

# Sensor-Based Shutdown Event Detection in Monopile-Supported Offshore Wind Turbines Using Machine Learning

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## ABSTRACT

Offshore wind turbines (OWTs) present significant challenges for structural health monitoring (SHM) because of varying environmental and operational conditions. This paper proposes a machine learning (ML) approach to detect emergency shutdown events using sensor data located at the top of the foundation. Shutdowns, caused by rapid blade feathering, induce transient stresses, which can provide valuable insights into the structural integrity of the structure when measured. An integrated finite element model is used to simulate OWT load states under varying conditions, generating synthetic data for supervised learning. A  $k$ -Nearest Neighbors classifier is trained to distinguish between nominal, shutdown, and parked states. Results suggest the classifier performs well across different environmental scenarios, including unseen conditions. While low wind speeds show reduced accuracy, this is not critical as the method reliably identifies transience in significant shutdown events, achieving its primary objective. The results demonstrate the feasibility of using ML for event detection in OWTs from foundation-level accelerometers and inclinometers, with potential applications in SHM and digital twin updating approaches.

## INTRODUCTION

Offshore wind turbines (OWTs) are dynamically sensitive structures that operate in challenging offshore environments and experience considerable environmental and operational variability (EOVs) [1], making effective structural health monitoring (SHM) more complex. Traditional active sensing approaches are often impractical for these large structures in challenging offshore conditions [2, 3]. While OWTs can be instrumented with sensors like accelerometers, inclinometers, and strain gauges to monitor fatigue [4], the dynamic sensitivity to EOVs hinders effective updating of digital twin model parameters. Consequently, identifying subtle structural changes indicative of damage or degradation remains a significant challenge.

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Emergency shutdown sequences, frequently triggered by high winds, rotor-nacelle assembly (RNA) faults, or grid loss, induce a transient vibration state due to rapid blade feathering. This process imposes large stresses on the turbine’s structure [5, 6]. Recognising that the precise RNA controller state may not always be apparent to all stakeholders, including foundation engineers, this paper aims to detect shutdown events using only sensor data from the primary structure of the foundation. Identifying these specific time periods offers a valuable opportunity to assess the turbine’s dynamic performance under a significant loading condition, allowing engineers to update the accuracy of lifetime fatigue estimates. A machine learning (ML) approach is proposed for identifying the occurrence of these emergency shutdowns in sensor signals, as a precursor to potentially leveraging these events as a pseudo-active sensing procedure to detect relative changes in OWT structural performance in future work.

ML is commonly used for fault and anomaly detection in structural data [2]. However, its application to identifying shutdown events in OWTs is underexplored. A supervised learning algorithm is used to classify shutdown events based on synthesised sensor data from an OWT-monopile FEM. To achieve this, an integrated FEM simulates three distinct OWT load states: nominal operation, the blade-feathering shutdown process, and a parked state. These simulations incorporate varying wind speeds and irregular wave states, representative of operational conditions. The resulting accelerations and inclinations at the tower-monopile interface provide the input for the supervised learning process to classify shutdown events in commissioned sensor data.

## THE FINITE ELEMENT MODEL

The integrated OWT-monopile system is modelled using a one-dimensional finite element approach. The monopile and tower sections are represented by vertical elastic Timoshenko beam elements. Soil-structure interaction is incorporated using a linearised  $p$ - $y$  approach, where the lateral soil resistance is modelled with the initial stiffness modulus of API sand springs with a friction angle of 35 degrees [7]. The rotor-nacelle assembly (RNA) is simplified as a lumped mass at the top of the tower. The dynamic motion of the blades is not considered. By considering the relevant degrees of freedom, accelerations and inclinations are obtained at the tower base, which is analogous to directly measuring these quantities with sensors at that location, effectively creating a virtual instrumented foundation. Figure 1 illustrates the finite element model, while Table I details the properties of the tower and monopile. The FEM and subsequent computations were developed and performed using MATLAB.

## SIMULATING A SHUTDOWN EVENT

The nominal thrust force  $F_T$  is calculated using Equation 1 and assumes a uniform wind speed  $U_0$ , modified by deterministic variations due to tower shadowing ( $U_{ts}$ ) and wind shear effects ( $U_{ws}$ ) [8]. These variations are modelled using Equations 2 and 3, where  $U_{ts}$  and  $U_{ws}$  depend on the blade azimuth angle  $\theta(t)$  and are derived from the rotor RPM regulation curves for a given wind speed  $U_0$ , shown in Figure 2.

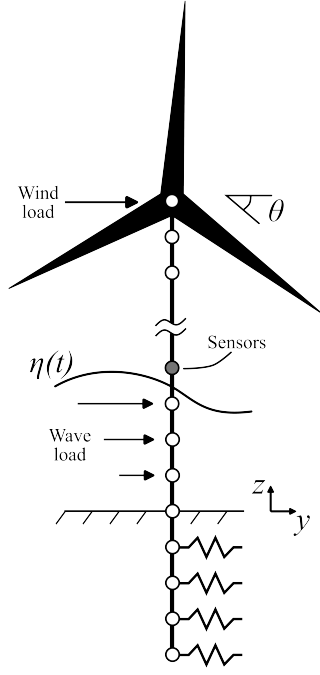


TABLE I. Properties of the tower and monopile used in the FEM.

Property	Tower	Monopile
Height (m)	100	30
Lower Dia. (m)	7	10
Upper Dia. (m)	10	10
Thickness (m)	0.045	0.055
Young's Mod. (GPa)	210	210
Density (kg/m <sup>3</sup> )	7850	7850

Figure 1. Finite element model with sensor locations and environmental loads.

$$F_T = \frac{\pi}{2} R^2 \rho_a C_T (U_0 + U_{ts} + U_{ws})^2 \quad (1)$$

$$U_{ts}(\theta) = \frac{U_0 a^2}{3(R - r_0)} \sum_{n=1}^3 \left( \frac{r_0}{r_0^2 \sin^2 \theta_n + b^2} - \frac{R}{R^2 \sin^2 \theta_n + b^2} \right) \quad (2)$$

$$U_{ws}(\theta) = \frac{1}{U_0} \left( 1 + \frac{\alpha(\alpha - 1)R^2}{8H^2} \right) \dots \left( \frac{\alpha(\alpha - 1)}{12} \left( \frac{(R - r_0)^2}{H} \right)^2 + \frac{\alpha(\alpha - 1)(\alpha - 2)}{96} \left( \frac{(R - r_0)^3}{H} \right) \cos 3\theta \right) \quad (3)$$

where  $H$  is the tower height,  $a$  is the the upper tower radius,  $b$  is the hub overhang (11.35 m),  $\rho_a$  is the air density taken as  $1.225 \text{ kg/m}^3$ ,  $\alpha$  is the wind shear exponent taken as 0.2 and  $C_T$  is the thrust coefficient, determined from the aerodynamic performance curve shown in Figure 2. The blade length  $R$  and root  $r_0$  are taken as 120 m and 5 m, respectively.  $n$  is considered as the blade number. The shutdown event is simulated by gradually reducing the  $F_T$  to zero over a specified interval to emulate blade-feathering. This reduction is governed by a shutdown factor  $\Psi_{SD}(t)$ , modelled using a sigmoid function (Equation 4), where the shutdown thrust is expressed as  $F_{SD} = F_T \Psi_{SD}(t)$ . An example thrust history is shown in Figure 3.

$$\Psi_{SD}(t) = \frac{1}{1 + \exp\left(\frac{12}{\Delta T_b}(t - T_b)\right)} \quad (4)$$

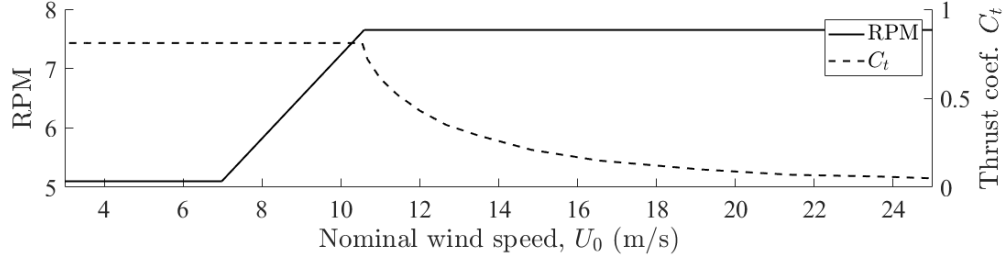


Figure 2. Performance curves for thrust coefficient  $C_T$  and rotor RPM regulation of a 15 MW OWT.

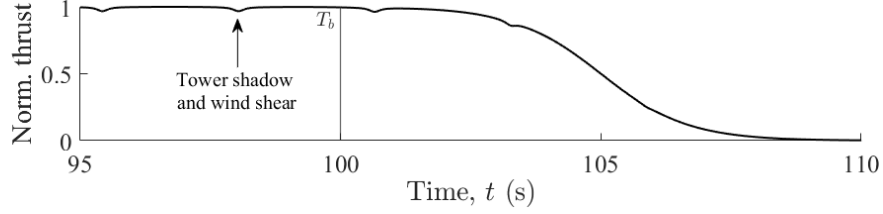


Figure 3. Example thrust history during a shutdown event occurring at  $T_b = 100$  s.

Wave loads are calculated by determining a random free surface elevation  $\eta(t)$  at the location of the monopile and the kinematics along the substructure are calculated using Airy's theory. Morison's equation determines drag and inertial forces based on the velocity and acceleration profile, respectively. The random surface is generated via spectral decomposition of a JONSWAP power spectrum, which is dependent on the significant wave height ( $H_s$ ) and the peak wave period ( $T_p$ ). The free surface is therefore:

$$\eta(t) = \sum_{i=1}^N A_i \sin(w_i t + \phi_i) \quad (5)$$

where  $N$  is the number of wave components,  $i$  is the component number,  $A_i$  is the wave amplitude,  $w_i$  is the angular frequency, and  $\phi_i$  is a random phase angle uniformly distributed between 0 and  $2\pi$ .

## CLASSIFICATION TRAINING

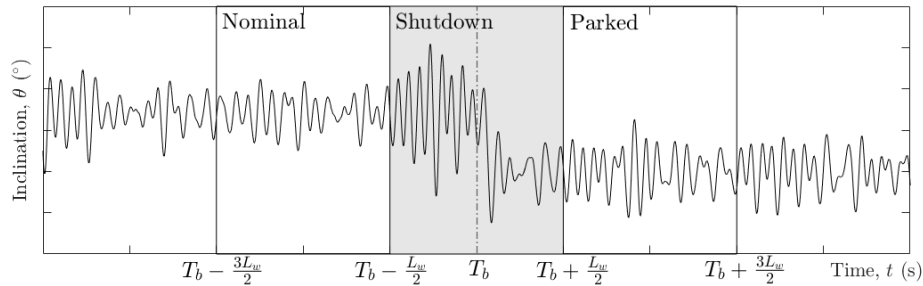


Figure 4. Classification of signals for an example inclinometer signal.

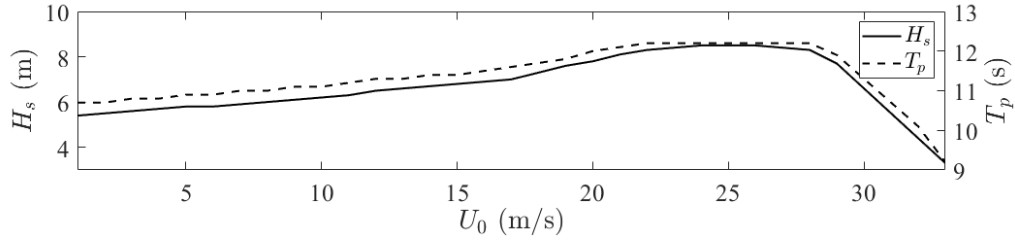


Figure 5.  $U_0$ - $H_s$ - $T_p$  relationships.

TABLE II. Extracted signal features ranked by significance.

Sensor Type	Feature	Rank Score (KW)
Inc.	Mean	1.0
Inc.	Shape Factor	0.84
Inc.	Maximum	0.82
Inc.	Autocorrelation Factor (lag 75)	0.82
Inc.	Minimum	0.81
Acc.	3rd Peak Amplitude	0.81
Inc.	Standard Deviation	0.80
Acc.	2nd Peak Frequency	0.58
Inc.	Total Harmonic Distortion	0.41

The data is divided into three classes: nominal, shutdown, and parked, each representing a 60-second window ( $L_w$ ) relative to the shutdown event ( $T_b$ ). The nominal class corresponds to pre-event performance, the shutdown class captures the event's transient response, and the parked class represents post-event performance, as illustrated in Figure 4.

Time-domain simulations use the Newmark-beta method with a 0.05 s time step over 640 s, discarding the first 100 s to remove initial transience. Shutdown occurs at  $T_b = 280$  s with a 10-second duration ( $\Delta T_b$ ). Acceleration and inclination data from the finite element model is modified with  $100 \mu g/\sqrt{\text{Hz}}$  noise density to emulate sensor performance under real noisy conditions. Wind speeds range from 10 m/s to 25 m/s, with corresponding  $H_s$  and  $T_p$  values derived from  $U_0$ - $H_s$ - $T_p$  relationships (Figure 5). The training dataset comprises 800 simulations across 16 environmental load cases (wind speeds: 10-25 m/s), each with 50 random wave profiles. These simulations are segmented into three classes, yielding 2400 samples (60 seconds each) for training, validation, and testing. Key time- and frequency-domain features are extracted from the synthesised accelerometer and inclinometer data to reduce dimensionality. Table II summarises these features and are sorted by importance using the Kruskal-Wallis (KW) rank test. The classification task employs a  $k$ -Nearest Neighbors ( $k$ NN) approach with  $k = 10$ , using euclidean distance and fifth-order cross-validation to enhance generality.

## RESULTS AND DISCUSSION

The classifier's robustness and generalisability were tested across diverse wind speeds

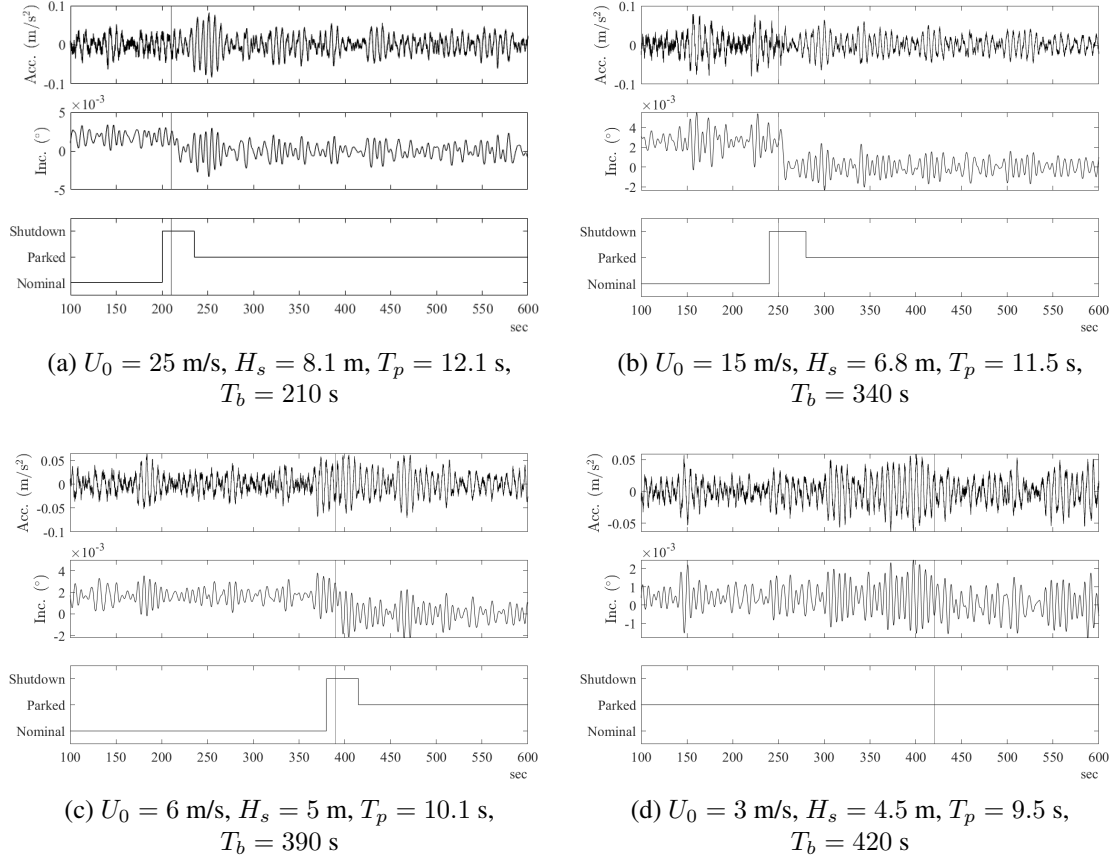


Figure 6. Classification results for testing simulations under varying environmental conditions.

( $U_0$ ), sea states ( $H_s$ ,  $T_p$ ), and shutdown events, with testing conditions outside the training set (Figure 5). 60-second segments of accelerometer and inclinometer signals were windowed every 10 seconds for feature extraction and classification. Figure 6 shows the model's predictions.

The algorithm detects shutdown events effectively under various conditions. For wind speeds within the training range (10-25 m/s), performance was good (Figures 6(a) and 6(b)), and generalisation to a lower wind speed of  $U_0 = 3$  m/s (Figure 6(c)) was observed. However, at a very low wind speed ( $U_0 = 3$  m/s, Figure 6(d)), the classifier could not distinguish between shutdown and parked states, classifying all windows as parked. This is due to minimal feature variation (mean, standard deviation, maximum) between nominal and parked conditions at low thrust, limiting discriminatory power. Nevertheless, this limitation does not compromise the framework's primary goal of identifying shutdown events with significant transient responses for structural health monitoring. The occurrence of false negatives in low wind speed conditions is not considered critical, as the methodology is intended to detect events that induce substantial structural response rather than to classify all operational states exhaustively. Overall, the classifier demonstrates robust performance in detecting shutdown events and differentiating operational states across a broad range of environmental conditions.

## CONCLUDING REMARKS

This study demonstrates the feasibility of using machine learning to detect shutdown events in offshore wind turbines using foundation-level sensors. A supervised  $k$ NN algorithm with 10 neighbors was trained on FEM-generated data simulating significant shutdown events under varying wind and wave conditions. The model performed well in most scenarios, but differentiating shutdowns at very low wind speeds (3 m/s) posed a challenge due to the minimal feature variation between parked and nominal states. This limitation is not critical, as the objective of this framework is to identify shutdown events that cause significant transience for further structural integrity analyses.

The FEM used in this study incorporates simplifications, including unidirectional wind and wave loads, exclusion of aero-servo-elasticity, multibody dynamics, and soil nonlinearities. These factors may influence results, particularly under extreme conditions. Future work should address these limitations and train models on real-world data, as distinguishing features in operational environments are likely more complex.

## ACKNOWLEDGMENT

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