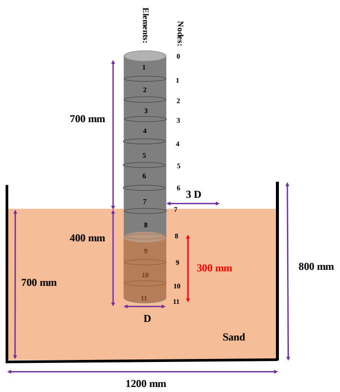

Figure 3. Schematic of the laboratory-scale offshore monopile model.

Raw vibration signals were recorded using seven accelerometers at a sampling frequency of 2000 Hz. Data acquisition was managed with LabVIEW Signal Express software, while post-processing was done using MATLAB. Initial tests were performed on the healthy structure, followed by similar tests for single and compound damage states. Figure 4 illustrates the raw vibration signals from the healthy structure under random excitation for the seven accelerometers. Hypothetical damage states were simulated by adding mounted masses of varying severities to different structural elements. Compound damage was simulated by applying masses with different severities simultaneously to two elements, causing changes in the structure's natural frequencies.

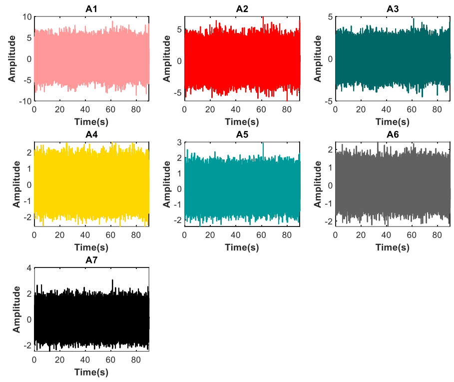

Fig. 10. Raw vibration signals of the healthy structure under white Gaussian noise excitation force for seven accelerometers.

Recorded vibration signals from structures often contain redundant and unrelated information due to measurement errors, varying loads, and environmental noise. This can lead to inaccuracies in feature learning and damage detection. To address this, it's essential to filter out redundant information while preserving critical damage-related features. When using WT for SHM or damage detection, the aim is to extract relevant features from the signal to assess structural condition. After extracting time samples, their time-frequency representations (TFRs) were obtained via WT, producing time-frequency images suitable for MIDCNN input.

III. Results and Discussion

Figure 4 displays examples of raw vibration signals acquired using accelerometer A3 for different states: healthy, damage D1, damage D2, and compound damage. Although the raw time signals for these states may look similar, their underlying characteristics differ due to structural damage. To effectively distinguish these differences and achieve accurate classification, it is essential to manually extract engineering features or use deep learning methods to derive high-level features from the raw time data [19]. Feature extraction techniques are designed to convert raw data into a form that preserves key information about the signal's characteristics for each state.

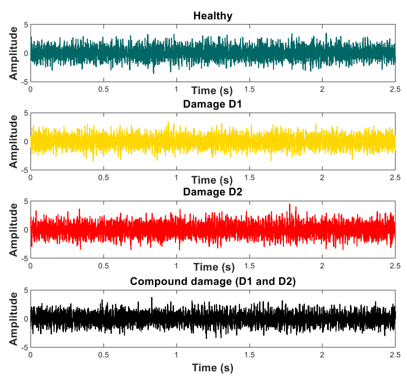

Figure 4. Raw vibration signals for each of the healthy, damage D1, damage D2, and compound damage.

Table 1 presents the classification performance of the proposed method alongside other methods, detailing accuracy rates for each class and the overall accuracy. The proposed method shows strong performance, with high accuracy in classifying test data for healthy and single damage states. Notably, it achieved an impressive 97% accuracy in classifying compound damage test data. This indicates that the model not only effectively learns features from raw time-frequency data generated by the WT but also excels in identifying features associated with untrained classes. In comparison, other methods demonstrated lower performance, particularly in classifying compound damage and single damage D1.

Table 1. Accuracy comparison of different methods for classifying each state and overall accuracy (models were only trained using healthy and single damage states).

Methods	Healthy (%)	D1 (%)	D2 (%)	D1 and D2 (compound state) (%)	Overall (%)
Raw frequency data-SNN [20]	100	85.0	97.5	88.5	92.7
VMD-TFR-CNN [13]	100	92.5	100	90.5	95.8
WT-TFR-MIDCNN (Proposed method)	**100**	**95.0**	**100**	**97.0**	**98.0**

IV. Conclusions

This paper tackles existing challenges by presenting an end-to-end approach that combines Wavelet Transform (WT) with a Multiple Interference Deep Convolutional Neural Network (MIDCNN). The key conclusions of the study are as follows:

1. Integrating WT for raw time-frequency data extraction with MIDCNN for direct feature learning eliminates the need for separate feature extraction and reduces computational load.
2. The proposed approach was validated using a laboratory-scale offshore monopile model with soil interaction, covering various damage scenarios. The MIDCNN, trained on healthy and single damage states, effectively classified untrained compound damage based on probabilistic conditions from Softmax output probabilities.
3. Results showed that the model excels in learning features from raw time-frequency data and can also handle untrained compound damage features.
4. Validation demonstrated high accuracy and effective pattern recognition for damage D1 and compound damage, outperforming existing methods.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contributions

Zohreh Mousavi: Conceptualization, Methodology, Investigation, Writing - Original Draft Preparation.

Meysam Bayat: Formal Analysis, Writing - Review & Editing, Visualization.

Wei-Qiang Feng: Formal Analysis, Writing - Review & Editing, Visualization.

Mir Mohammad Ettefagh: Formal Analysis, Writing - Review & Editing, Visualization.

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