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REPLY TO REVIEWERS

Manuscript No.:	wes-2026-70
Title:	Machine Learning Framework for Scour Detection Across Multiple Offshore Wind Farms
Authors:	Mahmoud Abdelhak; Luke J Prendergast; Jacques Tott-Buswell; Ramin Ghiasi; Abdollah Malekjafarian
Review for:	Wind Energy Science

NOTE TO REVIEWERS: We would like to express our gratitude to the Reviewers for the valuable remarks addressed in their reports regarding our manuscript, which helped us improve our work.

This letter serves as a guide to identifying all changes introduced into the reviewed version of the manuscript. It provides a point-by-point response to all pertinent remarks from the Reviewers. The changes in the manuscript are identified by blue text in the manuscript using the Track Changes tool in MS Word, in the file "Revised_Manuscript_with_Track_Changes".

Reviewer 2

Comment (1): This paper aims to apply machine learning to detect scour across multiple wind turbines using reinforcement learning (??) and a single accelerometer measurement. I am not able to comment in great detail on the different algorithms, but to me it seems that the work at present lacks sufficient explanation related to physical parameters, and there is insufficient detail regarding the generation of data.

Reply to Comment (1): The proposed framework does not employ reinforcement learning; rather, it is based on supervised deep learning combined with domain generalisation techniques to enable scour detection across multiple offshore wind turbines using data from a single tower-mounted accelerometer on a given source turbine. We have revised the manuscript to clarify this point and avoid any potential ambiguity regarding the machine learning methodology. In addition, a detailed description of the physical parameters and numerical data generation process is included. Therefore, the revised manuscript provides additional information regarding the physical modelling aspects, including the influence of soil properties, water depth, turbine characteristics, foundation stiffness, and scour-induced changes in the soil–structure interaction system. Furthermore, additional details have been included regarding the OpenFAST simulations, environmental loading conditions, SSI modelling approach, and the procedure used to generate the scour scenarios and corresponding acceleration responses.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 2.1, lines 123-132)

The proposed framework combines supervised deep learning with domain generalisation to learn scour-related representations from labelled source turbines and transfer this knowledge to previously unseen target turbines without requiring target-domain data during training. More details on DG methods being used are provided in Sections 2.3 and 2.4, with the DANN and CDDG methods selected for model development. Their methodologies and network architectures are described in Sections 2.2 and 2.3, respectively. The trained models are first evaluated on unseen target turbines to assess their ability to accurately predict scour conditions under unseen operating scenarios. To further enhance the models' generalisation capability across multiple wind farms, various training and testing protocols, outlined in Section 2.5, are incorporated. The proposed framework is validated using a training dataset generated from an integrated OpenFAST and SSI model, which accounts for variations in turbine structural properties, environmental conditions, soil characteristics, and scour-induced foundation degradation.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.3, lines292 - 370)

The dynamic response of each OWT is simulated using the aero-hydro-servo-elastic solver OpenFAST for the NREL 5 MW reference turbine model under combined aerodynamic and hydrodynamic loading. Turbulent wind fields are generated using TurbSim based on the IEC Kaimal turbulence model (IECKAI) (Cheynet et al., 2017), as recommended by the IEC 61400-1 standard for simulating atmospheric turbulence acting on wind turbines. A Normal Turbulence Model (NTM) with IEC turbulence class B and a turbulence intensity of 12% was adopted to represent typical offshore operating conditions. The mean wind speed at the reference height of 90 m was specified based on the defined environmental conditions in Section 3.2, while the vertical wind profile was modelled using the IEC power-law formulation. The resulting stochastic wind field captures the spatial and temporal fluctuations of atmospheric turbulence across the rotor plane, providing realistic aerodynamic loading for the OpenFAST simulations. Multiple stochastic wind conditions were generated for each turbine and environmental condition to capture the variability associated with turbulent loading. The wake effect was included in the OpenFAST Aerodyne module using the Blade Element Momentum (BEM) Theory. In addition, the irregular wave conditions are represented using the JONSWAP spectrum incorporated in OpenFAST, with the corresponding significant wave height and peak wave period defined according to the environmental conditions considered for each OWF, as indicated in Section 3.2. Aerodynamic loads are computed using Blade Element Momentum theory (Zhao et al., 2019), whereas hydrodynamic loads acting on the support structure are evaluated using Morison's equation (Wolfram & Naghipour, 1999). The sea current is incorporated using the normal current model. It is important to note that this study does not take yaw misalignment into account, which enables the analysis to concentrate only on changes in the dynamic response occurring due to the scour effect. Specifically, each simulation is performed for a total duration of 3700 s, with the initial 100 s discarded to eliminate transient effects associated with model initialisation. The simulation implemented a time step of 0.001 s, while the response outputs at every 0.01 seconds.

This study particularly focuses on evaluating the influence of domain shifts arising from environmental, geotechnical, and structural variations on scour detection performance. A fixed random seed is used for all OpenFAST simulations to ensure reproducibility and maintain consistency in the generation of stochastic environmental conditions, including wind and wave realisations. This ensures identical turbulent wind realisations were generated, allowing changes in the structural response to be attributed solely to the investigated scour conditions rather than variations in the environmental loading. This assumption is considered appropriate for evaluating the domain generalisation capability of the proposed framework, where the objective is to capture variations arising from different turbine and foundation characteristics rather than farm-level aerodynamic interactions. Variations in operational and site conditions are incorporated into both training and testing datasets to represent realistic OWT operating scenarios. The integration of these factors with SSI and turbine dynamic characteristics provides a comprehensive framework for representing realistic OWT behaviour. By incorporating site-specific operational conditions, the scenarios/ tasks defined in Section 2.5 are used to train, evaluate and validate the capability of the proposed framework to detect scour across multiple OWF environments under realistic operating conditions. In addition, variations in water depth, soil properties, turbine characteristics, and scour depth are considered to represent the heterogeneous conditions encountered across OWFs. The integration of these factors with SSI and turbine dynamic characteristics provides a comprehensive framework for representing realistic OWT behaviour. These variations ensure that the ML model is exposed to a wide range of dynamic responses associated with different turbine and foundation configurations.

Although the dynamic characteristics of OWTs are influenced by various factors, including environmental variability, soil–structure interaction conditions, and structural degradation mechanisms such as corrosion, marine growth, settlement, and grout deterioration, this study focuses exclusively on scour-induced changes resulting from reductions in foundation stiffness and modifications to boundary conditions. Accordingly, the proposed framework is intended to detect scour-related variations in the turbine's bending modal characteristics rather than serve as a universal diagnostic tool for all degradation mechanisms. Other operational uncertainties, including controller effects, rotor imbalance, sensor installation errors, measurement noise, and wake interactions between turbines in a wind farm, are not explicitly considered in the present numerical framework. The numerical simulations considered in this study primarily represent above-rated operating conditions, where the rotor speed is maintained close to the rated value through the turbine control system. Therefore, the 3P excitation frequency remains relatively consistent among the investigated turbines. However, the proposed scour detection framework does not rely on rotor harmonic components as the primary indicator of scour. Instead, it exploits changes in the global dynamic response of the OWT system resulting from variations in SSI performance and foundation stiffness. Above-rated operation represents an important condition for OWT monitoring because turbines frequently operate under these conditions during their service life. Nevertheless, extending the dataset to incorporate below-rated and transient operating conditions, where rotor speed and aerodynamic excitation vary significantly, represents an important direction for future research to evaluate the robustness and applicability of the proposed framework.

As OpenFAST assumes a rigid foundation and does not explicitly model SSI, a bespoke SSI model is developed in MATLAB and incorporated in OpenFAST by generating equivalent stiffness for zero-dimensional (0D) ground springs. The monopile foundation is represented using a modified Winkler formulation approach (Prendergast & Gavin, 2016), comprising distributed nonlinear lateral $p - y$ springs together with rotational $(m - \theta)$ and pile-tip springs to capture the flexibility of the pile–soil system (Tott-Buswell et al., 2024). The nonlinear soil resistance is derived from Cone Penetration Test (CPT)-based geotechnical properties using a modified $p - y$ approach, while the rotational resistance accounts for shaft-friction mobilisation generated during pile rotation (Byrne et al., 2015). The nonlinear load–displacement and moment–rotation responses are first evaluated in MATLAB under the mudline loading obtained from an equivalent rigid-foundation OpenFAST simulation. Equivalent lateral and rotational secant stiffnesses are then calculated and implemented in OpenFAST as zero-dimensional (0D) ground springs at the mudline. Consequently, although the underlying soil model is nonlinear, it is incorporated into OpenFAST through equivalent secant stiffness coefficients implemented as zero-dimensional (0D) ground springs at the mudline, resulting in a computationally efficient decoupled representation of foundation flexibility. To simulate the scoured conditions, the soil layer equivalent to the scour depth is removed, and the stiffness of the soil springs located within the scoured region is assigned to zero, effectively reducing the pile embedment and updating the foundation stiffness matrix. The updated equivalent stiffness matrix is then implemented in OpenFAST to simulate the dynamic response of the turbine under each scour condition. In this study, scour is characterised by scour depth, which represents the primary parameter influencing the loss of foundation stiffness and the resulting changes in turbine dynamic response. Other scour-hole geometrical parameters, such as scour width and slope angle, are not considered, as their influence on the global dynamic characteristics of the turbine is comparatively limited. This study covers nine scour states, each represented by a specific scour depth, with scour depths ranging from 1 m to 9 m (corresponding to S/D = 0.167–1.5) considered. The decoupled sub-structuring approach implemented herein has previously been validated against monotonic pile pushover experiments (Tott-Buswell et al., 2024) and has been successfully applied in previous OpenFAST-based scour modelling studies (Abdelhak et al., 2025); and (Abdelhak et al., 2026). In addition, simplified homogeneous soil profiles are adopted to isolate the influence of global soil stiffness on the dynamic response of OWTs and to evaluate the proposed framework under controlled geotechnical conditions. Although layered soil stratification can influence scour development and foundation dynamics, its effect on modal characteristics is generally smaller than that resulting from substantial changes in overall soil stiffness (e.g., dense versus loose sand) (Zefzouf et al., 2025). Therefore, the proposed framework is expected to remain effective under layered soil conditions, although its performance may be influenced by the degree of soil heterogeneity and layer configuration.

Comment (2): In order for such an approach to be believable, the numerical simulations providing the data should be sufficiently realistic: there needs to be enough stochastic variation in the wind fields/small errors in yaw and pitch control/rotor imbalance/noise in the measurements/misalignment of the accelerometer/wakes etc. Otherwise, given the approach, it is not easy to know if other signatures from the generated wind fields or other inputs are being detected rather than the desired output.

Reply to Comment (2): The reliability of an ML-based scour detection framework strongly depends on the realism and variability of the numerical dataset used for training and evaluation.

In particular, incorporating realistic operational uncertainties is essential to ensure that the model learns scour-related dynamic characteristics rather than artificial patterns associated with specific simulation conditions. To address this concern, the revised manuscript provides additional clarification regarding the stochastic variations included in the numerical simulations. The generated dataset accounts for variability in environmental loading conditions through multiple stochastic wind and wave realisations, including turbulent wind fields generated using the Kaimal turbulence model and stochastic wave loading represented by the JONSWAP spectrum. In addition, variations in turbine operating conditions, soil properties, water depths, turbine characteristics, and scour scenarios are incorporated to represent the domain shifts expected across different offshore wind farms.

Furthermore, the revised manuscript now clarifies that the objective of this study is to investigate the capability of DG methods to identify scour-related changes under varying environmental and structural conditions. While the current numerical framework captures the dominant sources of variability affecting the turbine–foundation dynamic response, additional operational uncertainties such as blade pitch and yaw controller errors, rotor imbalance, sensor misalignment, and measurement noise represent important aspects for future validation using field measurements or higher-fidelity simulations. The revised discussion also highlights that future work will focus on incorporating these additional uncertainties and validating the proposed framework using experimental and operational monitoring data to further assess its robustness under realistic field conditions.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.2, lines 270-280)

The environmental conditions for Farms 1–3 are presented in Appendix A (Tables A4–A6), respectively. To validate the proposed approach, numerical acceleration data were generated using an integrated OpenFAST-SSI model developed in MATLAB. For more details on the data generation process, refer to (Abdelhak et al., 2025). The acceleration data are generated at two sensor locations: sensor 1, located at the tower base, 10 m above sea level, and sensor 2, situated at the tower top, as shown in **Error! Reference source not found.**. Both sensor locations are used to extract acceleration signals from OpenFAST under various scenarios across the turbines within the considered farms. For each turbine, an OpenFAST-SSI model is developed to generate acceleration data based on the turbine's structural and site characteristics. Each turbine dataset contains healthy and nine scour states, corresponding to scour depths ($S = 1,\ 2\ , \dots\ ,\ 9\text{m}, \text{with}\ S/D = 0.167{:}\,1.5$) , resulting in an extensive farm-scale dataset under varying operational conditions and turbine characteristics. This provides realistic scenarios for model training and evaluation, reflecting the variation of the individual turbines and installation sites.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.3, lines292 - 342)

The dynamic response of each OWT is simulated using the aero-hydro-servo-elastic solver OpenFAST for the NREL 5 MW reference turbine model under combined aerodynamic and hydrodynamic loading. Turbulent wind fields are generated using TurbSim based on the IEC Kaimal turbulence model (IECKAI) (Cheynet et al., 2017), as recommended by the IEC 61400-1 standard for simulating atmospheric turbulence acting on wind turbines. A Normal Turbulence Model (NTM) with IEC turbulence class B and a turbulence intensity of 12% was adopted to represent typical offshore operating conditions. The mean wind speed at the reference height of 90 m was specified based on the defined environmental conditions in Section 3.2, while the vertical wind profile was modelled using the IEC power-law formulation. The resulting stochastic wind field captures the spatial and temporal fluctuations of atmospheric turbulence across the rotor plane, providing realistic aerodynamic loading for the OpenFAST simulations. Multiple stochastic wind conditions were generated for each turbine and environmental condition to capture the variability associated with turbulent loading. The wake effect was included in the OpenFAST Aerodyne module using the Blade Element Momentum (BEM) Theory. In addition, the irregular wave conditions are represented using the JONSWAP spectrum incorporated in OpenFAST, with the corresponding significant wave height and peak wave period defined according to the environmental conditions considered for each OWF, as indicated in Section 3.2. Aerodynamic loads are computed using Blade Element Momentum theory (Zhao et al., 2019), whereas hydrodynamic loads acting on the support structure are evaluated using Morison's equation (Wolfram & Naghipour, 1999). The sea current is incorporated using the normal current model. It is important to note that this study does not take yaw misalignment into account, which enables the analysis to concentrate only on changes in the dynamic response occurring due to the scour effect. Specifically, each simulation is performed for a total duration of 3700 s, with the initial 100 s discarded to eliminate transient effects associated with model initialisation. The simulation implemented a time step of 0.001 s, while the response outputs at every 0.01 seconds.

This study particularly focuses on evaluating the influence of domain shifts arising from environmental, geotechnical, and structural variations on scour detection performance. A fixed random seed is used for all OpenFAST simulations to ensure reproducibility and maintain consistency in the generation of stochastic environmental conditions, including wind and wave realisations. This ensures identical turbulent wind realisations were generated, allowing changes in the structural response to be attributed solely to the investigated scour conditions rather than variations in the environmental loading. This assumption is considered appropriate for evaluating the domain generalisation capability of the proposed framework, where the objective is to capture variations arising from different turbine and foundation characteristics rather than farm-level aerodynamic interactions. Variations in operational and site conditions are incorporated into both training and testing datasets to represent realistic OWT operating scenarios. The integration of these factors with SSI and turbine dynamic characteristics provides a comprehensive framework for representing realistic OWT behaviour. By incorporating site-specific operational conditions, the scenarios/ tasks defined in Section 2.5 are used to train, evaluate and validate the capability of the proposed framework to detect scour across multiple OWF environments under realistic operating conditions. In addition, variations in water depth, soil properties, turbine characteristics, and scour depth are considered to represent the heterogeneous conditions encountered across OWFs. The integration of these factors with SSI and turbine dynamic characteristics provides a comprehensive framework for representing realistic OWT behaviour. These variations ensure that the ML model is exposed to a wide range of dynamic responses associated with different turbine and foundation configurations.

Although the dynamic characteristics of OWTs are influenced by various factors, including environmental variability, soil–structure interaction conditions, and structural degradation mechanisms such as corrosion, marine growth, settlement, and grout deterioration, this study focuses exclusively on scour-induced changes resulting from reductions in foundation stiffness and modifications to boundary conditions. Accordingly, the proposed framework is intended to detect scour-related variations in the turbine's bending modal characteristics rather than serve as a universal diagnostic tool for all degradation mechanisms. Other operational uncertainties, including controller effects, rotor imbalance, sensor installation errors, measurement noise, and wake interactions between turbines in a wind farm, are not explicitly considered in the present numerical framework. The numerical simulations considered in this study primarily represent above-rated operating conditions, where the rotor speed is maintained close to the rated value through the turbine control system. Therefore, the 3P excitation frequency remains relatively consistent among the investigated turbines. However, the proposed scour detection framework does not rely on rotor harmonic components as the primary indicator of scour. Instead, it exploits changes in the global dynamic response of the OWT system resulting from variations in SSI performance and foundation stiffness. Above-rated operation represents an important condition for OWT monitoring because turbines frequently operate under these conditions during their service life. Nevertheless, extending the dataset to incorporate below-rated and transient operating conditions, where rotor speed and aerodynamic excitation vary significantly, represents an important direction for future research to evaluate the robustness and applicability of the proposed framework.

Comment (3): It is not entirely clear to me how the effect of scour has been included in the OpenFAST/SSI model: is the soil interaction simply removed over a certain depth, or are other changes also made?

Reply to Comment (3): A clear description of how scour is incorporated into the OpenFAST–SSI modelling framework is essential to ensure the physical interpretation of the generated vibration responses. A detailed description on the *p-y* approach and rotational springs are included. In the revised manuscript, additional details have been provided to clarify the scour modelling procedure. In the proposed approach, scour is not represented simply by removing a portion of the soil interaction without further modification. Instead, the scour depth is introduced by reducing the effective embedded pile length and updating the corresponding soil–pile interaction characteristics within the SSI model. Specifically, the soil springs located within the eroded soil layer are removed, and the remaining soil resistance along the embedded pile is recalculated according to the modified soil profile. Consequently, the distributed lateral stiffness, rotational stiffness, and pile-tip contribution of the foundation are altered, resulting in a scour-dependent foundation stiffness matrix. The updated foundation stiffness properties are subsequently incorporated into OpenFAST to simulate the dynamic response of the turbine under different scour conditions. This approach enables the influence of scour-induced changes in soil support and foundation stiffness on the turbine dynamic behaviour to be captured.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.3, lines 343-370)

As OpenFAST assumes a rigid foundation and does not explicitly model SSI, a bespoke SSI model is developed in MATLAB and incorporated in OpenFAST by generating equivalent stiffness for zero-dimensional (0D) ground springs. The monopile foundation is represented using a modified Winkler formulation approach (Prendergast & Gavin, 2016), comprising distributed nonlinear lateral $p-y$ springs together with rotational $(m-\theta)$ and pile-tip springs to capture the flexibility of the pile–soil system (Tott-Buswell et al., 2024). The nonlinear soil resistance is derived from Cone Penetration Test (CPT)-based geotechnical properties using a modified $p-y$ approach, while the rotational resistance accounts for shaft-friction mobilisation generated during pile rotation (Byrne et al., 2015). The nonlinear load–displacement and moment–rotation responses are first evaluated in MATLAB under the mudline loading obtained from an equivalent rigid-foundation OpenFAST simulation. Equivalent lateral and rotational secant stiffnesses are then calculated and implemented in OpenFAST as zero-dimensional (0D) ground springs at the mudline. Consequently, although the underlying soil model is nonlinear, it is incorporated into OpenFAST through equivalent secant stiffness coefficients implemented as zero-dimensional (0D) ground springs at the mudline, resulting in a computationally efficient decoupled representation of foundation flexibility. To simulate the scoured conditions, the soil layer equivalent to the scour depth is removed, and the stiffness of the soil springs located within the scoured region is assigned to zero, effectively reducing the pile embedment and updating the foundation stiffness matrix. The updated equivalent stiffness matrix is then implemented in OpenFAST to simulate the dynamic response of the turbine under each scour condition. In this study, scour is characterised by scour depth, which represents the primary parameter influencing the loss of foundation stiffness and the resulting changes in turbine dynamic response. Other scour-hole geometrical parameters, such as scour width and slope angle, are not considered, as their influence on the global dynamic characteristics of the turbine is comparatively limited. This study covers nine scour states, each represented by a specific scour depth, with scour depths ranging from 1 m to 9 m (corresponding to S/D = 0.167–1.5) considered. The decoupled sub-structuring approach implemented herein has previously been validated against monotonic pile pushover experiments (Tott-Buswell et al., 2024) and has been successfully applied in previous OpenFAST-based scour modelling studies (Abdelhak et al., 2025); and (Abdelhak et al., 2026). In addition, simplified homogeneous soil profiles are adopted to isolate the influence of global soil stiffness on the dynamic response of OWTs and to evaluate the proposed framework under controlled geotechnical conditions. Although layered soil stratification can influence scour development and foundation dynamics, its effect on modal characteristics is generally smaller than that resulting from substantial changes in overall soil stiffness (e.g., dense versus loose sand) (Zefzouf et al., 2025). Therefore, the proposed framework is expected to remain effective under layered soil conditions, although its performance may be influenced by the degree of soil heterogeneity and layer configuration.

Comment (4): The manuscript does not document the natural periods of the scoured and healthy structures - this would be useful to understand what magnitude of changes are being detected. The "high energy" content region ranges from 0 - 8 Hz. It would be useful to see examples of the acceleration spectra for healthy and scoured structures. The upper end of this range seems fairly high, and I am missing discussion of what the important physical processes at these frequencies are.

Reply to Comment (4):

Presenting the natural frequencies of healthy and scoured structures is important to demonstrate the physical basis of the vibration changes detected by the machine learning framework. To address this comment, additional modal analyses have been conducted for the healthy and different scour conditions, and the corresponding natural frequencies have been included in the revised manuscript (see Table 3). Natural frequencies for healthy and scoured cases have been added to illustrate the changes in the frequency-domain response caused by scour-induced foundation degradation. In addition, Figure represents the PSD for turbines (T1.1, T2.1, and T3.1) in both healthy and 9m scour states. The additional analysis confirms that scour reduces the soil–structure interaction stiffness, leading to a reduction in the natural frequencies of the turbine–foundation system. Scour induced noticeable impact on higher order frequencies while the first order frequency experiences negligible change. Second mode natural frequency show the highest effect due to scour. The magnitude of this frequency shift depends on the scour severity and the initial stiffness characteristics of the foundation. These changes provide the physical basis for the extracted frequency-domain features used by the proposed framework.

Regarding the selected frequency range (0–8 Hz), the revised manuscript now provides further clarification. This range was selected to capture the dominant dynamic response of the offshore wind turbine structure, including the first global tower–foundation modes and higher structural modes (2^{nd}, 3^{rd} and 4^{th}) influenced by foundation stiffness variations. Although the turbine operating frequency 1P (approximately 0.14 Hz for an 8.4 rpm rotor speed) and aerodynamic loading components occur at lower frequencies, the higher-frequency region contains structural vibration information associated with the tower, monopile, and soil–structure interaction system. The acceleration spectra demonstrate that the selected frequency range captures the relevant scour-induced variations while avoiding unnecessary inclusion of higher-frequency components dominated by mechanical system, or numerical noise.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.4, lines 379-385)

The selected frequency range of 0-8 Hz captures the dominant structural responses of the turbine, including the first four global bending frequency modes affected by variations in foundation stiffness, as well as the dynamic response associated with scour development within the given wind farms. Although the rotor excitation frequency 1P is located at a much lower frequency range, the structural modes within 0-8Hz range contain important information regarding changes in the system dynamic behaviour. Therefore, the extracted spectral features within this frequency range provide physically meaningful indicators for identifying scour-induced degradation.

<u>A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.5, lines 425-456)</u>

To further investigate the physical influence of scour on the turbine dynamic response, the natural frequencies of the healthy and scoured foundation conditions are estimated from the simulated acceleration responses using the Frequency Domain Decomposition (FDD) method. **Error! Reference source not found.** shows the natural frequencies for the first four bending modes as well as the rate of variation/ reduction under different scour states (3m, 6m, and 9m scour depth) based on healthy state measurements. It represents the natural frequencies for different turbines, characterised with various water depths and soil densities (T1, T6, and T11) across different wind farms. The results demonstrate that increasing scour depth leads to a reduction in the effective foundation stiffness due to the progressive loss of soil support, resulting in a decrease in the tower natural frequencies. Specifically, the first bending natural frequency shows a negligible impact due to scour severity progression. However, the 2nd mode shows increased impact, where it decreases from 1.422Hz for the healthy condition to 1.081Hz for the maximum considered scour depth of 9m, corresponding to a frequency reduction of 24%. The magnitude of this frequency shift increases consistently with scour severity, confirming that scour-induced degradation of the soil–foundation system directly modifies the global dynamic characteristics of the offshore wind turbine. The effect of increasing the scour severity on the dynamic response of multiple turbines within different wind farms is assessed. In addition, decreasing the soil density while keeping the water depth constant leads to further reduction in the natural frequencies (1.422Hz for T1.1, 1.24Hz for T2.1, and 1.148Hz for T3.1). A similar trend is noticed for higher-order frequencies. Increasing the water depth leads to slight variation in natural frequencies compared with those caused by changes in soil properties. At a constant water depth of 20m, reducing soil density at turbines T1.1, T2.1, and T3.1 decreases the lateral foundation stiffness, increasing the flexibility of the soil–foundation system and consequently reducing the natural frequencies. In contrast, greater water depths increase the unsupported tower height and global structural flexibility, with more pronounced effects observed at higher-order modes. The first-order natural frequency, however, shows negligible variation with turbine location or scour state. Specifically, 2nd order mode natural frequency shows the highest reduction due to scour depth increase. This trend is consistent across different turbines within the wind farm. These observations indicate that both soil stiffness and water depth significantly influence the dynamic characteristics of OWTs, which enables the selection of representative source turbines to enhance the model generalisation capacity.

Table 1: First four bending mode natural frequencies of healthy and scoured turbines across different farms

		Damage Condition				Percentage of change		
Turbine	**Mode**	**Healthy (Hz)**	**3m (Hz)**	**6m (Hz)**	**9m (Hz)**	**3m (%)**	**6m (%)**	**9m (%)**
T1.1	1st mode	0.244	0.244	0.244	0.244	0.0	0.0	0.0
	2nd Mode	1.422	1.337	1.210	1.081	6.0	14.9	24.0
	3rd Mode	2.909	2.844	2.705	2.611	2.2	7.0	10.2
	4th Mode	6.595	6.479	6.273	6.116	1.8	4.9	7.3
T1.6	1st mode	0.246	0.246	0.244	0.244	0.0	0.8	0.8
	2nd Mode	1.399	1.337	1.210	1.131	4.4	13.5	19.2
	3rd Mode	2.992	2.916	2.781	2.659	2.5	7.1	11.1
	4th Mode	6.755	6.568	6.411	6.097	2.8	5.1	9.7

T1.11	1st mode	0.244	0.244	0.244	0.244	0.0	0.0	0.0
	2nd Mode	1.422	1.348	1.210	1.148	5.2	14.9	19.3
	3rd Mode	3.095	3.019	2.844	2.746	2.5	8.1	11.3
	4th Mode	6.866	6.758	6.500	6.273	1.6	5.3	8.6
T2.1	1st mode	0.248	0.248	0.244	0.244	0.0	1.6	1.6
	2nd Mode	1.244	1.210	1.140	1.100	2.7	8.4	11.6
	3rd Mode	2.792	2.732	2.652	2.568	2.1	5.0	8.0
	4th Mode	6.416	6.292	6.150	6.039	1.9	4.1	5.9
T2.6	1st mode	0.248	0.248	0.248	0.244	0.0	0.0	1.6
	2nd Mode	1.228	1.159	1.064	1.100	5.6	13.4	10.4
	3rd Mode	2.791	2.752	2.650	2.568	1.4	5.1	8.0
	4th Mode	6.405	6.260	6.098	6.039	2.3	4.8	5.7
T2.11	1st mode	0.244	0.244	0.244	0.244	0.0	0.0	0.0
	2nd Mode	1.324	1.210	1.164	1.092	8.6	12.1	17.5
	3rd Mode	2.945	2.881	2.801	2.698	2.2	4.9	8.4
	4th Mode	6.561	6.518	6.308	6.163	0.7	3.9	6.1
T3.1	1st mode	0.244	0.244	0.244	0.244	0.0	0.0	0.0
	2nd Mode	1.148	1.099	1.047	0.968	4.3	8.8	15.7
	3rd Mode	2.661	2.617	2.542	2.450	1.7	4.5	7.9
	4th Mode	6.212	6.108	6.029	5.972	1.7	2.9	3.9
T3.6	1st mode	0.244	0.244	0.244	0.244	0.0	0.0	0.0
	2nd Mode	1.210	1.132	1.074	1.011	6.4	11.2	16.4
	3rd Mode	2.737	2.687	2.642	2.542	1.8	3.5	7.1
	4th Mode	6.293	6.212	6.044	6.029	1.3	4.0	4.2
T3.11	1st mode	0.248	0.248	0.248	0.235	0.0	0.0	5.2
	2nd Mode	1.210	1.159	1.098	1.024	4.2	9.3	15.4
	3rd Mode	2.820	2.790	2.714	2.628	1.1	3.8	6.8
	4th Mode	6.365	6.283	6.162	6.070	1.3	3.2	4.6

Figure 1 represents the PSD for turbines (T1.1, T2.1, T3.1) in both healthy and scoured states at the 0-8Hz range, with the frequency ranges corresponding to the first, second, third, and fourth modes highlighted. As shown, the first-mode natural frequency exhibits the smallest variation with changes in scour condition and turbine location. In contrast, higher modes, particularly the second mode, exhibit greater sensitivity to changes in scour condition, along with additional variations associated with turbine location. A similar trend is expected for the higher modes, including the third and fourth modes.

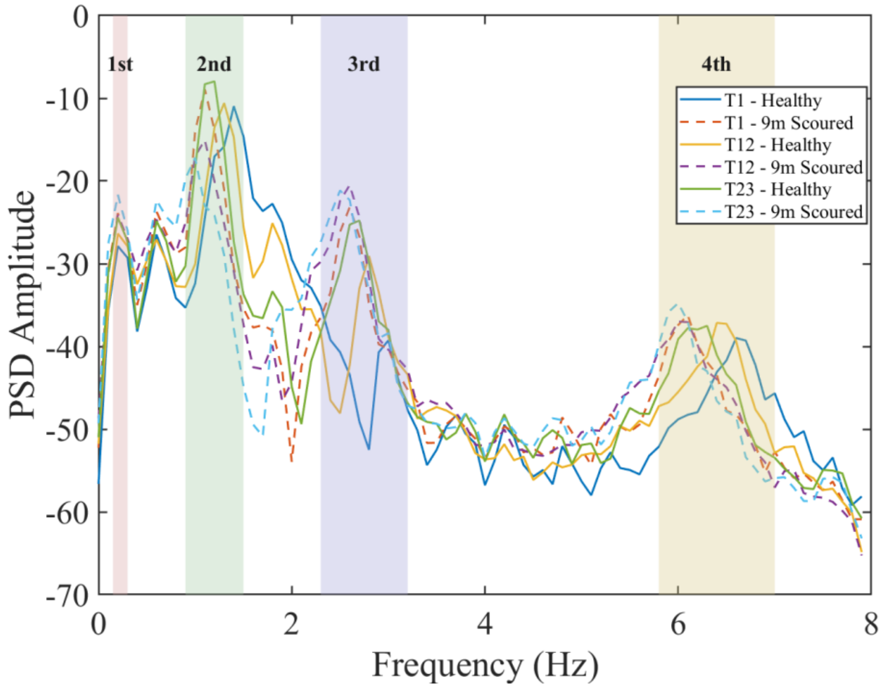


Figure 1: **PSD for turbines (T1.1, T2.1, T3.1) in both healthy and scoured states at the 0-8Hz range.**

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.2, lines 281-290)

The acceleration time histories presented in **Error! Reference source not found.** correspond to representative responses for both healthy and 9m scoured conditions, extracted from sensors 1 and 2 (corresponding to the numerical model nodes) using OpenFAST simulations under combined turbulent wind and irregular wave loading. The numerical model accounts for the structural damping; however, hydrodynamic damping associated with the submerged components is not considered in the present model. The damping assumptions adopted in the numerical simulations are based on a 1% damping ratio for the first and second tower fore–aft modes, as well as the tower side–side modes. Variations in SSI behaviour due to different soil properties and scour depths are represented through modifications of the foundation stiffness, which influence the system natural frequencies and, consequently, the resonant response characteristics.

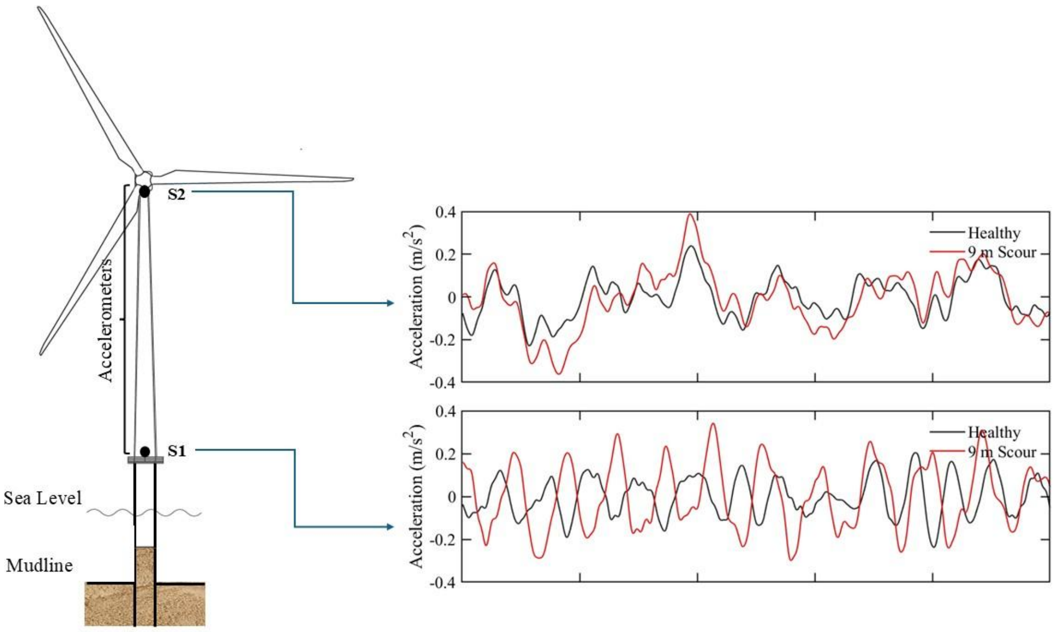


Figure 2: **Acceleration response obtained from sensors 1 and 2 at healthy and 9m scour states.**

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.4, lines 379-385)

The selected frequency range of 0-8 Hz captures the dominant structural responses of the turbine, including the first four global bending frequency modes affected by variations in foundation stiffness, as well as the dynamic response associated with scour development within the given wind farms. Although the rotor excitation frequency 1P is located at a much lower frequency range, the structural modes within 0-8Hz range contain important information regarding changes in the system dynamic behaviour. Therefore, the extracted spectral features within this frequency range provide physically meaningful indicators for identifying scour-induced degradation.

Comment (5): I don't know if the time series in Figure 3 are purely illustrative or if they are representative - there appears to be significant resonant response, based on the very narrow-banded characteristics, which also leads to the question of damping. What types of damping are included and what is exciting the resonance?

Reply to Comment (5): The acceleration time histories presented in Figure 3 are purely illustrative. A representative acceleration response for healthy and scoured conditions using data from sensor 1 and 2 are now presented in the revised manuscript instead. The excitation mechanisms, and the damping assumptions used in the numerical simulations are as follows: 1% are used for the Tower 1st and 2nd fore-aft mode as well as side-side structural damping ratio (Rayleigh) added to the manuscript. The acceleration responses shown in the revised

Figure 3 are obtained directly from the OpenFAST simulations under combined aerodynamic and hydrodynamic loading conditions, rather than illustrative signals. The narrowband characteristics observed in the acceleration response are associated with the dynamic behaviour of the OWT, where the response is dominated by excitation near the global structural modes where a small damping percentage included.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.2, lines 281-290)

The acceleration time histories presented in **Error! Reference source not found.** correspond to representative responses for both healthy and 9m scoured conditions, extracted from sensors 1 and 2 (corresponding to the numerical model nodes) using OpenFAST simulations under combined turbulent wind and irregular wave loading. The numerical model accounts for the structural damping; however, hydrodynamic damping associated with the submerged components is not considered in the present model. The damping assumptions adopted in the numerical simulations are based on a 1% damping ratio for the first and second tower fore–aft modes, as well as the tower side–side modes. Variations in SSI behaviour due to different soil properties and scour depths are represented through modifications of the foundation stiffness, which influence the system natural frequencies and, consequently, the resonant response characteristics.

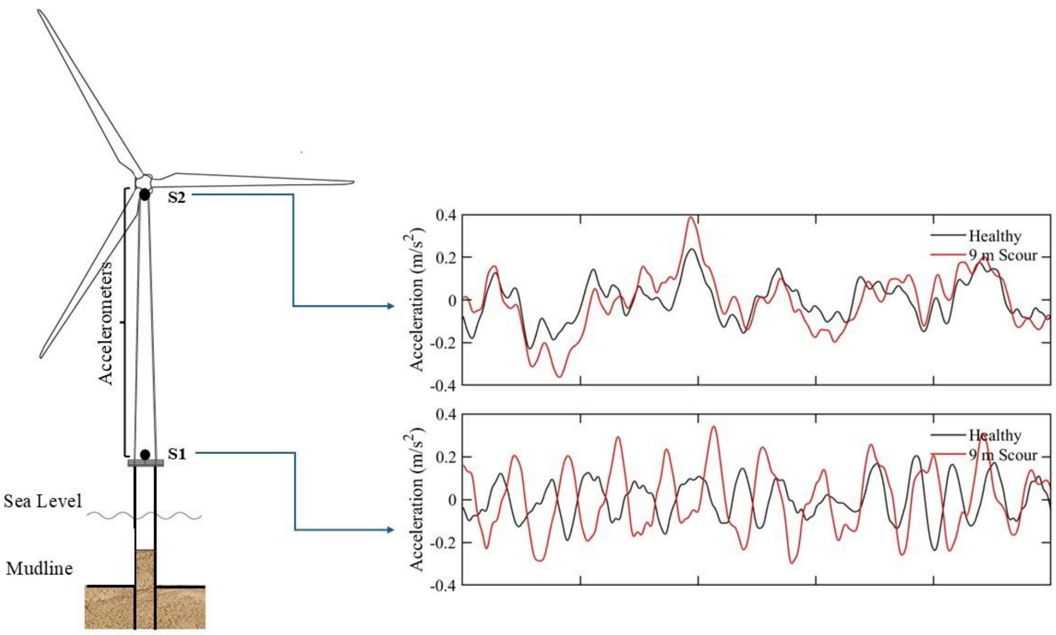


Figure 3: **Acceleration response obtained from sensors 1 and 2 at healthy and 9m scour states.**

Comment (6): Wind field generation and wave field generation are not discussed. I am assuming that the authors are using "significant wave height" and "peak period" rather than "wave height" and "wave period", but this should be corrected as well. How many different wind fields are generated? How is the turbulence intensity determined? How are wake effects included? Is there any relationship in the wind field generation for turbines in the same farm?

Reply to Comment (6): A detailed description of the wind and wave field generation process is necessary to improve the transparency and reproducibility of the numerical simulations. To address this comment, the revised manuscript now provides additional details regarding the environmental loading generation. The terminology has also been corrected, where significant wave height (H_s) and peak spectral period (T_p) are used instead of the general terms wave height and wave period. The turbulent wind fields were generated using TurbSim based on the Kaimal turbulence model with a turbulence intensity of 12%, representing offshore operational conditions.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.3, lines292 - 342)

The dynamic response of each OWT is simulated using the aero-hydro-servo-elastic solver OpenFAST for the NREL 5 MW reference turbine model under combined aerodynamic and hydrodynamic loading. Turbulent wind fields are generated using TurbSim based on the IEC Kaimal turbulence model (IECKAI) (Cheynet et al., 2017), as recommended by the IEC 61400-1 standard for simulating atmospheric turbulence acting on wind turbines. A Normal Turbulence Model (NTM) with IEC turbulence class B and a turbulence intensity of 12% was adopted to represent typical offshore operating conditions. The mean wind speed at the reference height of 90 m was specified based on the defined environmental conditions in Section 3.2, while the vertical wind profile was modelled using the IEC power-law formulation. The resulting stochastic wind field captures the spatial and temporal fluctuations of atmospheric turbulence across the rotor plane, providing realistic aerodynamic loading for the OpenFAST simulations. Multiple stochastic wind conditions were generated for each turbine and environmental condition to capture the variability associated with turbulent loading. The wake effect was included in the OpenFAST Aerodyne module using the Blade Element Momentum (BEM) Theory. In addition, the irregular wave conditions are represented using the JONSWAP spectrum incorporated in OpenFAST, with the corresponding significant wave height and peak wave period defined according to the environmental conditions considered for each OWF, as indicated in Section 3.2. Aerodynamic loads are computed using Blade Element Momentum theory (Zhao et al., 2019), whereas hydrodynamic loads acting on the support structure are evaluated using Morison's equation (Wolfram & Naghipour, 1999). The sea current is incorporated using the normal current model. It is important to note that this study does not take yaw misalignment into account, which enables the analysis to concentrate only on changes in the dynamic response occurring due to the scour effect. Specifically, each simulation is performed for a total duration of 3700 s, with the initial 100 s discarded to eliminate transient effects associated with model initialisation. The simulation implemented a time step of 0.001 s, while the response outputs at every 0.01 seconds.

This study particularly focuses on evaluating the influence of domain shifts arising from environmental, geotechnical, and structural variations on scour detection performance. A fixed random seed is used for all OpenFAST simulations to ensure reproducibility and maintain consistency in the generation of stochastic environmental conditions, including wind and wave realisations. This ensures identical turbulent wind realisations were generated, allowing changes in the structural response to be attributed solely to the investigated scour conditions rather than variations in the environmental loading. This assumption is considered appropriate for evaluating the domain generalisation capability of the proposed framework, where the objective is to capture variations arising from different turbine and foundation characteristics rather than farm-level aerodynamic interactions. Variations in operational and site conditions are incorporated into both training and testing datasets to represent realistic OWT operating scenarios. The integration of these factors with SSI and turbine dynamic characteristics provides a comprehensive framework for representing realistic OWT behaviour. By incorporating site-specific operational conditions, the scenarios/ tasks defined in Section 2.5 are used to train, evaluate and validate the capability of the proposed framework to detect scour across multiple OWF environments under realistic operating conditions. In addition, variations in water depth, soil properties, turbine characteristics, and scour depth are considered to represent the heterogeneous conditions encountered across OWFs. The integration of these factors with SSI and turbine dynamic characteristics provides a comprehensive framework for representing realistic OWT behaviour. These variations ensure that the ML model is exposed to a wide range of dynamic responses associated with different turbine and foundation configurations.

Although the dynamic characteristics of OWTs are influenced by various factors, including environmental variability, soil–structure interaction conditions, and structural degradation mechanisms such as corrosion, marine growth, settlement, and grout deterioration, this study focuses exclusively on scour-induced changes resulting from reductions in foundation stiffness and modifications to boundary conditions. Accordingly, the proposed framework is intended to detect scour-related variations in the turbine's bending modal characteristics rather than serve as a universal diagnostic tool for all degradation mechanisms. Other operational uncertainties, including controller effects, rotor imbalance, sensor installation errors, measurement noise, and wake interactions between turbines in a wind farm, are not explicitly considered in the present numerical framework. The numerical simulations considered in this study primarily represent above-rated operating conditions, where the rotor speed is maintained close to the rated value through the turbine control system. Therefore, the 3P excitation frequency remains relatively consistent among the investigated turbines. However, the proposed scour detection framework does not rely on rotor harmonic components as the primary indicator of scour. Instead, it exploits changes in the global dynamic response of the OWT system resulting from variations in SSI performance and foundation stiffness. Above-rated operation represents an important condition for OWT monitoring because turbines frequently operate under these conditions during their service life. Nevertheless, extending the dataset to incorporate below-rated and transient operating conditions, where rotor speed and aerodynamic excitation vary significantly, represents an important direction for future research to evaluate the robustness and applicability of the proposed framework.

Comment (7): The conditions are primarily above rated - which leads to similar 3P for many cases. How does this affect the algorithm's applicability?

Reply to Comment (7): The operating condition of the turbine can influence its dynamic response through variations in rotor speed, aerodynamic loading, and harmonic excitation components such as the 3P frequency. The revised manuscript now clarifies that the simulations considered in this study primarily represent above-rated operating conditions, where the turbine operates at approximately constant rated rotor speed. Consequently, the 3P excitation frequency remains relatively consistent among the investigated cases. Nevertheless, the objective of the proposed framework is not to identify scour based on changes in rotor-related excitation frequencies, but rather to detect modifications in the turbine–foundation dynamic characteristics caused by changes in soil–structure interaction and foundation stiffness. The domain generalisation framework learns scour-induced variations in the structural response while accounting for differences in turbine, environmental, and geotechnical conditions. The revised manuscript also acknowledges that future work should extend the validation dataset to include a wider range of operating conditions, including below-rated operation, transition regions, and variable rotor-speed conditions, to further assess the robustness of the proposed framework under the full operational envelope of offshore wind turbines.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 3.3, lines 327-342)

Although the dynamic characteristics of OWTs are influenced by various factors, including environmental variability, soil–structure interaction conditions, and structural degradation mechanisms such as corrosion, marine growth, settlement, and grout deterioration, this study focuses exclusively on scour-induced changes resulting from reductions in foundation stiffness and modifications to boundary conditions. Accordingly, the proposed framework is intended to detect scour-related variations in the turbine's bending modal characteristics rather than serve as a universal diagnostic tool for all degradation mechanisms. Other operational uncertainties, including controller effects, rotor imbalance, sensor installation errors, measurement noise, and wake interactions between turbines in a wind farm, are not explicitly considered in the present numerical framework. The numerical simulations considered in this study primarily represent above-rated operating conditions, where the rotor speed is maintained close to the rated value through the turbine control system. Therefore, the 3P excitation frequency remains relatively consistent among the investigated turbines. However, the proposed scour detection framework does not rely on rotor harmonic components as the primary indicator of scour. Instead, it exploits changes in the global dynamic response of the OWT system resulting from variations in SSI performance and foundation stiffness. Above-rated operation represents an important condition for OWT monitoring because turbines frequently operate under these conditions during their service life. Nevertheless, extending the dataset to incorporate below-rated and transient operating conditions, where rotor speed and aerodynamic excitation vary significantly, represents an important direction for future research to evaluate the robustness and applicability of the proposed framework.

Comment (8): Some of the tables could be shown with colour coding similar to Fig 5.

In Fig 5, the quantity of comparison is not very well defined. It is also somewhat remarkable that - for many cases - increasing scour depth does not lead to better identification after approximately 4 m scour depth.

Reply to Comment (8): Appropriate visualisation of the comparative results can improve the readability and interpretation of the presented findings. Therefore, colour coding has been added to the relevant result tables to provide a clearer indication of relative model performance and facilitate comparison between different training tasks, target turbines, and scour conditions. Regarding Figure 5, we appreciate the reviewer's observation regarding the relationship between scour depth and identification performance. The revised manuscript now provides additional clarification regarding the interpretation of this figure. As scour depth increases, the foundation stiffness decreases, resulting in a more flexible support system. Initially, the structural response is dominated by bending behaviour; however, as scour progresses, the response may gradually transition towards a more rigid-body rotational mode. Consequently, the incremental changes in the dynamic characteristics may become smaller with increasing scour depth, potentially making the detection of deeper scour levels more challenging. This trend is also reflected in the diminishing rate of increase in the natural period (or corresponding reduction in natural frequency) as scour depth continues to increase. The quantity presented in Figure 5 represents the classification performance of the proposed model for each scour condition, rather than a direct relationship between scour depth and detection accuracy.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 4.1, lines 590-605)

To further evaluate the effectiveness of the proposed DG-based training strategy, an additional baseline is considered in which the model is trained exclusively using data from Turbine 1.1, representing the shallowest water depth and lowest foundation stiffness among the investigated OWTs. **Error! Reference source not found.** represents the performance of the single-source DG model, developed using the PSD features extracted from the acceleration responses of Turbine 1.1 under healthy and 1 m scour conditions. The model is evaluated for scour-state detection across multiple target turbines located in Farms 1, 2, and 3. Compared with that of the proposed DG-based framework using the same unseen target turbines, the single-source model achieves satisfactory results for detecting the scour state at the same farm (Farm 1). However, in terms of its performance in detecting scour at Farm 2, its capability to detect scour deteriorates significantly at other farms (Farm 2 and 3), failing fully to detect any scour scenario at any target turbines within these farms. Although the single-source model achieves satisfactory performance for turbines with similar dynamic characteristics, its prediction accuracy decreases as the discrepancy between the source and target turbines increases. In contrast, the DG-based framework consistently demonstrates improved prediction accuracy and robustness across the diverse target turbines. These findings indicate that the enhanced performance of the proposed framework is primarily attributed to the increased diversity of the source-domain data, which enables the model to learn more generalised scour-related features, rather than relying on the characteristics of a single favourable source turbine.

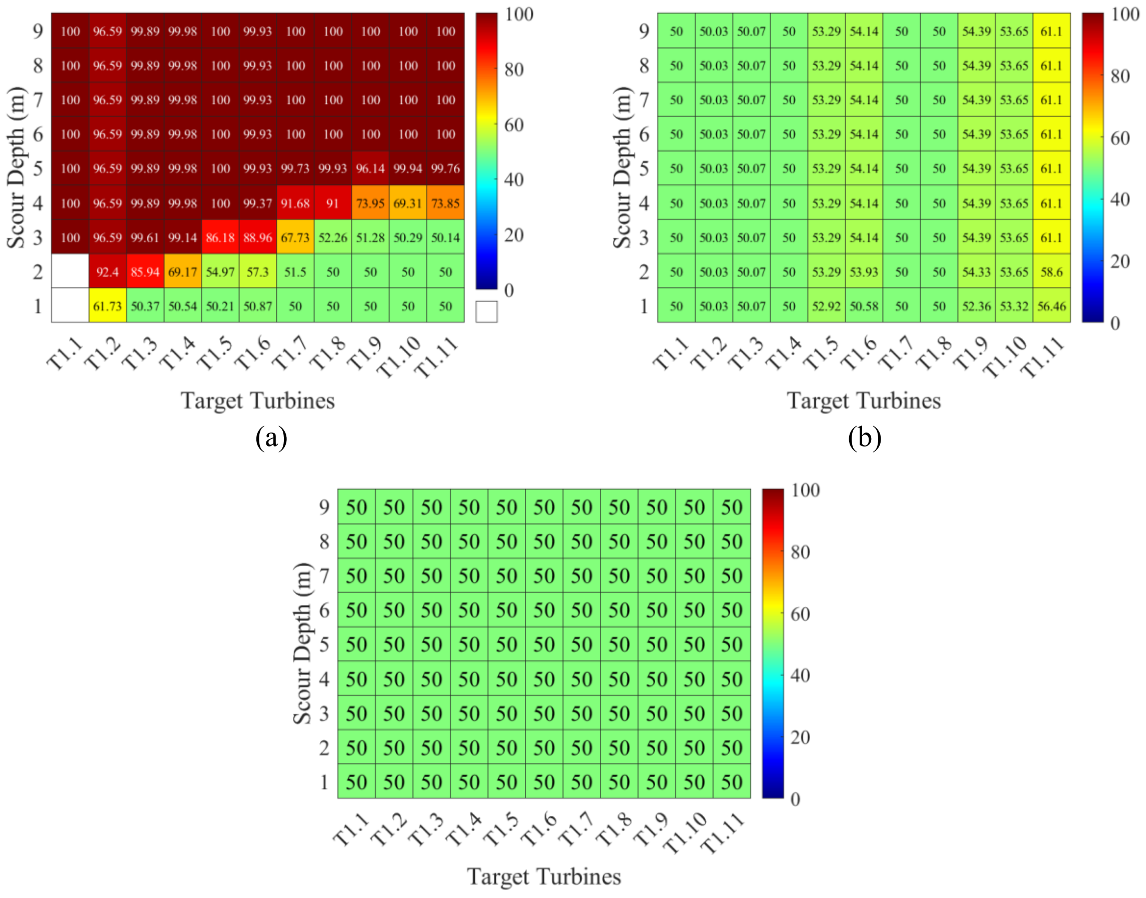
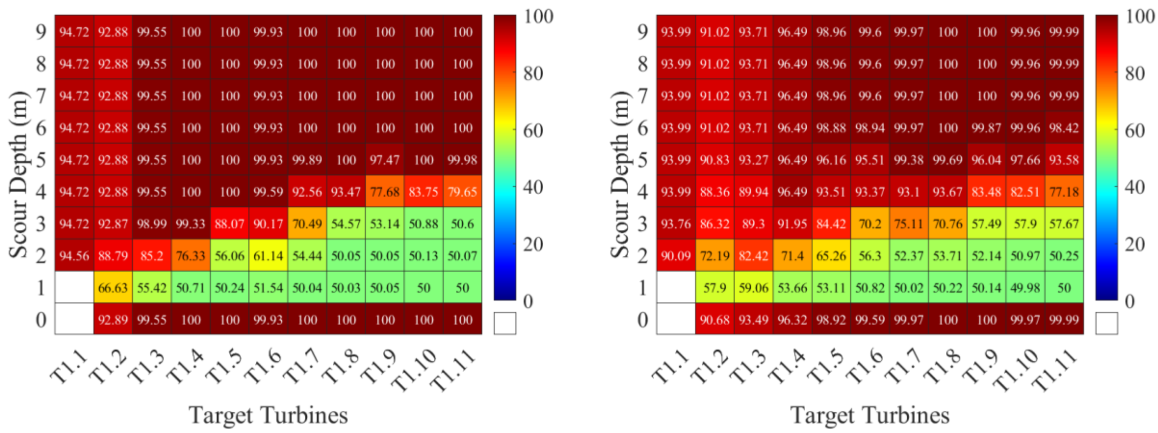
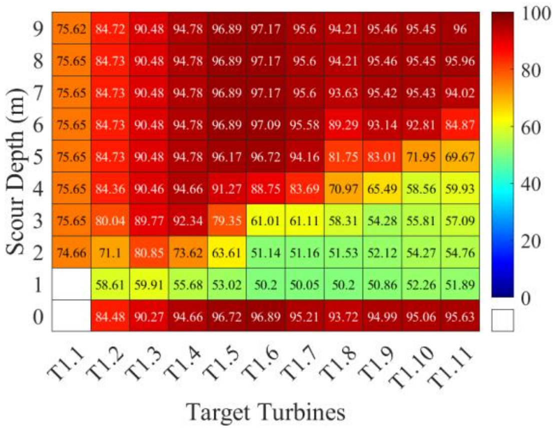


Figure 4: the performance of a single model when trained on turbine T1.1 and evaluated on target OWTs located at a) Farm 1, b) Farm 2, and c) Farm 3

<u>A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section Appendix A , lines 859-870)</u>

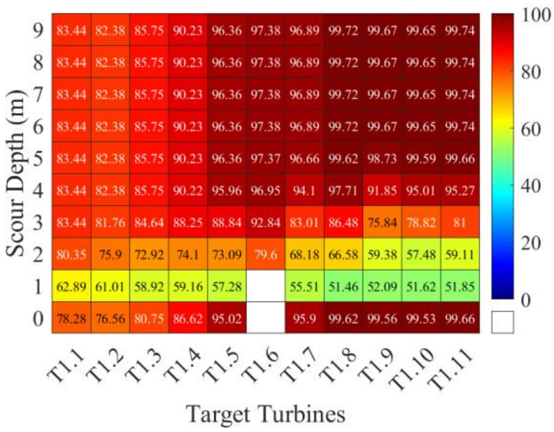


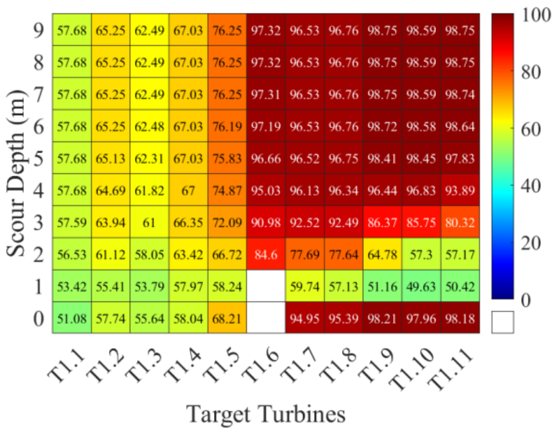
(a) (b)



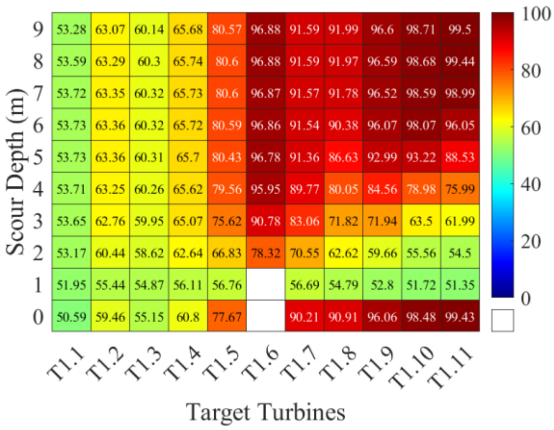
(c)

Figure A1: The baseline model performance when trained on Task 1 and evaluated on target OWTs located at a) Farm 1, b) Farm 2, and c) Farm 3.



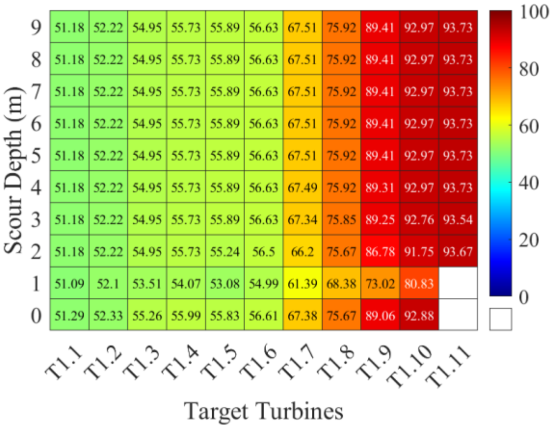


(a) (b)

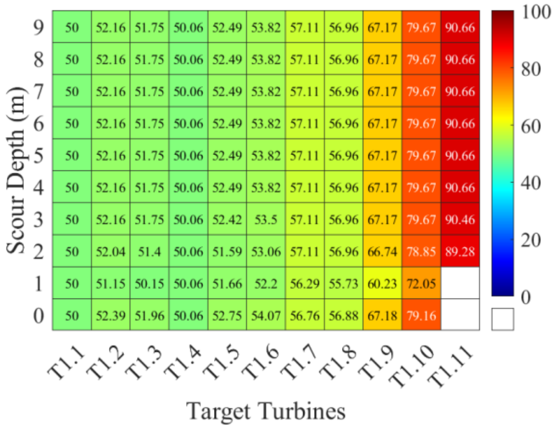


(c)

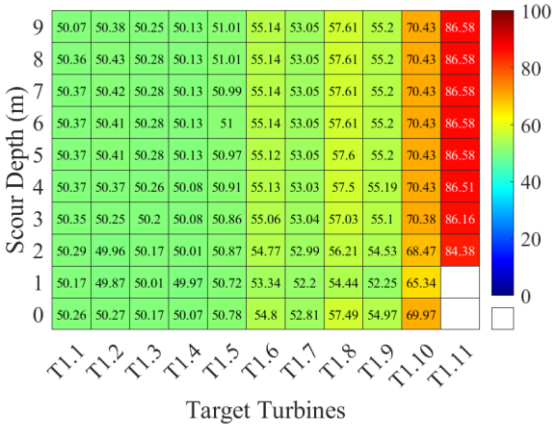
Figure A2: The baseline model performance when trained on Task 2 and evaluated on target OWTs located at a) Farm 1, b) Farm 2, and c) Farm 3.



(a)



(b)



(c)

Figure A3: The baseline model performance when trained on Task 3 and evaluated on target OWTs located at a) Farm 1, b) Farm 2, and c) Farm 3.

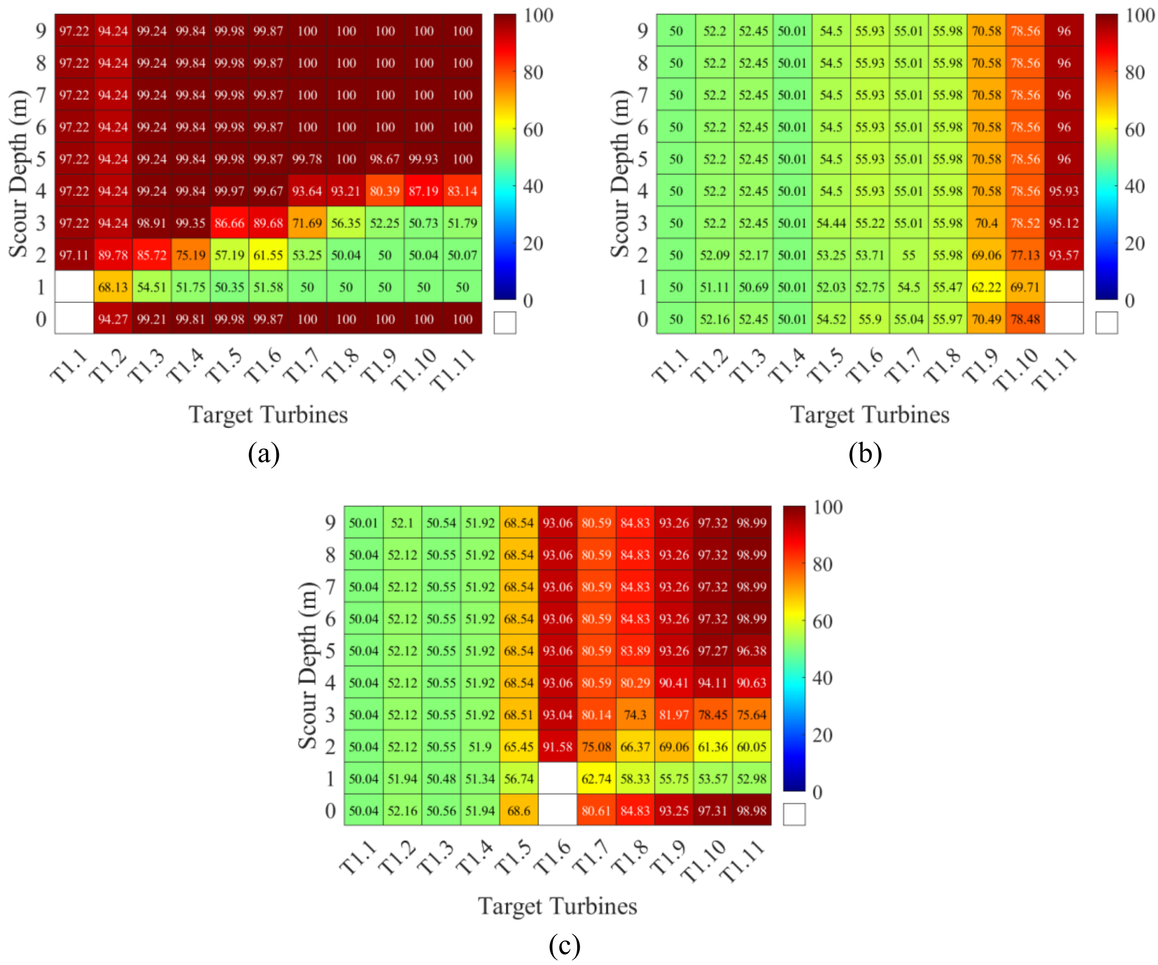


Figure A4: The baseline model performance when trained on Task 4 and evaluated on target OWTs located at a) Farm 1, b) Farm 2, and c) Farm 3.

Comment (9): The fact that the performance is generally better for the tower base sensor rather than tower top suggests that scour has an important effect on the second mode and that this can be useful for detection. This would be useful to discuss and show.

Reply to Comment (9): The improved performance obtained using the tower base accelerometer provides important information regarding the relationship between sensor location, structural modes, and scour-induced dynamic changes. To address this comment, additional discussion has been included in the revised manuscript to explain the physical mechanisms behind the observed performance difference between the tower base and tower top measurements. The additional analysis indicates that scour-induced degradation primarily affects the global dynamic characteristics of the turbine–foundation system, particularly the second structural mode, which exhibits greater sensitivity to variations in foundation stiffness compared with higher tower-dominated modes (Jawalageri et al., 2022). Measurements closer to the tower base are more effective in capturing these scour-related changes. In contrast, tower top measurements are influenced by the cumulative dynamic response of the entire structure and may contain stronger contributions from aerodynamic excitation and higher-order structural effects, which can reduce the sensitivity to foundation-related changes. Therefore, the improved performance of the tower base sensor is attributed to its higher sensitivity to the lower structural modes affected by soil–structure interaction and scour-induced stiffness degradation.

A paragraph of text has been added to the revised manuscript, shown in blue text. For convenience, this is also shown below. (Relevant text from manuscript Section 4.2, lines 621-634)

The superior scour detection performance achieved using the tower base accelerometer highlights the importance of sensor location in capturing scour-induced dynamic variations. The foundation degradation caused by scour primarily affects the SSI system and consequently modifies the global vibration characteristics of the turbine, particularly the second mode, which involves significant deformation near the tower base and foundation region. The second structural mode is expected to exhibit increased sensitivity to foundation stiffness variations because its deformation pattern includes a greater contribution from the lower tower and foundation response. Measurements obtained near the tower base are therefore more representative of changes in the foundation dynamic behaviour and provide enhanced sensitivity to scour-induced variations. Conversely, tower top measurements are influenced by the response of the entire turbine structure and may include additional contributions from aerodynamic loading and higher-order structural effects, reducing the relative contribution of foundation-related changes. These observations demonstrate that appropriate sensor placement can significantly enhance vibration-based scour detection performance by improving the sensitivity to the structural modes affected by foundation degradation.

Table 2: The impact of sensor location at the source turbines on the scour detection accuracy at the target turbines across the farms.

Farm	Sensor Location		Average scour state detection accuracy across multiple farms under different scour states (%)									
			Healthy	**1 m**	**2 m**	**3 m**	**4 m**	**5 m**	**6 m**	**7 m**	**8 m**	**9 m**
Farm 1	Sensor 1	Avg.	99.3	56.4	65.6	77.9	93.4	99.5	99.6	99.6	99.6	99.6
		Std	±1.9	±14.0	±18.3	±21.3	±8.00	±0.80	±0.80	±0.80	±0.80	±0.80
	Sensor 2	Avg.	99.3	54.9	61.7	72.2	82.5	95.9	98.9	99.0	99.0	99.0
		Std	±1.7	±11.0	±16.9	±21.2	±19.4	±4.40	±2.20	±2.30	±2.30	±2.30
Farm 2	Sensor 1	Avg.	97.4	56.2	63.7	76.2	90.4	96.2	97.9	98.2	98.2	98.2
		Std	±3.8	±12.2	±14.6	±14.8	±7.20	±2.00	±2.10	±2.20	±2.20	±2.20
	Sensor 2	Avg.	97.4	54.2	60.9	68.2	76.9	88.4	96.3	98.0	98.3	98.3
		Std	±3.8	±7.90	±14.9	±19.6	±18.7	±13.1	±3.70	±2.80	±2.80	±2.80
Farm 3	Sensor 1	Avg.	92.9	56.3	64.6	73.4	83.4	91.6	97.6	99.5	99.6	99.1
		Std	±3.5	±6.80	±12.2	±14.5	±13.0	±9.20	±2.70	±0.60	±0.90	±1.90
	Sensor 2	Avg.	98.5	53.2	59.4	67.4	76.1	84.4	91.6	96.4	97.8	98.1
		Std	±1.5	±5.00	±11.7	±17.9	±18.0	±16.3	±9.80	±3.60	±2.80	±2.90

References

Abdelhak, M., Prendergast, L. J., Tott-Buswell, J., Ghiasi, R., & Malekjafarian, A. (2026). Wind farm-level scour detection around offshore monopile foundations using unsupervised domain adaptation. *Mechanical Systems and Signal Processing*, *251*, 114186. https://doi.org/https://doi.org/10.1016/j.ymssp.2026.114186

Abdelhak, M., Tott-Buswell, J., Prendergast, L. J., Ghiasi, R., & Malekjafarian, A. (2025). Scour identification around offshore wind turbine monopile foundations using an unsupervised anomaly detection approach. *Ocean Engineering*, *340*, 122365. https://doi.org/https://doi.org/10.1016/j.oceaneng.2025.122365

Byrne, B., McAdam, R., Burd, H., Houlsby, G., Martin, C., Zdravkovic, L., Taborda, D. M. G., Potts, D., Jardine, R., Sideri, M., Schroeder, F., Gavin, K., Doherty, P., Igoe, D., Wood, A., Kallehave, D., & Gretlund, J. (2015). *New design methods for large diameter piles under lateral loading for offshore wind applications*. https://doi.org/10.1201/b18442-96

Cheynet, E., Jakobsen, J. B., & Obhrai, C. (2017). Spectral characteristics of surface-layer turbulence in the North Sea. *Energy Procedia*, *137*, 414-427. https://doi.org/https://doi.org/10.1016/j.egypro.2017.10.366

Jawalageri, S., Prendergast, L. J., Jalilvand, S., & Malekjafarian, A. (2022). Effect of scour erosion on mode shapes of a 5 MW monopile-supported offshore wind turbine. *Ocean Engineering*, *266*. https://doi.org/10.1016/j.oceaneng.2022.113131

Prendergast, L. J., & Gavin, K. (2016). A comparison of initial stiffness formulations for small-strain soil–pile dynamic Winkler modelling. *Soil Dynamics and Earthquake Engineering*, *81*, 27-41. https://doi.org/https://doi.org/10.1016/j.soildyn.2015.11.006

Tott-Buswell, J., Prendergast, L. J., & Gavin, K. (2024). A CPT-based multi-spring model for lateral monopile analysis under SLS conditions in sand. *Ocean Engineering*, *293*, 116642. https://doi.org/https://doi.org/10.1016/j.oceaneng.2023.116642

Wolfram, J., & Naghipour, M. (1999). On the estimation of Morison force coefficients and their predictive accuracy for very rough circular cylinders. *Applied Ocean Research*, *21*(6), 311-328. https://doi.org/https://doi.org/10.1016/S0141-1187(99)00018-8

Zefzouf, M., Chioukh, N., Castro, M., Miranda, F., Leal Sousa, R., Carvalho, E., Rosa-Santos, P., Taveira-Pinto, F., & Fazeres-Ferradosa, T. (2025). Laboratory study on scour development around a monopile in layered soils. *Ocean Engineering*, *342*, 122968. https://doi.org/https://doi.org/10.1016/j.oceaneng.2025.122968

Zhao, D., Han, N., Goh, E., Cater, J. E., & Reinecke, A. (2019). Offshore wind turbine aerodynamics modelling and measurements. *Wind Turbines and Aerodynamics Energy Harvesters*.