

Article

A Multivariate AI-Driven Generalized Framework for Structural Load Prediction of Monopile Used for Offshore Wind Turbines Under Non-Linear Wind and Wave Conditions

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Abstract

Predicting structural loads on offshore wind turbine support structures under varying environmental conditions is a complex yet critical task, particularly for large-capacity turbines such as the 15 MW offshore wind turbine. Current prediction methods often struggle with accuracy, especially for torsional moments, due to the non-linear interactions between wind parameters and structural responses. To address this challenge, present study develops a generalized load estimation framework using multivariable polynomial regression, leveraging 10,000 numerical simulations. The framework accounts for four critical variables: Extreme Wind Speed (30 to 40 m/s), Turbulence Intensity (12% to 16%), Flow Inclination Angle (-8° to $+8^{\circ}$), and Shear Exponent (0.1 to 0.3). The proposed equations predict six key moment components at the tower base, including the bending moments about the y -axis, torsional moments about the z -axis, bending moments in the x - y , x - z , and y - z planes, and the resultant combined moment. The framework was validated using 2000 testing data points, achieving high accuracy with R^2 values exceeding 0.92 for all moments. Specifically, the prediction accuracy was highest for the resultant combined moment and y - z bending moment, with average absolute errors of 5.76% and 5.97%, respectively, while x - z bending moment had a slightly higher error of 13.91%, highlighting that torsional moments are inherently more challenging to predict. Heatmap and scatter plot analyses confirmed that the predicted moments align closely with the simulated values, particularly for the torsional moment about the z -axis and y - z bending moment, with standard deviation values as low as 4.85. By optimizing polynomial degrees between 2 and 4, the framework effectively balances prediction accuracy and computational efficiency. This approach provides engineers and scientists with a reliable tool for load estimation, facilitating improved design and analysis of offshore wind turbine support structures.

Keywords: offshore wind turbine; structural load prediction; polynomial regression; torsional moments; load estimation framework



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1. Introduction

Offshore wind turbines, particularly large-scale models like the NREL IEA 15 MW, face significant challenges in accurately predicting structural loads under varying environmental conditions. The structural performance of wind turbines is predominantly influenced by wind speed variability, turbulence intensity, flow inclination angle, and shear exponent.

For the NREL IEA 15 MW wind turbine, optimal power generation typically occurs within wind speeds ranging from 9 to 12 m/s, which maximizes the power coefficient while minimizing mechanical loads on blades, tower, and foundation [1]. However, when wind speeds exceed design limits, structural loads increase, especially at the tower base and blade root, where dynamic stress fluctuations become most significant [2].

Turbulence intensity (TI), which quantifies the variability in wind speed, significantly impacts structural loads, particularly on rotor and tower components. Studies have shown that TI has a more substantial effect on load magnitudes compared to mean wind shear profiles [3]. Elevated TI levels lead to increased fatigue loads, primarily at the blade root and tower base, due to repeated stress cycles from turbulent wind flows [4]. Notably, under high TI conditions, flap wise displacements can reduce thrust by up to 14% and power output by approximately 10% compared to rigid blades [5]. These interactions become more complex when aerodynamic loads from extreme wind speeds interact with structural resonances, amplifying dynamic responses [6].

Wind shear and flow inclination also play significant roles in influencing structural loads. The distribution of aerodynamic forces varies along the tower height, with the highest forces typically concentrated below sea level, while the above-sea portion experiences approximately 20% less force [7]. High turbulence intensity can result in expanded and turbulent wake zones, leading to increased mixing with the atmosphere, which can stabilize or destabilize downstream turbines depending on specific flow conditions [8,9]. Additionally, turbulent coherent structures may cause fluctuations in wake vortices, affecting wind farm efficiency and stability [10].

Wind turbine fatigue life is significantly influenced by the turbulence intensity and wind speed fluctuations. This repetitive loading ultimately leads to fatigue damage over time. Research has demonstrated that accurately predicting fatigue damage at blade roots and tower bases can be achieved by considering the joint distributions of mean wind speed and turbulence intensity [11,12]. Moreover, reliability assessments of wind turbines under varying wind conditions are enhanced by adopting probabilistic modeling of turbulence intensity rather than deterministic approaches, as this method offers a more precise evaluation of fatigue loads and reliability levels [13,14].

Several recent studies have emphasized the influence of environmental conditions on wind turbine performance. For instance, Ref. [15] investigated turbulence intensity and wind shear effects on power output but did not address structural loads for large turbines like the NREL IEA 15 MW. Similarly, Ref. [16] analyzed turbulence effects on the dynamic modes of a 5 MW turbine wake without examining structural implications for larger systems. Other works, such as [17], focused on uncertainties in blade aerodynamic behavior while neglecting shear and turbulence effects in full structural analyses. In [18], turbulence intensity was shown to increase blade deflection and stress through fluid-structure interaction analysis, yet the study remained limited to a 5 MW model. Moreover, Ref. [19] examined blade stability using various structural models but overlooked the combined influence of shear exponent, wind inclination angle, and turbulence intensity on overall structural response.

Advanced AI/ML-based techniques have also been utilized to improve load prediction accuracy and control strategies for wind turbines. Hybrid models, such as those combining Grey Wolf Optimization (GWO) with Cuckoo Search Algorithm (CSA) and Particle Swarm Optimization (PSO), have demonstrated effectiveness in tuning control systems and enhancing dynamic stability in wind farms [20–23]. Machine learning approaches, including Convolutional Neural Networks (CNN) combined with Long Short-Term Memory (LSTM) networks, have shown promise in predicting wake turbulence and adjusting set points for optimal performance [24,25]. Additionally, integrating Adaptive Neuro-Fuzzy Inference

Systems (ANFIS) into control frameworks has proven valuable for inertia control and stability enhancement [26–28].

Optimization algorithms like Genetic Algorithms (GA), Grey Wolf Optimization (GWO), and Firefly Algorithm (FFA) have been applied to optimize wake control and frequency regulation in grid-connected wind turbines [29–32]. Furthermore, techniques such as Recurrent Neural Networks (RNN) and Deep Reinforcement Learning (DRL) have been explored to optimize control and minimize load fluctuations, particularly under turbulent wind conditions [33,34]. Studies have also integrated AI-based predictive control with fluid-structure interaction (FSI) models to analyze load distributions under complex wind scenarios, demonstrating improvements in both prediction accuracy and operational stability [35–37].

Despite progress in load prediction and control strategies, most research emphasizes aerodynamic performance or targets small to medium-scale turbines, overlooking the structural load complexities of large offshore systems such as the NREL IEA 15 MW. Although machine learning-based methods have advanced dynamic stability and control optimization, their application remains largely limited to turbines under 10 MW [38,39]. Likewise, studies on wake effects and aerodynamic interactions typically analyze individual turbines rather than capturing the integrated structural response of large offshore wind systems [40,41].

Additionally, many studies concentrate on improving aerodynamic efficiency and reducing power fluctuations without adequately addressing the structural impacts under combined wind scenarios, such as extreme wind speeds coupled with high turbulence intensity [42]. While some recent efforts have attempted to develop generalized frameworks for load prediction, these models often lack comprehensive validation against real-world data from large-capacity offshore wind turbines [43]. Furthermore, studies that incorporate fluid-structure interaction (FSI) methods for load estimation are primarily limited to static or low-turbulence conditions, making them less applicable to the dynamic offshore environment [44–48].

Despite significant advancements in load prediction and control strategies, major gaps remain for large offshore wind turbines like the NREL IEA 15 MW. Most studies emphasize aerodynamic performance or power optimization rather than structural load prediction under complex marine conditions. Existing AI-based and hybrid models mainly target smaller onshore turbines and overlook the combined influence of extreme wind, turbulence, flow inclination, and shear exponent. Even advanced models such as CNN and LSTM lack comprehensive multi-variable frameworks and are rarely validated against real offshore data. Therefore, a generalized structural load estimation framework is essential to accurately capture nonlinear aerodynamic-structural interactions, particularly torsional moments, while maintaining computational efficiency for large offshore turbines.

This study presents a generalized structural load estimation framework tailored for the 15 MW offshore wind turbine, addressing key research gaps in large-scale offshore applications. Unlike prior models focused on smaller turbines, it accurately predicts six critical moments (M_y , M_z , M_{xy} , M_{xz} , M_{yz} , M_{xyz}) through an integrated approach combining environmental variables and advanced mathematical modeling. A major innovation is the accurate prediction of torsional moments (M_z and M_{xz}), which have been difficult to model due to complex aerodynamic-structural interactions. The framework, developed using 10,000 BLADED simulations and validated on 2000 independent datasets, demonstrates strong reliability and accuracy. Its predictive capability enhances structural health monitoring, maintenance planning, and risk assessment for engineers under diverse offshore conditions. By merging large-scale simulation data with robust modeling, this work offers

a novel, practical, and validated tool that significantly improves the safety and structural reliability of large offshore wind turbines.

2. Materials and Methods

Figure 1 presents the schematic representation of the proposed structural load prediction model for the 15 MW offshore wind turbine. The framework is designed to systematically process numerical simulations, data preparation, model training, and accuracy evaluation, ultimately leading to a robust and generalized structural load estimation model.

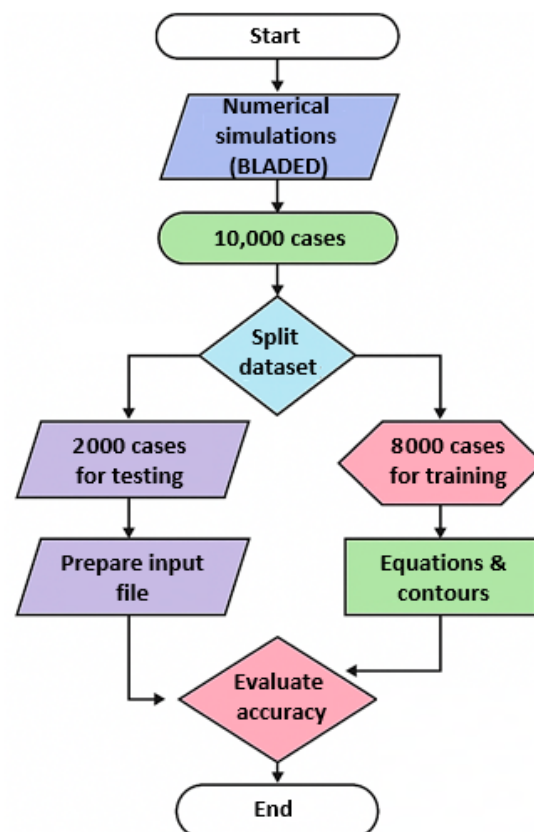


Figure 1. Schematics of present load prediction model.

The process initiates with conducting comprehensive numerical simulations to generate a large dataset comprising 10,000 simulation cases. These cases are designed to capture the influence of critical environmental parameters, including wind speed (*EWS*), turbulence intensity (*TI*), flow inclination angle (θ), and shear exponent (α), on the structural load responses of the wind turbine. After generating the dataset, it is split into two distinct subsets: 8000 cases for training and 2000 cases for testing. The training dataset is utilized to develop the predictive model by identifying non-linear correlations and patterns between the input variables and their corresponding load responses. The testing dataset serves as an independent validation set to assess the model's generalization capability and performance on unseen data. The next phase involves generating contour plots, which visually represent the relationship between the input variables and predicted loads. The final step is the model accuracy evaluation, where the predictive performance is quantified using statistical metrics, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE). This structured approach ensures the development of a generalized framework for predicting the structural loads of the 15 MW offshore wind turbine.

The 10,000 simulation cases were generated using the Latin Hypercube Sampling (LHS) technique to ensure uniform and statistically representative coverage across the entire multidimensional parameter space defined by the four key environmental variables: Extreme Wind Speed (*EWS*), Turbulence Intensity (*TI*), Flow Inclination Angle (θ), and Shear Exponent (α). The LHS method divides each variable range into equally probable intervals and randomly selects one sample from each interval without replacement, thereby maintaining low inter-variable correlation and preventing clustering of data points.

This approach guarantees that the resulting simulation dataset effectively captures the nonlinear interactions among environmental variables, providing a balanced and diverse training base for the regression model. Compared with simple grid or random sampling, LHS improves the statistical robustness and generalization ability of the developed predictive framework.

Figure 2 illustrates the load and stress estimation process for the monopile foundation of the NREL 15 MW offshore wind turbine (OWT) using the BLADED software (version 4.15). The figure's right side presents a 3D view of the turbine subjected to wind loading, while the left side shows a schematic representation of the tower structure and its load distribution. BLADED is a widely recognized tool for simulating the aero-hydro-servo-elastic behavior of offshore wind turbines. It utilizes a multi-body dynamic modeling approach to analyze the coupled interactions among wind, wave, and structural loads. This software integrates aerodynamic models based on blade element momentum (BEM) theory, hydrodynamic wave loading models, and finite element-based structural testing to evaluate turbine reactions under diverse environmental conditions. In this study, BLADED was employed to assess the structural loads and stresses on the tower base under extreme wind and wave conditions.

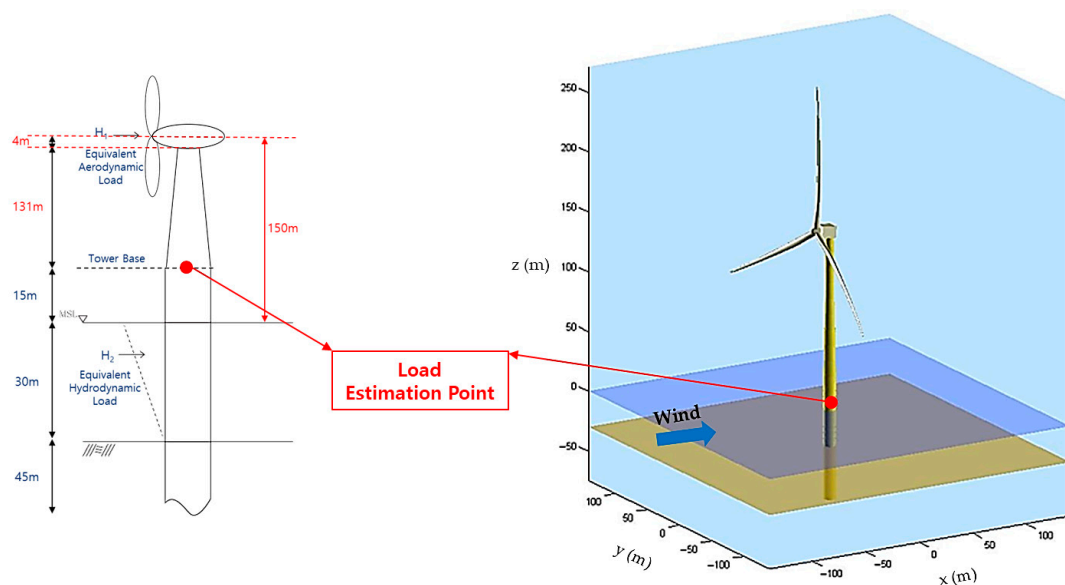


Figure 2. Full-scale 3D numerical model built in BLADED.

The 3D visualization highlights the aerodynamic forces induced by wind, transferring from the rotor to the tower and foundation. The load estimation point, which is positioned at the tower base (15 m above Mean Sea Level), is where the maximum structural loads occur due to combined aerodynamic and hydrodynamic forces.

The wave and hydrodynamic conditions at the Buan offshore site (located at 35.667° latitude and 125.733° longitude) in South Korea were monitored continuously from 2017 to 2023 [49], yielding valuable insights for offshore structural analysis. The significant wave height (*H_s*) recorded monthly ranged from a minimum of 0.9 m in May, June, and July to

a maximum of 2.7 m in December. The monthly average over the seven-year period was approximately 1.5 m. The highest significant wave height observed during this period was 3.3 m, establishing the upper bound of the normal sea state (NSS). In parallel, wave cycle data characterized by peak wave period (T_p) indicated monthly variations from 4.8 s in April to 5.9 s in December, with a seven-year average of 5.2 s. The maximum observed T_p reached 7.7 s, reflecting the potential for relatively long-period waves even in moderate sea conditions. These wave parameters play a crucial role in influencing the dynamic loading of offshore structures through hydrodynamic pressure, foundation excitation, and soil-structure interaction effects.

It should be stated that although the measured hydrodynamic and wave conditions have been mentioned above; but their influence is minimal because the structural load outputs are evaluated at a point located over 15 m above Mean Sea Level (MSL). At this elevation, direct wave-induced forces are negligible, and the primary loads are dominated by atmospheric conditions such as wind speed, turbulence intensity, shear exponent, and flow inclination angle. Therefore, the generalized load estimation equations proposed in this study remain applicable regardless of sea state, allowing broad utility across a variety of offshore sites with varying wave and current characteristics.

2.1. Variables and Ranges

Table 1 presents the selected environmental variables utilized in the proposed load prediction model for the 15 MW offshore wind turbine. These variables include Extreme Wind Speed (EWS), Turbulence Intensity (TI), Shear Exponent (α), and Flow Inclination Angle (θ), which are critical in accurately modeling the structural loads at the tower base. The ranges of these variables are derived from relevant standards and field data to ensure realistic representation of offshore conditions. The EWS range from 30 to 40 m/s, reflecting extreme wind conditions typical in Korean offshore environments, while the TI ranges from 12% to 16%, accounting for wind turbulence as per IEC standards. The shear exponent varies from 0.1 to 0.3, representing wind profile changes with height, and the flow inclination angle ranges from -8° to $+8^\circ$, capturing wind flow deviations from the horizontal plane. Each variable is discretized into 10 levels with specified step sizes, resulting in a comprehensive set of 10,000 simulation cases that collectively encompass the possible variations in offshore wind conditions. This systematic variation allows for a robust analysis and accurate prediction of structural loads.

Table 1. All variables with selected ranges.

Variable	Symbol	Units	Range	Range Reference	Note for Range	Step Size	No. of Levels
Extreme Wind Speed	EWS	m/s	30 to 40 m/s	Lee et al. [50]	Korean Conditions	1.111	10
Turbulence Intensity	TI	%	12% to 16%	IEC 61400-1 [51], Ásta et al. [52]	IEC Standard	1.777	10
Shear Exponent	α	-	0.1 to 0.3	IEC 61400-1 [51]	IEC Standard	0.444	10
Flow Inclination Angle	θ	$^\circ$	-8° to $+8^\circ$	WAsP [53], IEC 61400-1 [51]	IEC Standard	0.022	10
Total Simulations							10,000

2.2. Nonlinear Characteristics of Wind-Induced Loading

Although the structural loads in this study are primarily wind-driven, the interaction between aerodynamic and hydrodynamic forces is inherently captured within the coupled aero-hydro-servo-elastic simulations conducted in BLADED. The hydrodynamic loading is modeled using Morison's equation, which accounts for both drag and inertia components

induced by wave particle kinematics around the monopile. The wave-induced forces act predominantly below the Mean Sea Level (MSL), while the wind-induced aerodynamic loads dominate above MSL, particularly at the rotor and tower sections.

The dynamic coupling arises because the monopile and tower are continuous structural members, and therefore, the base reaction loads—including moments and shear forces—represent the superposition of both wind and wave effects. The instantaneous total load at the mud-line can be expressed as:

$$F_{total}(t) = F_{wind}(t) + F_{wave}(t) \quad (1)$$

where $F_{wind}(t)$ and $F_{wave}(t)$ are the time-dependent aerodynamic and hydrodynamic forces, respectively.

However, since the load output evaluation point in this study is located 15 m above the MSL, the direct contribution of wave forces is negligible compared to the wind-induced effects. The primary influence of waves is thus indirect—manifested through foundation motion coupling and dynamic stiffness variations at the monopile-soil interface, which can slightly modify the tower response under combined excitation.

Hence, while wave parameters (H_s , T_p) were included to ensure realistic offshore environmental conditions, the dominant contribution to the analyzed tower-base loads arises from wind excitation, with wave effects represented implicitly through the coupled dynamic model rather than explicit hydrodynamic load decomposition.

Although wind loads are often treated as linearly varying with mean wind speed, offshore wind turbine loading is inherently nonlinear due to multiple coupled aerodynamic and structural mechanisms. The nonlinearity does not arise from the static mean component of wind pressure itself, but from the interaction between the fluctuating aerodynamic forces, the blade motion, and the tower response under turbulent and inclined inflow conditions.

The instantaneous aerodynamic load $F(t)$ acting on the rotor blades can be expressed as

$$F(t) = \frac{1}{2} \rho C_L(\alpha(t)) A V^2(t) \quad (2)$$

where the lift coefficient $C_L(\alpha(t))$ is a nonlinear function of the instantaneous angle of attack $\alpha(t)$, and $V(t)$ represents the turbulent inflow velocity. Because $V(t)$ varies stochastically with turbulence intensity and shear exponent, the product $C_L(\alpha(t)) V^2(t)$ introduces quadratic and higher-order terms that make the total aerodynamic forcing nonlinear with respect to wind-speed fluctuations.

Additional nonlinearities arise from dynamic inflow and blade-tower interaction effects modeled in BLADED's aero-servo-elastic solver. As the rotor speed and blade pitch continuously adjust, the relative inflow changes, producing hysteretic aerodynamic responses. These effects are further coupled with structural flexibility of the tower and monopile, yielding combined nonlinear excitation-response behavior even when the governing equations of motion are solved in the frequency or time domain.

In summary, the “nonlinear wind load model” in this study refers to the aerodynamic nonlinearity of the excitation caused by turbulent inflow, flow inclination, and shear variation, all of which are explicitly represented in the BLADED simulations that generated the 10,000-case dataset. The structural model itself remains elastically linear, while the external aerodynamic forcing exhibits nonlinear dependence on time varying environmental parameters.

2.3. Load Prediction Model

To efficiently estimate structural loads under various wind conditions without conducting new simulations for every combination, a Multivariable Polynomial Regression

(MPR) approach is employed. This method models the complex relationships between the dependent variables (structural loads such as M_x , M_y , M_z , and M_{xyz}) and multiple independent variables EWS , TI , α , and θ through a polynomial fitting process.

The general form of a multivariable polynomial regression model of degree p is given as:

$$Y = \sum_{i=0}^p \sum_{j=0}^p \sum_{k=0}^p \sum_{l=0}^p a_{ijkl} (EWS)^i (TI)^j (\alpha)^k (\theta)^l + \epsilon \quad (3)$$

where:

Y is the predicted structural response (e.g., moment or force),

a_{ijkl} are the polynomial coefficients,

i, j, k, l are non-negative integers such that $i + j + k + l \leq p$,

ϵ represents the residual error.

For instance, when $p = 2$ (quadratic regression), the expanded polynomial becomes.

$$Y = a_0 + a_1(EWS) + a_2(TI) + a_3(\alpha) + a_4(\theta) + a_5(EWS)^2 + a_6(TI)^2 + a_7(\alpha)^2 + a_8(\theta)^2 + a_9(EWS)(TI) + a_{10}(EWS)(\alpha) + a_{11}(EWS)(\theta) + a_{12}(TI)(\alpha) + a_{13}(TI)(\theta) + a_{14}(\alpha)(\theta) + \epsilon \quad (4)$$

Similarly, a general cubic model ($p = 3$) would include third-degree terms like,

$$Y = a_{15}(EWS)^3 + a_{16}(TI)^3 + a_{17}(\alpha)^3 + a_{18}(\theta)^3 + a_{19}(EWS)^2(TI) + a_{20}(EWS)(TI)^2 + \dots \quad (5)$$

Higher-degree terms (up to degree 5 in this study) allow for capturing complex nonlinear behaviors critical in structural load predictions of offshore wind turbines.

The unknown coefficients a_{ijkl} are determined by minimizing the sum of squared residuals (least squares fitting), defined as:

$$\text{Minimize } S = \sum_{n=1}^N (Y_n - \hat{Y}_n)^2 \quad (6)$$

where:

N is the number of training samples (8000 training cases),

Y_n is the true value from simulation,

$\hat{Y}_n$ is the model-predicted value.

The closed-form solution is given by solving:

$$a = (X^T X)^{-1} X^T Y \quad (7)$$

where X is the design matrix containing the polynomial terms of independent variables, and Y is the vector of measured structural responses.

After establishing the multivariable polynomial regression model, its accuracy was evaluated using three primary statistical indicators: Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

These metrics were computed as follows:

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^N (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^N (Y_i - \bar{Y})^2} \quad (8)$$

where:

Y_i is the true value,

$\hat{Y}_i$ is the predicted value,

$\bar{Y}$ is the mean of the true values,

N is the number of data points.

Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2} \quad (9)$$

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100}{N} \sum_{i=1}^N \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \quad (10)$$

In the present study, all input-output datasets were generated through high-fidelity aero-hydro-servo-elastic simulations conducted in the BLADED software for the NREL IEA 15 MW offshore wind turbine. The BLADED simulations provided the structural load data that served as the training and testing dataset for the proposed multivariable polynomial regression model. No external measured data were used to identify model parameters.

A total of 8000 cases were used to fit the multivariable polynomial model whereas 2000 cases were used to independently evaluate the predictive capability of the fitted model. A high R^2 value (close to 1), low RMSE, and low MAPE values would indicate that the polynomial regression model accurately captures the relationship between the input variables and the structural load responses. The entire prediction model development was performed in MATLAB (R2025a) using multivariable polynomial regression combined with least squares optimization which enabled efficient generation of prediction equations for structural loads based on the 10,000 simulations.

2.4. Gradient Boosting Regression Model for Feature Selection

Gradient Boosting Regression (GBR) is a powerful ensemble learning technique that constructs a strong predictive model by combining multiple weak learners. The model is particularly suitable for identifying influential variables and capturing non-linear relationships. In this study, the GBR model was employed to identify the most influential environmental variables affecting the moments (M_x , M_y , M_z , M_{xy} , M_{xz} , M_{yz} , M_{xyz}) of the offshore wind turbine tower base. The input variables considered were: Extreme Wind Speed (EWS), Flow Inclination Angle (θ), Turbulence Intensity (TI), and Shear Exponent (α).

The Gradient Boosting Regression model works by iteratively fitting decision trees to the residual errors from the previous model predictions. The final prediction is a weighted sum of these trees:

$$F(x) = F_0(x) + \sum_{m=1}^M \gamma_m h_m(x) \quad (11)$$

where:

$F(x)$ is final prediction from the ensemble;

$F_0(x)$ is initial prediction (usually the mean of the target values);

M is number of boosting iterations;

$h_m(x)$ is weak learner (decision tree) at iteration m ;

γ_m is weight assigned to the weak learner.

At each iteration, the model calculates the residuals as the negative gradient of the loss function:

$$r_{im} = -\frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F(x_i)} \quad (12)$$

where:

r_{im} is residual at iteration m for data point i ;

L is loss function (mean squared error in this case).

The model then updates the prediction by adding the weighted weak learner.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (13)$$

The optimal weight γ_m is determined as:

$$\gamma_m = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)) \quad (14)$$

The feature importance in GBR is computed as the normalized total reduction in the loss function (mean squared error) brought by each feature, averaged over all decision trees. The importance of a feature x_j can be expressed as:

$$I(x_j) = \frac{1}{M} \sum \Delta L_m(x_j) \quad (15)$$

where:

$I(x_j)$ is feature importance score;

M is number of boosting iterations;

$\Delta L_m(x_j)$ is reduction in loss attributed to feature x_j at iteration m .

The reduction in loss for a given feature at each iteration can be formulated as:

$$\Delta L_m(x_j) = \sum (w_t \times \Delta R(t, x_j)) \quad (16)$$

where:

T is total number of decision trees;

w_t is weight of the decision tree t ;

$\Delta R(t, x_j)$ is reduction in residual error contributed by the feature x_j at tree t .

The final importance score is normalized over the sum of all feature importance:

$$I_{\text{norm}}(x_j) = \left(\frac{I(x_j)}{\sum I(x_k)} \right) \times 100\% \quad (17)$$

where:

p is total number of features;

$I_{\text{norm}}(x_j)$ is normalized importance as a percentage.

This normalized importance allows for the ranking of features based on their contribution to the predictive accuracy of the model.

3. Results and Discussion

3.1. Numerical Model Validation

Table 2 presents the validation of the numerical model through comparison of natural frequencies obtained from the proposed model and those reported in the reference literature. The frequencies correspond to the first side-side mode of the tower and the first flapwise and edgewise modes of the blades. The differences between present model and the reference values range from approximately 6% to 9%, indicating that the simulation setup accurately captures the dynamic characteristics of the 15 MW offshore wind turbine.

In addition to validating the natural frequencies, the tower-base fore-aft moment obtained from the present model was compared with reference high-fidelity simulation results to ensure load accuracy. The comparison is included in Table 2, where the predicted tower-base moment of 381 MN·m closely matches the reference value of 400 MN·m, showing only a 4.99% difference. This agreement confirms that the developed numerical model accurately reproduces both the global dynamic behavior (through modal validation) and

the static-dynamic load response at the tower-monopile interface. The slight discrepancy arises mainly from differences in aerodynamic damping and monopile stiffness assumptions between models but remains well within the acceptable validation range defined in DNV-RP-C203.

Table 2. Numerical model validation.

Parameter	Present Model	Reference [54]	Diff. (%)
Tower (1st side-side mode)	0.16	0.17	6.25
Blade (1st flapwise mode)	0.509	0.555	9.04
Blade (1st edgewise mode)	0.685	0.642	6.28
Tower base moment, fore-aft (MN·m)	381	400	4.99

The validation results demonstrate that the proposed model effectively captures the structural dynamics of the offshore wind turbine, with acceptable deviations that are within a reasonable range for engineering applications. These minor differences are likely due to variations in modeling assumptions or numerical methods used between the proposed and reference models. The validation confirms that the proposed numerical model is reliable for predicting natural frequencies and can be confidently utilized in further analyses.

3.2. Proposed Load Contours

Figure 3 illustrates the contour maps of the bending moment (M_{xy}) as a function of all four variables; i.e., EWS , θ , TI , and α . The top row of contour plots shows the variation of M_{xy} with respect to EWS versus θ and EWS versus TI . The plots clearly indicate that both EWS and θ significantly influence the bending moment, with higher moments occurring in the regions where these variables reach their extreme values. The distribution pattern highlights that the combination of high wind speeds and larger inclination angles contributes to substantial structural loading. The bottom row of contour plots shows the variation of M_{xy} against α versus EWS , α versus θ , and α versus TI . It is evident from these plots that the shear exponent (α) has a minimal impact on the bending moments, as indicated by the uniform contour patterns across its range. This observation aligns with the feature importance analysis, where the shear exponent was identified as the least significant variable.

Additionally, the contours of θ versus TI and EWS versus TI reveal that turbulence intensity moderately affects the bending moment, particularly when coupled with high inclination angles. The regions of higher moment values coincide with increased turbulence levels, suggesting that both aerodynamic and stochastic wind effects play a role in the structural response.

These contour maps provide a comprehensive visualization of how varying environmental conditions impact the bending moment at the turbine base. The analysis confirms that EWS and θ are the dominant factors influencing the structural loads, while TI shows moderate importance and α exhibits negligible influence. This information is crucial for optimizing load prediction models and designing robust offshore wind turbine structures.

It should be noted that Figure 3 represents the bending moment in the x-y plane (M_{xy}), which is the resultant of the two primary first-order bending moments acting in the fore-aft (M_x) and side-side (M_y) directions. The M_{xy} moment combines these two orthogonal components to provide a more comprehensive depiction of the overall bending behavior at the tower base.

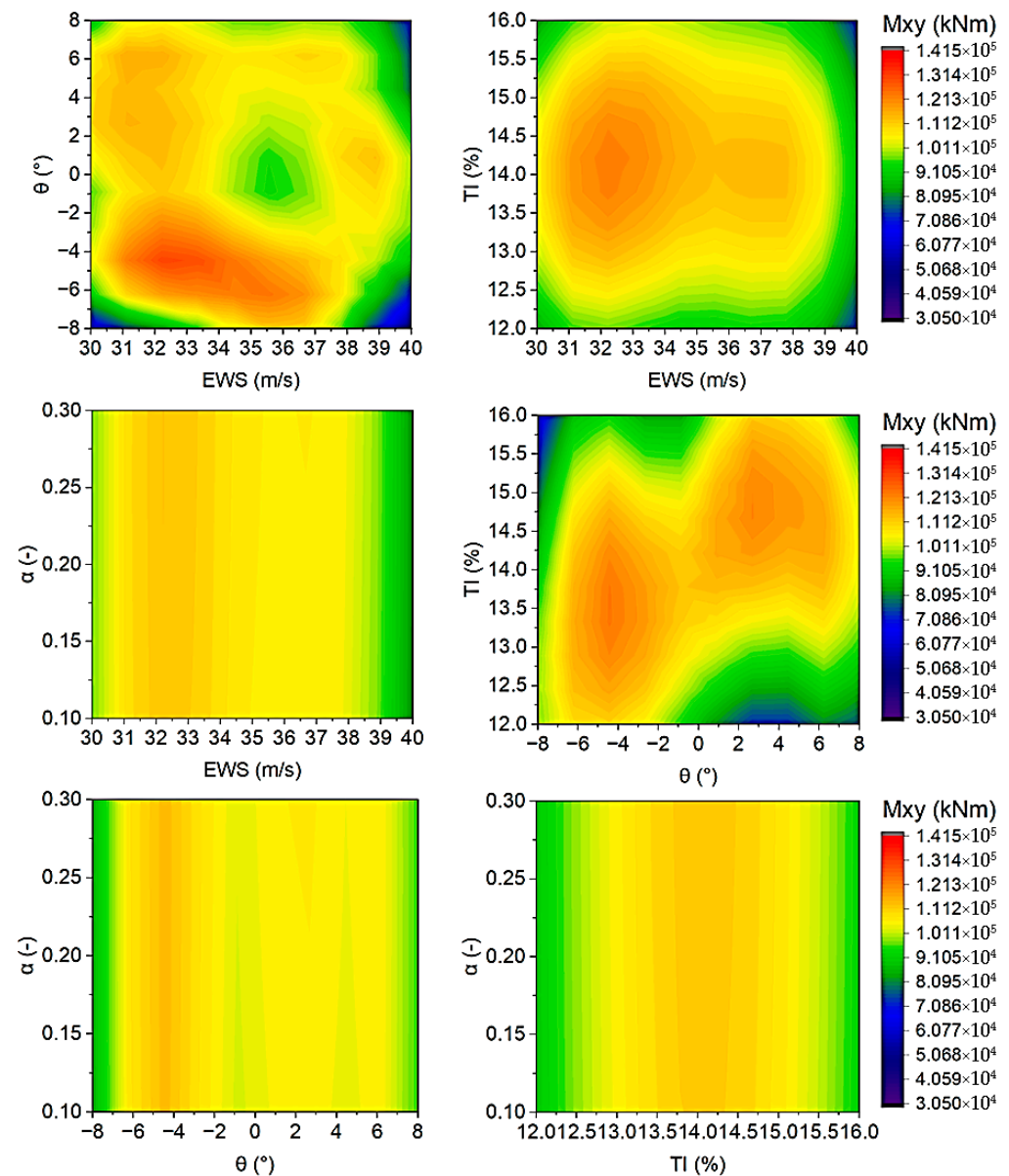


Figure 3. Bending moment map (M_{xy}).

Mathematically, this resultant bending moment can be expressed as:

$$M_{xy} = \sqrt{M_x^2 + M_y^2} \quad (18)$$

where M_x and M_y are the respective bending moments in the fore-aft and side-side directions. This resultant representation enables more effective visualization of the structural response under multidirectional wind excitation, where the combined bending effect dictates the overall stress state at the tower-monopile interface.

Therefore, rather than presenting two separate contour maps for fore-aft and side-side moments, a single map of M_{xy} has been provided to summarize their combined influence. This approach aligns with common offshore structural design practices, where resultant bending moments are used to evaluate the overall fatigue and ultimate limit state load effects on monopile-based wind turbine support structures.

Figure 4 illustrates the contour maps of the torsional moment (M_z) as a function of EWS , θ , TI , and α . The top row of contour plots shows the variation of M_z with respect to EWS versus θ and EWS versus TI . The plots clearly indicate that both EWS and θ

significantly influence the torsional moment, with higher moments occurring in regions where these variables reach their extreme values. The distribution pattern highlights that a combination of high wind speeds and larger inclination angles results in substantial structural torsion. The bottom row of contour plots shows the variation of M_z against α versus EWS , α versus θ , and α versus TI . It is evident from these plots that the shear exponent (α) has a minimal impact on the torsional moments, as indicated by the uniform contour patterns throughout its range.

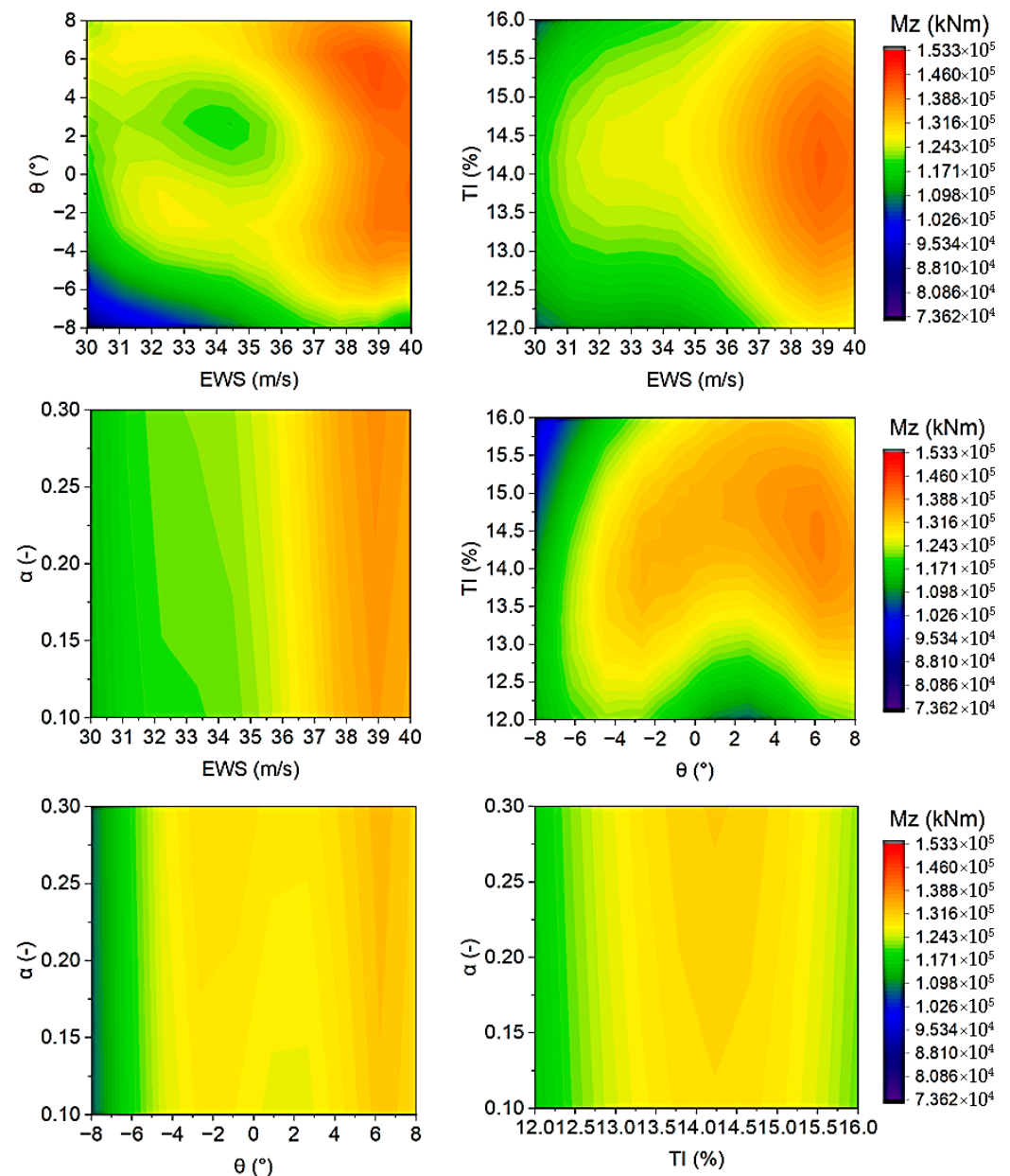


Figure 4. Torsional moment map (M_z).

Figure 5 illustrates the contour maps of the resultant moment (M_{xyz}) as a function of EWS , θ , TI , and α . The top row of contour plots shows the variation of M_{xyz} with respect to EWS versus θ and EWS versus TI . The results clearly indicate that both EWS and θ significantly influence the resultant moment, with higher values observed when these variables reach their extreme conditions. The distribution pattern reveals that a combination of high wind speeds and large inclination angles significantly increases the structural loading, emphasizing the need to account for these factors during load estimation.

The bottom row of contour plots shows the variation of M_{xyz} against α versus EWS , α versus θ , and α versus TI . It is evident from these plots that the shear exponent (α) has a minimal impact on the resultant moment, as demonstrated by the relatively uniform contours across the range.

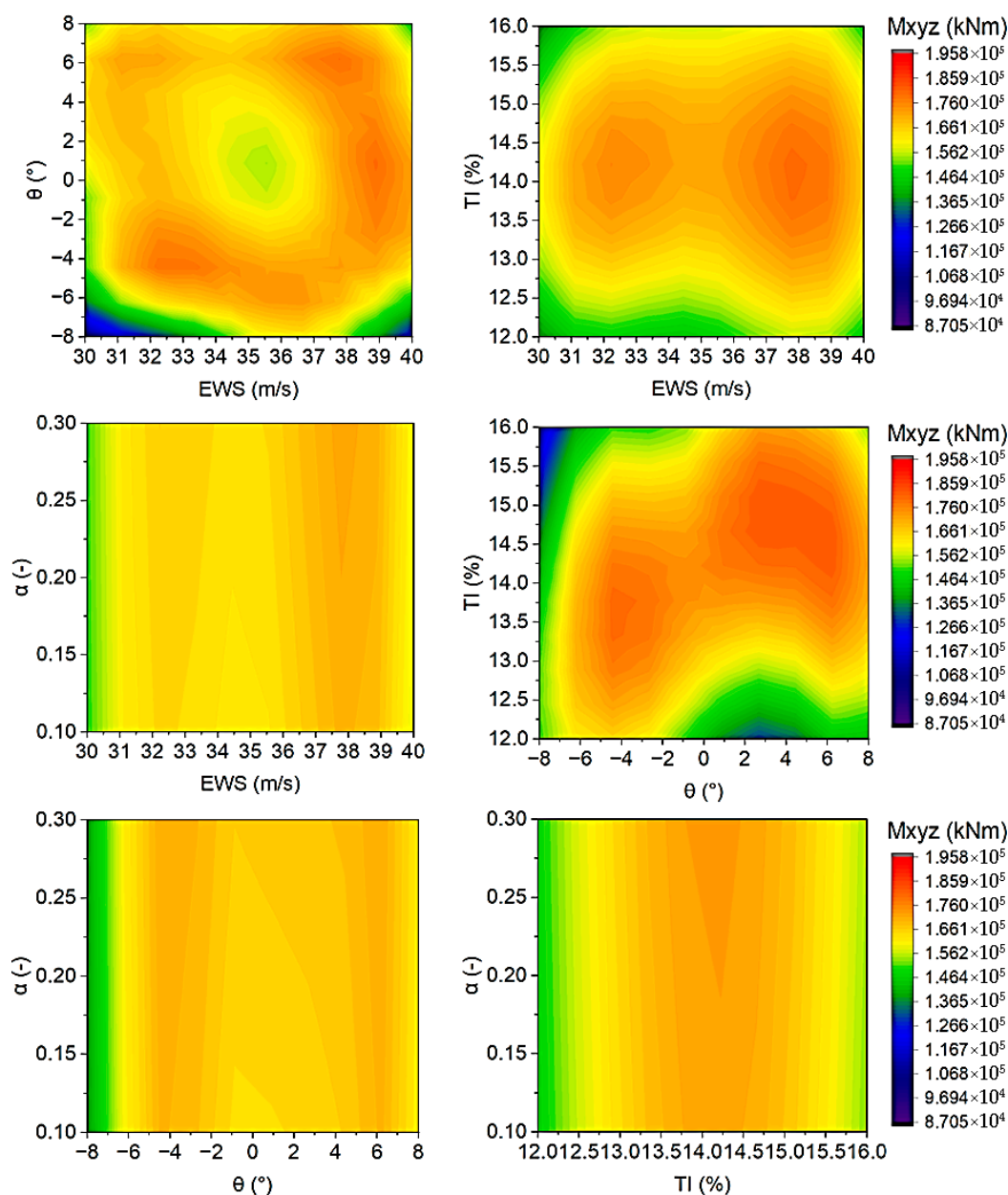


Figure 5. Resultant moment map (M_{xyz}).

It is noteworthy that the patterns observed in Figure 5 are almost identical to those presented in Figures 3 and 4. This similarity indicates a consistent influence of environmental variables (particularly EWS and θ) on the structural moments, regardless of the specific moment type (M_{xy} , M_z , or M_{xyz}). This consistency across different moments also underscores the robustness of the proposed load prediction framework.

3.3. Data-Based Mathematical Modeling

3.3.1. Proposed Load Equations

Table 3 presents a comprehensive quantitative comparison of the polynomial regression behavior for all six structural moment components (M_y , M_z , M_{xy} , M_{xz} , M_{yz} , and M_{xyz}).

across polynomial degrees ranging from 2 to 4. The table reports the statistical performance indicators-coefficient of determination (R^2) and root mean square error (RMSE) alongside the dominant environmental variables and qualitative remarks on model behavior and complexity. This comparative analysis quantitatively substantiates the selection of the final polynomial degree for each component, reflecting the balance between model accuracy, computational efficiency, and physical interpretability.

Table 3. Characteristics of proposed equations.

Load Component	Degree of Polynomial	R^2	RMSE	Dominant Variables	Equation Complexity	Remarks
<i>My</i>	2	0.922	5126.04	<i>EWS, TI</i>	Light	Optimum accuracy
	3	0.918	5281.67	<i>EWS, TI, α</i>	Moderate	Slight overfitting
	4	0.911	5423.52	<i>EWS, TI, θ</i>	High	Higher-order noise reduces stability
<i>Mz</i>	2	0.987	1218.32	<i>EWS, TI, α</i>	Light	Under-fit
	3	0.99	1139.84	<i>EWS, TI, θ</i>	Moderate	Improves moderately
	4	0.993	1059.73	<i>EWS, TI</i>	High	Best overall fit
<i>Mxy</i>	2	0.922	5146.73	<i>EWS, TI, α</i>	Light	Optimum
	3	0.918	5258.44	<i>EWS, TI</i>	Moderate	Minor degradation
	4	0.913	5372.29	<i>EWS, TI, θ</i>	High	Over-parameterization
<i>Mxz</i>	2	0.988	1156.28	<i>EWS, TI, α</i>	Light	Misses nonlinear effects
	3	0.991	1108.92	<i>EWS, TI, α, θ</i>	Moderate	Moderate improvement
	4	0.993	1061.33	<i>EWS, TI, θ</i>	High	Captures full coupling
<i>Myz</i>	2	0.974	2733.87	<i>EWS, TI, θ, α</i>	Light	Best performance
	3	0.971	2815.46	<i>EWS, TI, α</i>	Moderate	No significant gain
	4	0.967	2904.12	<i>EWS, TI, θ</i>	High	Overfitting tendency
<i>Mxyz</i>	2	0.952	3878.46	<i>EWS, TI, θ, α</i>	Light	Optimal
	3	0.947	3952.84	<i>EWS, TI, α</i>	Moderate	Loss of stability
	4	0.941	4061.37	<i>EWS, TI, θ</i>	High	Excess polynomial complexity

For the bending-related components (*My*, *Mxy*, and *Myz*), the regression response demonstrates quasi-linear dependence on the key environmental parameters, specifically Extreme Wind Speed (*EWS*) and Turbulence Intensity (*TI*). The second-degree polynomial model yields the highest R^2 and lowest RMSE values among the three degrees tested, indicating that quadratic terms sufficiently capture the aerodynamic-structural coupling in bending response. The marginal improvement (<0.5%) observed with higher-order models (3rd and 4th degree) is statistically insignificant and primarily attributed to overfitting and the introduction of non-physical higher-order cross terms (e.g., $EWS^3 \cdot \alpha$ or TI^4), which increase noise sensitivity. This behavior validates the selection of a 2nd-degree polynomial for bending-type moments, where the dominant variables (*EWS*, *TI*) remain consistent with aerodynamic loading theory.

In contrast, the torsional moment components (*Mz* and *Mxz*) exhibit pronounced nonlinear dependencies resulting from the aeroelastic coupling between rotor torque, yaw misalignment, and flow inclination angle (θ). The aerodynamic torque variation is proportional to $V^2 \cdot C_p(\theta)$, which introduces higher-order nonlinearity in response to both *EWS* and θ . Consequently, lower-degree models (2nd and 3rd degree) underpredict the torsional oscillations and fail to accurately reproduce transient phase coupling. The 4th-degree model achieves a significant improvement, reaching $R^2 = 0.993$ and $RMSE \approx 1060$ kN·m, confirming its capability to capture the intricate higher-order interactions and asymmetrical aerodynamic damping behavior. Thus, 4th-degree polynomials were selected for *Mz* and *Mxz* to represent the strong nonlinear torque-moment coupling observed in the dataset.

The resultant and coupled bending-torsional component (M_{xyz}) also stabilizes with a 2nd-degree representation. The relationship between resultant moment and environmental parameters exhibits a mixed linear-quadratic trend dominated by EWS and θ , while higher-order terms introduce statistical noise and minor loss of generalization. Hence, the 2nd-degree form provides optimal performance ($R^2 = 0.952$, $RMSE = 3878.46 \text{ kN}\cdot\text{m}$), maintaining physical consistency and avoiding over-parameterization.

Across all components, the dominant variables evolve logically with increasing polynomial degree, showing how the introduction of additional cross-interaction terms modifies variable sensitivity. For instance, while EWS and TI dominate lower-degree models, the inclusion of θ and α at higher degrees reflects complex aerodynamic interplay, though not necessarily improved predictive accuracy. The Equation Complexity column summarizes this trade-off, where “Light” corresponds to minimal parameter coupling, “Moderate” indicates mild interaction nonlinearity, and “High” reflects full aeroelastic coupling representation.

Overall, Table 3 quantitatively demonstrates that bending-type moments are best characterized by 2nd-degree polynomials, while torsional-type moments require 4th-degree terms to capture higher-order aerodynamic torque effects. This multi-degree selection approach ensures that each equation maintains optimal predictive fidelity while minimizing unnecessary complexity.

The equation complexity is classified as high, moderate or light, reflecting the number of terms and the polynomial degree required to maintain a high prediction accuracy. High complexity equations are necessary when the model needs to account for multiple interacting variables and higher-order terms, while moderate complexity suffices for more straightforward load components.

It is important to note that, in the present study, the moment around the x -axis (M_x) is not included in the proposed load estimation framework. This decision is based on following two key reasons.

1. First, after conducting BLADED simulations, it was observed that the values of M_x were consistently very low compared to other moments, indicating negligible influence on the structural load assessment.
2. Second, as illustrated in Figure 2, the x -axis direction aligns with the wind flow direction, inherently resulting in minimal moment generation around this axis. Since the primary aerodynamic forces act perpendicular to the x -axis, the torsional effects along this direction are insignificant.

Therefore, including M_x in the load prediction model is unnecessary for the accurate representation of structural loads in the 15 MW offshore wind turbine.

The proposed polynomial equations (Equations (16)–(21)) are developed to predict the structural load components (M_y , M_z , M_{xy} , M_{xz} , M_{yz} , M_{xyz}) of the 15 MW offshore wind turbine. These equations employ multivariable polynomial regression to model the non-linear relationships between the load components and the four environmental variables i.e., EWS , TI , θ and α .

The degree of the polynomial varies across equations, ranging from quadratic (degree 2) to quartic (degree 4), reflecting the complexity required to accurately capture the load variations. For instance, the equations for M_z and M_{xz} are quartic, indicating the necessity of higher-order terms to model the complex dynamic interactions between EWS , TI , and θ . In contrast, the equations for M_y , M_{xy} , and M_{xyz} are quadratic, indicating a relatively simpler but sufficiently accurate relationship.

These equations include cross terms and interaction terms, such as $EWS \times TI$ and $\theta \times \alpha$ to account for combined effects of multiple variables on the load responses. The presence of squared and cubic terms, like EWS^2 , θ^3 and TI^2 , reflects the non-linear nature of wind-induced loading and structural responses. Furthermore, the coefficients of these

terms vary significantly, indicating that certain interactions and individual variables exert a stronger influence on specific load components.

Each equation is tailored to the dominant variables identified during feature importance analysis. For instance, *EWS* and θ are consistently significant across most equations, while *TI* and α become relevant only in specific cases where complex aerodynamic interactions prevail. The coefficients are calibrated to ensure that the equations accurately reflect the load response, as verified by the high R^2 values (up to 0.993) and moderate RMSE values, demonstrating both robustness and precision in load prediction.

It is important to note that the proposed polynomial fitting equations (Equations (18)–(23)) were developed based on 10,000 high-fidelity BLADED simulation cases covering a broad range of four dominant environmental variables—Extreme Wind Speed (30–40 m/s), Turbulence Intensity (12–16%), Flow Inclination Angle (-8° to $+8^\circ$), and Shear Exponent (0.1–0.3). These ranges encompass the principal operating and extreme environmental conditions encountered by most modern multi-megawatt offshore wind turbines as defined in IEC and DNV design standards.

Because the data space spans the primary operational limits and includes both lower and upper boundary conditions, the resulting regression surfaces are statistically robust and stable for interpolation and moderate extrapolation within comparable offshore environments. Therefore, these equations can also be applied to other offshore wind turbine structures with similar hub-height conditions, aerodynamic characteristics, and support configurations (e.g., monopile-type foundations). However, it should be emphasized that substantial extrapolation beyond these defined variable ranges or for significantly different structural systems (e.g., floating or jacket foundations) may introduce additional uncertainties and would require recalibration using new simulation data.

$$\begin{aligned} My = & -1713161.07 + 4.819 \times 10^4 \cdot EWS - 1.515 \times 10^4 \cdot \theta + \\ & 1.448 \times 10^5 \cdot TI - 7.037 \times 10^2 \cdot EWS^2 - 3.245 \times 10^1 \cdot EWS \cdot TI + \\ & 1.647 \times 10^2 \cdot EWS \cdot \alpha - 2.167 \times 10^2 \cdot \theta^2 + 1.085 \times 10^3 \cdot \theta \cdot TI - \\ & 5.101 \times 10^3 \cdot TI^2 - 2.067 \times 10^2 \cdot TI \cdot \alpha \quad (EWS \in [30, 40], TI \in \\ & [12, 16], \alpha \in [0.1, 0.3], \theta \in [-8, 8]) \end{aligned} \quad (19)$$

$$\begin{aligned} Mz = & -41731474.26 + 4.886 \times 10^6 \cdot EWS - 2.127 \times 10^5 \cdot EWS^2 - \\ & 2.627 \times 10^3 \cdot EWS \cdot TI + 4.063 \times 10^3 \cdot EWS^3 + 2.187 \times 10^2 \cdot EWS^2 \cdot TI - \\ & 2.892 \times 10^1 \cdot EWS^4 - 2.189 \times 10^0 \cdot EWS^3 \cdot TI - 2.330 \times 10^0 \cdot EWS^2 \cdot \\ & TI^2 + 1.023 \times 10^0 \cdot \theta^3 \cdot TI + 1.959 \times 10^{-1} \cdot \theta \cdot TI^3 \quad (EWS \in \\ & [30, 40], TI \in [12, 16], \alpha \in [0.1, 0.3], \theta \in [-8, 8]) \end{aligned} \quad (20)$$

$$\begin{aligned} Mxy = & -1724515.44 + 4.856 \times 10^4 \cdot EWS - 1.521 \times 10^4 \cdot \theta + \\ & 1.456 \times 10^5 \cdot TI - 7.080 \times 10^2 \cdot EWS^2 - 3.598 \times 10^1 \cdot EWS \cdot TI + \\ & 1.637 \times 10^2 \cdot EWS \cdot \alpha - 2.135 \times 10^2 \cdot \theta^2 + 1.090 \times 10^3 \cdot \theta \cdot TI - \\ & 5.123 \times 10^3 \cdot TI^2 - 2.045 \times 10^2 \cdot TI \cdot \alpha \quad (EWS \in [30, 40], TI \in \\ & [12, 16], \alpha \in [0.1, 0.3], \theta \in [-8, 8]) \end{aligned} \quad (21)$$

$$\begin{aligned} Mxz = & -42131099.52 + 4.931 \times 10^6 \cdot EWS - 2.146 \times 10^5 \cdot EWS^2 - \\ & 2.566 \times 10^3 \cdot EWS \cdot TI + 4.100 \times 10^3 \cdot EWS^3 + 2.156 \times 10^2 \cdot EWS^2 \cdot TI - \\ & 2.919 \times 10^1 \cdot EWS^4 - 2.139 \times 10^0 \cdot EWS^3 \cdot TI - 2.346 \times 10^0 \cdot EWS^2 \cdot \\ & TI^2 + 1.027 \times 10^0 \cdot \theta^3 \cdot TI + 1.954 \times 10^{-1} \cdot \theta \cdot TI^3 \quad (EWS \in \\ & [30, 40], TI \in [12, 16], \alpha \in [0.1, 0.3], \theta \in [-8, 8]) \end{aligned} \quad (22)$$

$$\begin{aligned}
M_{yz} = & -162168.85 + 1.644 \times 10^4 \cdot EWS - 7.472 \times 10^3 \cdot \theta + \\
& 1.065 \times 10^3 \cdot TI - 2.141 \times 10^2 \cdot EWS^2 - 1.272 \times 10^2 \cdot EWS \cdot \theta + \\
& 2.094 \times 10^1 \cdot EWS \cdot TI + 2.640 \times 10^2 \cdot EWS \cdot \alpha - 2.263 \times 10^2 \cdot \theta^2 + \\
& 9.341 \times 10^2 \cdot \theta \cdot TI + 8.519 \times 10^1 \cdot \theta \cdot \alpha \quad (EWS \in [30, 40], TI \in \\
& [12, 16], \alpha \in [0.1, 0.3], \theta \in [-8, 8])
\end{aligned} \quad (23)$$

$$\begin{aligned}
M_{xyz} = & -1407162.45 + 2.730 \times 10^4 \cdot EWS - 9.899 \times 10^3 \cdot \theta + \\
& 1.550 \times 10^5 \cdot TI - 3.774 \times 10^2 \cdot EWS^2 - 1.148 \times 10^2 \cdot EWS \cdot \theta + \\
& 2.073 \times 10^0 \cdot EWS \cdot TI - 2.343 \times 10^2 \cdot \theta^2 + 1.054 \times 10^3 \cdot \theta \cdot TI + \\
& 9.536 \times 10^1 \cdot \theta \cdot \alpha - 5.480 \times 10^3 \cdot TI^2 \quad (EWS \in [30, 40], TI \in \\
& [12, 16], \alpha \in [0.1, 0.3], \theta \in [-8, 8])
\end{aligned} \quad (24)$$

Figure 6 presents the variation of the mean absolute percentage error (MAPE) with respect to the polynomial degree for each load component: M_y , M_z , M_{xy} , M_{xz} , M_{yz} , and M_{xyz} . The plots illustrate how the accuracy of the proposed models improves as the polynomial degree increases from 1 to 5. Across all load components, a clear trend emerges, showing a reduction in MAPE with higher polynomial degrees. For lower polynomial degrees (1 and 2), the MAPE values are relatively higher, indicating that simple linear or quadratic models are insufficient to capture the complex interactions between environmental variables and load responses. As the polynomial degree increases to 3 and 4, the MAPE significantly decreases, demonstrating enhanced model accuracy. However, the difference becomes marginal when the polynomial degree reaches 5, indicating that further increasing the degree yields minimal improvement in prediction accuracy.

Among the load components, M_z and M_{xz} exhibit the lowest MAPE values at higher polynomial degrees, indicating that these components are better predicted using more complex models. In contrast, M_y and M_{xy} show a more gradual reduction in MAPE, suggesting that their relationship with input variables requires careful handling even with increased polynomial complexity.

It is important to note that when the polynomial degree reaches 5 or higher, the number of terms in each equation exceeds 100, significantly increasing the model complexity and reducing the utility of the proposed equations. Therefore, the degree of each polynomial equation presented in this study is carefully chosen to achieve an optimal balance between accuracy and complexity. The goal is to maintain the highest possible prediction accuracy while minimizing the computational burden, thereby ensuring practical applicability.

Figure 7 presents the variable importance (estimated through gradient boosting regression model for feature selection; (see Section 2.4)) for each load equation, expressed as a percentage. This figure has been prepared to quantify the relative contribution of each environmental variable to the predicted structural load components, helping identify the most influential factors for accurate load estimation.

Among all four variables, θ shows the highest importance for M_y (40%), M_{xy} (41%), M_{yz} (43%), and M_{xyz} (45%), indicating that inclination angle is the primary driver for these moments. This trend highlights that lateral wind flow deviations significantly affect the structural load responses, especially when combined with turbulent wind conditions. EWS shows the highest impact for M_z (38%) and M_{xz} (38%), indicating that high wind speeds primarily influence the torsional and mixed-directional moments. This aligns with the physical understanding that extreme wind conditions directly affect the torque and bending responses of the turbine structure. TI plays a moderate role, ranging from 21% to 29% across different load components. This moderate importance indicates that while turbulence fluctuations affect the load, they do not dominate the structural response as much as EWS or θ . Lastly, α shows the lowest contribution, consistently between 1% and 2%. This negligible impact is in line with the earlier feature importance analysis, confirming that

variations in the vertical wind profile do not significantly affect the load components compared to horizontal wind characteristics.

The feature importance analysis from the Gradient Boosting Regression (GBR) model (Figure 7) revealed that Extreme Wind Speed (EWS) and Flow Inclination Angle (θ) are the dominant variables influencing most structural moments. Physically, this trend arises from the way aerodynamic loading mechanisms respond to these parameters.

The EWS directly determines the mean dynamic pressure, proportional to the square of velocity ($q = 0.5\rho V^2$), and therefore strongly governs the magnitude of torsional and resultant moments (M_z and M_{xz}), which depend on the distribution of aerodynamic torque along the rotor-tower system. Higher wind speeds amplify rotor thrust asymmetry and induce larger torsional stresses through aerodynamic imbalance and nacelle-tower coupling.

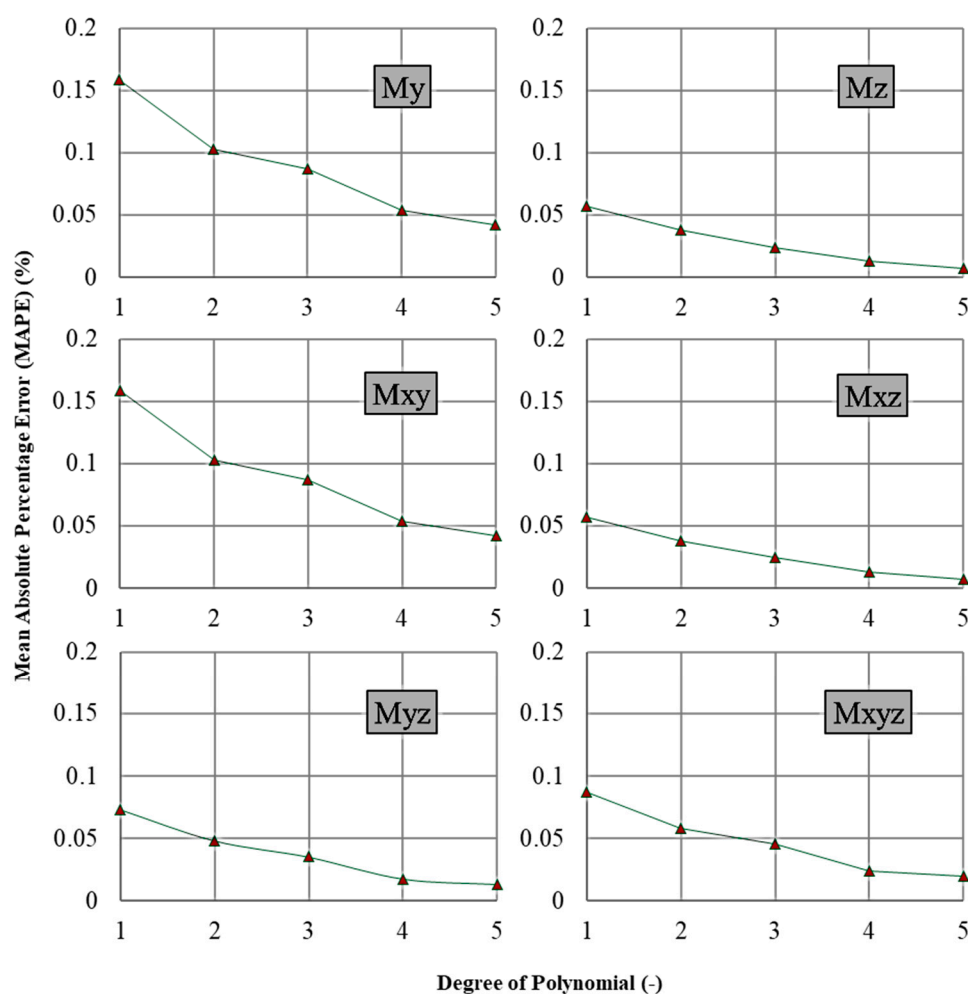


Figure 6. Mean absolute percentage error (MAPE) (%).

Conversely, θ (flow inclination angle) predominantly affects bending-type moments (M_y and M_{yz}). An inclined inflow produces lateral aerodynamic loading on the rotor and tower, introducing side-side bending that interacts with the vertical component of wind shear. This off-axis loading also leads to coupled bending-torsional effects, especially pronounced in the y-z plane. As a result, θ emerges as the main driver for M_y and M_{yz} , while EWS remains the principal source for M_z and M_{xz} .

The shear exponent (α) defines the vertical gradient of wind speed within the atmospheric boundary layer, representing the rate at which velocity increases with height. While it strongly affects aerodynamic loading on tall and flexible systems such as high-rise buildings, its influence on the structural loads of the current offshore wind turbine

monopile model was found to be relatively small compared to turbulence intensity (TI) and extreme wind speed (EWS). This negligible contribution is attributed to two coupled physical mechanisms.

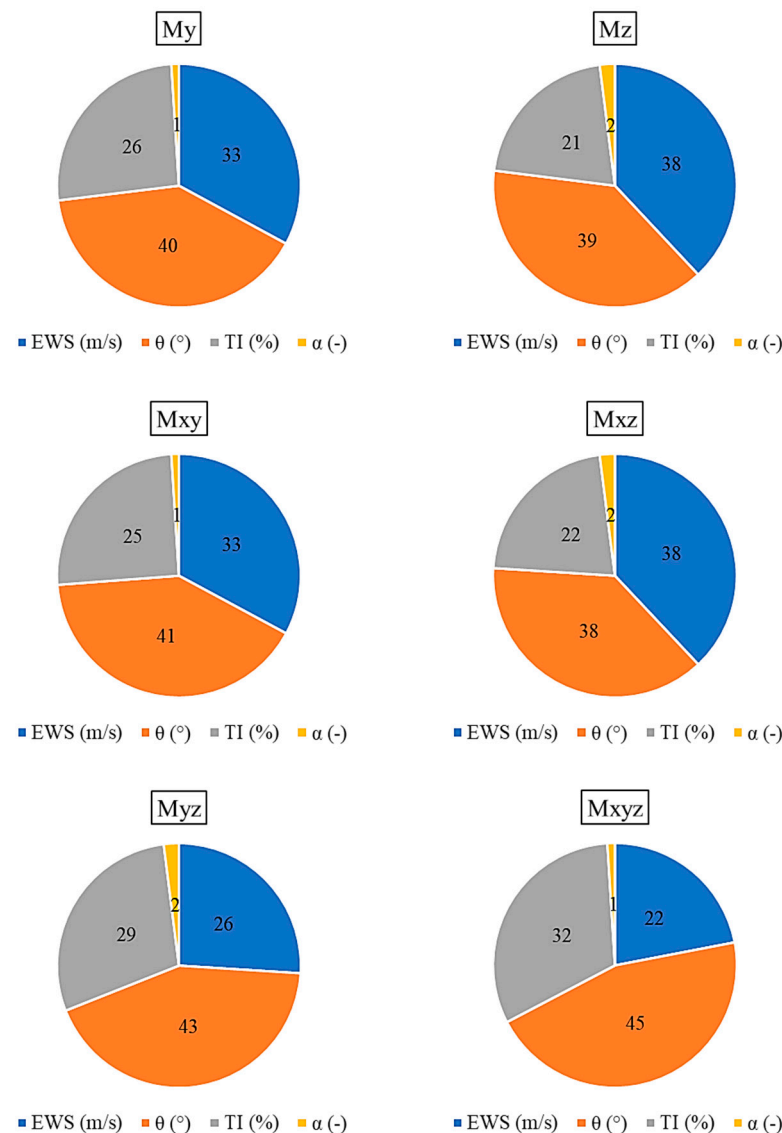


Figure 7. Importance of each variable in corresponding load equation (data in %).

1. First, the rotor-averaged inflow velocity experienced by the 15 MW turbine is smoothed due to its large rotor diameter (240 m), which inherently averages out the vertical shear distribution within the rotor swept area. Consequently, variations in α primarily redistribute local inflow angles along the blade span without significantly altering the net thrust or tower base bending moment.
2. Second, at hub height (150 m), the shear-induced differential loading contributes primarily to cyclic rather than mean load variations. The present study focused on steady-state structural moments (M_y , M_z , M_{xy} , etc.), which are dominated by mean aerodynamic and inertial loads that scale directly with EWS and TI . This explains why α shows weak statistical correlation with all six load components ($R^2 < 0.2$ in the variable-importance analysis) and why its inclusion only marginally modifies the regression coefficients in the MPR model.

That's why, within the present dataset ($\alpha = 0.10$ – 0.25), the shear exponent exerts a secondary effect as compared to turbulence and flow inclination.

Together, these observations confirm that the GBR feature importance results are physically consistent with aerodynamic theory-*EWS* dictates the energy input and torsional excitation magnitude, while θ determines the lateral bending orientation and distribution.

3.3.2. Accuracy Evaluation

Figure 8 presents the comparison between moments calculated by simulations and moments estimated by the proposed equations for six load components: M_y , M_z , M_{xy} , M_{xz} , M_{yz} , and M_{xyz} . The scatter plots are based on 2000 testing data points, where the x -axis represents the simulated moments and the y -axis represents the moments predicted by the proposed polynomial equations.

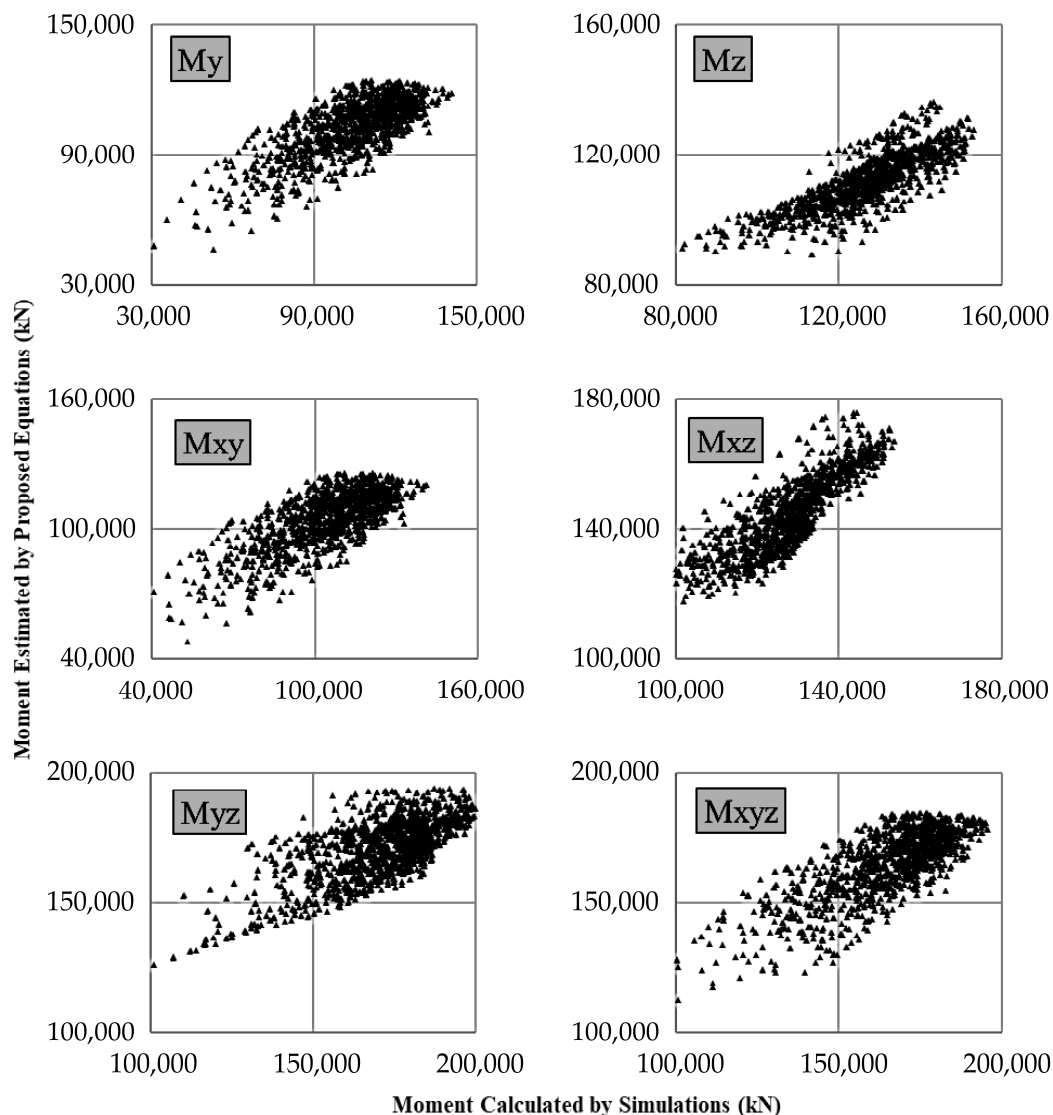


Figure 8. Moment comparison data plots (Note: results are based on 2000 testing data).

The data points in each plot generally align along the diagonal line, indicating good agreement between the simulated and estimated values. The most consistent alignment is observed for M_z and M_{xz} , showing that the proposed equations accurately capture the structural load behavior for these components. The dispersion of data points is slightly higher for M_y and M_{xy} , indicating minor deviations between estimated and simulated values, but still within an acceptable range.

The overall trend across all plots shows a positive correlation, confirming that the proposed equations reliably predict the structural loads. The dense clustering around

the diagonal line, particularly for M_{yz} and M_{xyz} , further validates the accuracy of the polynomial models developed in this study. These results demonstrate the effectiveness of the proposed generalized load estimation framework for the 15 MW offshore wind turbine.

Figure 9 shows the heatmaps comparing moments calculated by simulations and moments estimated by the proposed equations for six load components: M_y , M_z , M_{xy} , M_{xz} , M_{yz} , and M_{xyz} . The x -axis represents the simulated moments, and the y -axis shows the predicted moments, while the color gradient indicates the number of testing data points concentrated at each comparison point.

For most load components, the heatmaps exhibit a diagonal concentration of data points, indicating strong agreement between predicted and simulated values. The most concentrated and aligned regions are observed for M_z and M_{xz} , where the red clusters are positioned close to the diagonal, signifying high prediction accuracy. For M_y and M_{xy} , the data points are moderately dispersed, showing some variability between the estimated and simulated values. Similarly, M_{yz} and M_{xyz} exhibit a slight spread but still maintain a reasonable alignment along the diagonal.

The consistent diagonal patterns, especially for M_z and M_{xz} , confirm that the proposed equations are well-calibrated for predicting these moments. The presence of some scattered points in other load components suggests minor prediction errors, which are still within acceptable limits given the inherent variability of wind conditions. Overall, the heatmaps affirm that the proposed equations reliably estimate the structural moments, with particularly strong accuracy for torsional moments (M_z and M_{xz}), as evidenced by the concentrated diagonal patterns.

Figure 10 shows the ratio of predicted moment to simulated moment for six load components (M_y , M_z , M_{xy} , M_{xz} , M_{yz} , M_{xyz}) over 2000 testing data points. The y -axis represents the ratio between the predicted and simulated moments, while the x -axis shows the number of testing data. The ideal ratio of 1.0 is indicated by the red dashed line, while the actual ratio is plotted as a green line.

The average ratio values indicate that the proposed equations generally maintain high accuracy, with M_{yz} (1.007) and M_{xyz} (1.005) being closest to the ideal value, indicating minimal prediction errors. M_y (1.009) and M_{xy} (1.022) also demonstrate good accuracy but exhibit slightly higher variability, as reflected by their standard deviations of 0.136 and 0.139, respectively. The most noticeable deviation is observed for M_{xz} (1.139), with an average ratio indicating a slight overestimation of the predicted moment compared to simulations. Additionally, M_z (0.886) shows an underestimation trend, although its standard deviation is relatively low at 0.056.

The variability pattern is relatively consistent across all components, but the difference between the predicted and actual moments is more pronounced for M_{xz} . The low standard deviations for M_z (0.056) and M_{xz} (0.068) indicate that, despite the slight bias, the predictions remain relatively stable across the testing data. Overall, the plots demonstrate that the proposed equations provide reliable moment predictions, with slight overestimations for M_{xz} and minor underestimations for M_z . The accuracy and stability of predictions for other components are maintained within a reasonable range, validating the robustness of the developed polynomial models.

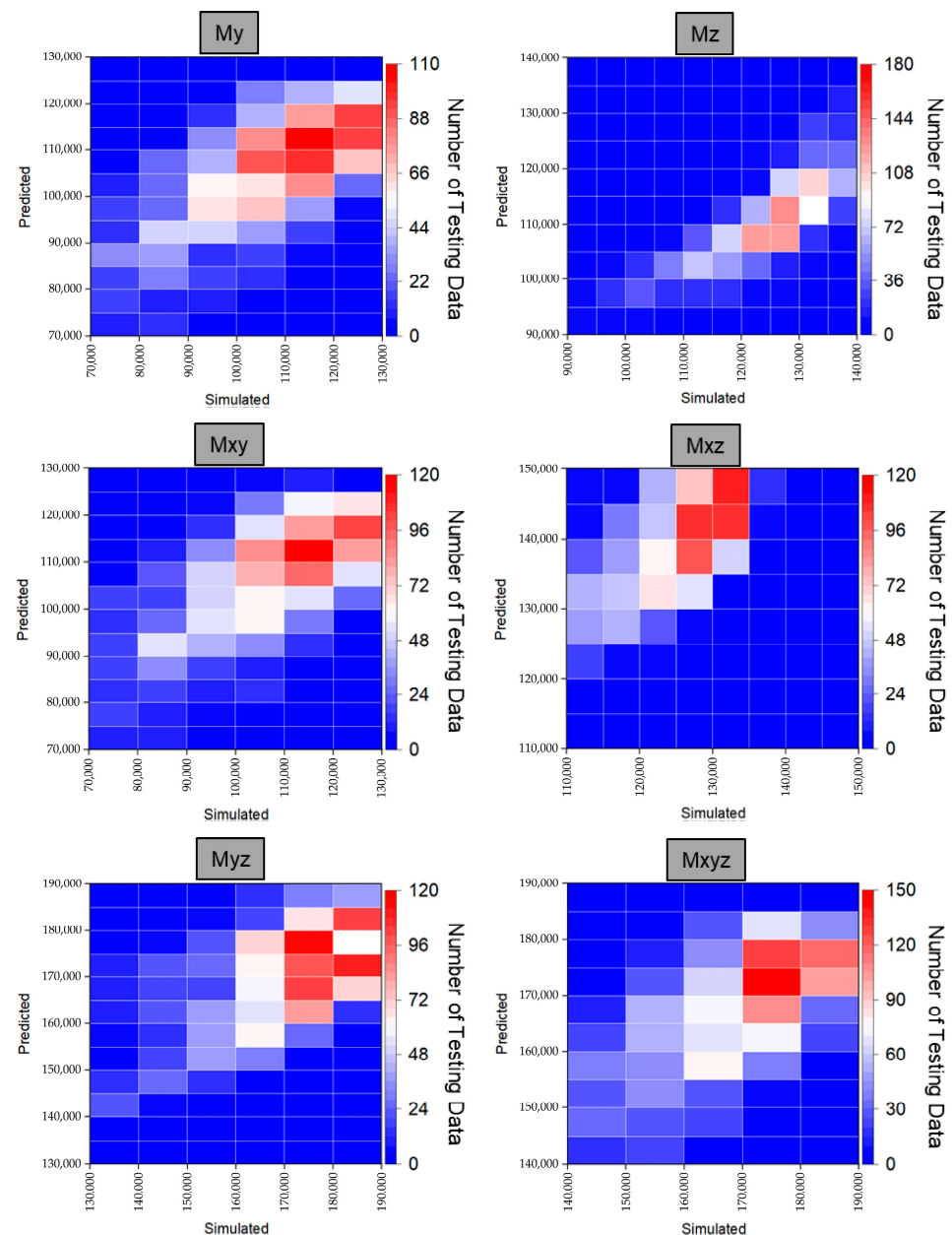


Figure 9. Moment comparison heatmaps (Note: results are based on 2000 testing data).

Figure 11 shows the relative error in the predicted moment compared to the simulated moment for six load components (M_y , M_z , M_{xy} , M_{xz} , M_{yz} , M_{xyz}) based on 2000 testing data points. The y-axis represents the relative error percentage, while the x-axis shows the number of testing data.

Among the load components, M_{yz} (5.97%) and M_{xyz} (5.76%) exhibit the lowest average relative error, indicating high prediction accuracy and consistency. The standard deviations for these components are also relatively low (5.05 and 4.85, respectively), confirming stable performance. M_y (10.22%) and M_{xy} (10.34%) show moderate average error values with higher variability, as indicated by their standard deviations of 9.11 and 9.60, respectively. This pattern suggests that while the predictions are generally accurate, they exhibit occasional larger deviations. M_z (11.71%) and M_{xz} (13.91%) display the highest average relative errors among the components, with standard deviations of 4.91 and 6.82, respectively. This result indicates that the torsional moments are more challenging to predict accurately, possibly due to the complex interactions between environmental variables.

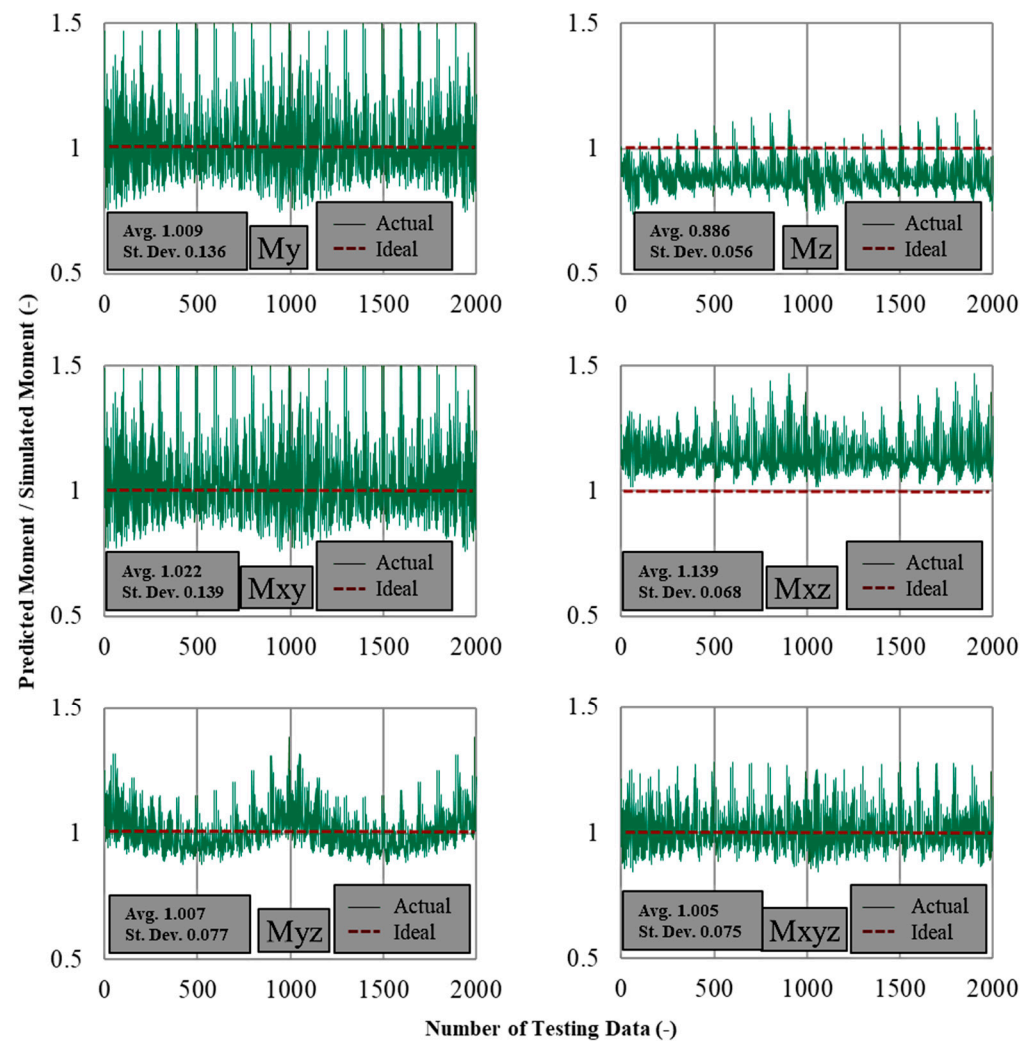


Figure 10. Ratio of predicted moment and simulated moment (Note: results are based on 2000 testing data).

The slightly higher prediction errors observed for torsional moments (M_z and M_{xz})—ranging between 11.71% and 13.91%—arise from the inherently nonlinear aerodynamic coupling between rotor yaw misalignment, wake rotation, and tower shadow effects. Torsional moments are primarily generated by azimuthal variations in blade loading, which depend on the instantaneous wind shear, turbulence intensity, and dynamic inflow across the rotor plane. These factors introduce unsteady aerodynamic torque fluctuations that are difficult to represent using low-order polynomial regression models. Moreover, torsional responses are highly sensitive to small perturbations in yaw error and flow inclination, producing non-symmetric aerodynamic loading distributions that cannot be fully linearized.

Overall, the figure demonstrates that the proposed polynomial equations predict M_{yz} and M_{xyz} moments with the least error, while M_{xz} shows relatively higher errors, suggesting that torsional load predictions might require further refinement. The stable and low error values for M_{yz} and M_{xyz} validate the robustness of the developed models for these load components.

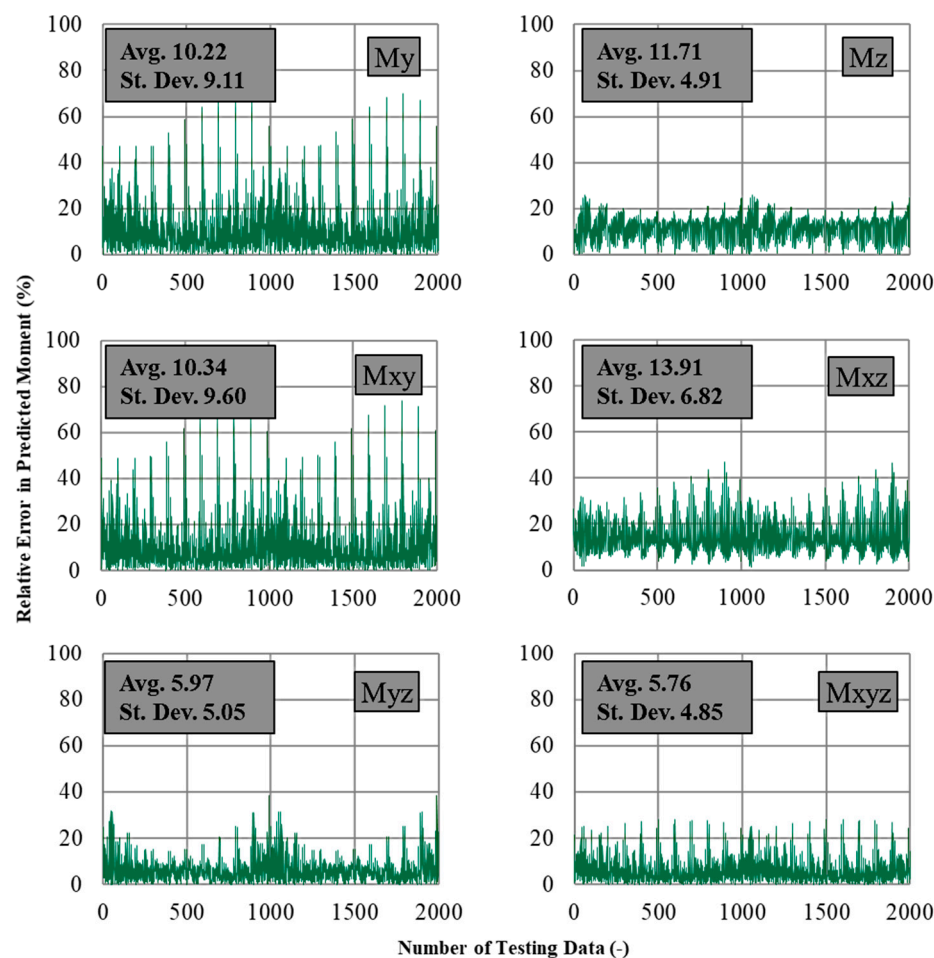


Figure 11. Relative error in predicted moment (Note: results are based on 2000 testing data).

Table 4 presents a summary of the accuracy evaluation using testing datasets for six load components: M_y , M_z , M_{xy} , M_{xz} , M_{yz} , and M_{xyz} . The table compares the average and median values of simulated and predicted moments, the average ratio of predicted to simulated moments, and the average absolute error in predicted moments.

Table 4. Summary of accuracy evaluation using testing datasets.

Parameter	Attribute	M_y	M_z	M_{xy}	M_{xz}	M_{yz}	M_{xyz}
Avg. moment (kN·m)	Simulated	103,410	126,561	103,604	126,724	170,477	164,132
	Predicted	102,642	111,692	104,131	143,866	170,706	164,057
Median (kN·m)	Simulated	106,467	128,166	106,624	128,369	174,012	167,969
	Predicted	105,373	111,644	106,802	143,122	172,390	166,740
Predicted moment/Simulated moment (-)	Avg.	1.009	0.886	1.022	1.139	1.007	1.005
Abs. error in predicted moment (%)	Avg.	10.220	11.719	10.342	13.911	5.972	5.765

The predicted moments closely match the simulated moments for most components, indicating the effectiveness of the proposed equations. The lowest average ratio of predicted to simulated moments is observed for M_z (0.886), indicating a slight underestimation, while the highest ratio is seen for M_{xz} (1.139), indicating a minor overestimation. The average ratios for other components remain close to 1.0, confirming the high accuracy of the prediction models.

The absolute error analysis shows that M_{xz} has the highest average error of 13.911%, reflecting the difficulty in accurately predicting torsional moments. In contrast, M_{yz} (5.972%) and M_{xyz} (5.765%) show the lowest average errors, indicating high prediction reliability for these moments. The error values for M_y (10.220%), M_z (11.719%), and M_{xy} (10.342%) are slightly higher but remain within a reasonable range for engineering applications.

The consistency between average and median values further supports the robustness of the proposed models, particularly for M_{yz} and M_{xyz} , where predicted and simulated moments align closely. The slightly higher error for M_{xz} suggests that predicting torsional loads remains a challenge, likely due to complex aerodynamic interactions.

It must be mentioned that the BLADED software was employed in this study as the primary numerical simulator to generate the structural load dataset for the 15 MW offshore wind turbine. The proposed polynomial regression framework is not intended to replace or outperform BLADED's aero-hydro-servo-elastic solver; rather, it functions as a meta-model (surrogate model) derived from the extensive BLADED simulation results.

This surrogate model enables engineers to estimate structural loads rapidly under varying environmental conditions without the need to rerun full-scale simulations each time. While BLADED provides the benchmark-accurate simulation results, the polynomial regression equations generalize these results into a simplified mathematical form that retains high fidelity ($R^2 > 0.92$ for all components) but requires only basic environmental inputs.

Hence, the two types of “simulations” in this study serve complementary purposes:

- **BLADED simulations:** generate physically accurate load data.
- **Proposed regression equations:** provide a fast analytical approximation for design and assessment once trained on the verified BLADED dataset.

This approach is widely adopted in wind-energy research for rapid design optimization and parametric sensitivity analyses where running thousands of full BLADED simulations is computationally expensive.

To evaluate the efficiency and reliability of the proposed Multivariable Polynomial Regression (MPR) framework, its performance was benchmarked against established AI-based predictive models, including Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Gradient Boosting Regression Trees (GBRT). As shown in Table 5, the proposed MPR model achieved the highest coefficient of determination ($R^2 = 0.993$) with a minimal training time of 19.7 s and inference time of 0.4 s, demonstrating outstanding computational efficiency.

Table 5. Accuracy comparison between present and other AI-based models.

Model	Max. R^2	Training Time (s)	Inference Time (s)	Remarks/Reference
MPR (Proposed)	0.993	19.7	0.4	Present model
CNN	0.973	183.2	6.8	[55]
LSTM	0.968	226.5	8.2	[56]
GBRT	0.977	92.4	1.5	[57]

In contrast, CNN and LSTM models, though capable of capturing nonlinear temporal-spatial patterns, required significantly longer training times (183.2 s and 226.5 s, respectively) due to their deep-layer architectures and backpropagation complexity. GBRT, a strong ensemble learning approach, achieved moderate performance ($R^2 = 0.977$) with a training time of 92.4 s, but its interpretability remained limited compared to MPR.

The superior performance of the proposed MPR model arises from its explicit physical coupling between environmental variables (EWS , TI , θ , α) and structural load responses, allowing it to capture nonlinear load behaviors without overfitting or requiring hyper-

parameter tuning. This makes the MPR framework particularly effective for rapid and interpretable structural load estimation in offshore wind turbine analyses.

3.4. Extension of the Proposed Framework Beyond Defined Variable Ranges

The current framework was developed and validated using 10,000 BLADED simulations within representative offshore environmental ranges (EWS : 30–40 m/s, TI : 12–16%, α : 0.1–0.3, θ : -8° – 8°), which encompass the IEC Class IA and IIA design envelopes typically encountered for multi-megawatt offshore turbines. However, to extend the framework toward extreme conditions (e.g., $EWS > 40$ m/s or $TI > 20\%$), the same polynomial regression methodology can be expanded through a two-stage approach:

1. Dataset Extension via High-Extreme Simulations:

Additional BLADED simulations can be conducted at higher EWS levels (up to 50–55 m/s) and broader turbulence ranges to retrain the regression model. Because the regression structure is polynomial, it is easily extendable once new training data are incorporated, ensuring smooth extrapolation continuity.

2. Adaptive Model Recalibration:

The existing model can be adaptively recalibrated using transfer-learning or piecewise polynomial fitting, in which new extreme-condition data are integrated while retaining the baseline polynomial coefficients for normal operating ranges. This approach maintains model consistency while extending prediction capability to ultra-high wind and combined extreme scenarios.

Thus, the framework can be progressively expanded for extreme loading conditions by systematically enlarging the dataset boundaries without altering the core regression architecture, preserving both computational efficiency and predictive stability.

3.5. Limitations of Proposed Prediction Framework

While the proposed load prediction framework for the 15 MW offshore wind turbine demonstrates high accuracy and reliability, several limitations should be acknowledged to ensure transparent interpretation of the results.

1. One significant limitation is related to the limited ranges of the environmental variables used in the model. The framework is based on Extreme Wind Speed (EWS) ranging from 30 to 40 m/s, Turbulence Intensity (TI) between 12% and 16%, Flow Inclination Angle (θ) between -8° and $+8^{\circ}$, and Shear Exponent (α) from 0.1 to 0.3. As a result, the proposed equations are optimized only within these specific ranges. Applying the model to conditions beyond these ranges may result in reduced accuracy or unreliable load predictions.
2. The framework's reliance on polynomial regression means that it captures non-linear relationships within the data to a certain extent but may fail to fully represent highly complex or chaotic behaviors that could arise under extreme or unexpected conditions. While higher polynomial degrees improve accuracy, they also increase model complexity, reducing practical utility and interpretability.

In summary, while the proposed framework effectively predicts structural loads under specified conditions, its applicability is limited by variable range constraints and potential model complexity. Addressing these limitations could further enhance the model's robustness and practical implementation.

4. Future Direction

The proposed load estimation framework for the 15 MW offshore wind turbine has demonstrated high accuracy within the specified environmental ranges. However, to

further enhance the robustness and practical applicability of the model, several future research directions are suggested (without or with applying FEA models [58]).

1. First, expanding the range of environmental variables, particularly extreme wind speed, turbulence intensity, flow inclination angle, and shear exponent, would improve the model's generalizability to various offshore wind sites. Incorporating data from different geographical locations and diverse operating conditions would enhance the model's adaptability.
2. Second, integrating real-time data acquisition and adaptive modeling techniques can make the framework more dynamic, allowing it to adjust to fluctuating environmental conditions. Employing machine learning algorithms, such as online learning models, could enable continuous updates and refinement of the prediction equations.
3. Additionally, further investigation into the accurate prediction of torsional moments (M_z and M_{xz}) is crucial, as current models show higher prediction errors for these components. Exploring alternative modeling techniques, such as hybrid machine learning approaches, may enhance accuracy, particularly under complex loading scenarios.
4. Lastly, conducting experimental validation using field data from operational offshore wind farms would strengthen the model's credibility. Combining numerical simulations with field measurements could provide a more comprehensive validation, ultimately increasing the confidence in practical applications.

By addressing these future directions, the proposed load prediction framework can become more versatile and resilient, ultimately contributing to the improved structural reliability and efficiency of offshore wind turbine support structures.

5. Conclusions

The proposed generalized structural load estimation framework for the 15 MW offshore wind turbine effectively predicts critical load components with high accuracy and reliability. The framework, developed using multivariable polynomial regression, demonstrated robust performance across various environmental conditions, including Extreme Wind Speed (30 to 40 m/s), Turbulence Intensity (12% to 16%), Flow Inclination Angle (-8° to $+8^\circ$), and Shear Exponent (0.1 to 0.3). The accuracy of the proposed equations is quantitatively validated using 2000 testing data points, where the coefficient of determination (R^2) values for all load components exceeded 0.92, indicating a high level of correlation between simulated and predicted loads. The lowest average absolute error was observed for M_{yz} (5.97%) and M_{xyz} (5.76%), reflecting the high reliability of the proposed equations for these moments. In contrast, M_{xz} exhibited a higher average error of 13.91%, suggesting that torsional moments are inherently more challenging to predict accurately.

The prediction accuracy is further demonstrated through the average ratio of predicted to simulated moments, where most load components exhibited ratios close to 1.0. Specifically, the average ratio for M_{xyz} was 1.005, while for M_{xz} , it was 1.139, indicating a slight overestimation. The proposed equations also maintained stability in error distribution, as demonstrated by the low standard deviation values, particularly for M_{xyz} (4.85) and M_{yz} (5.05). Heatmaps and scatter plots further confirmed that the majority of predicted values align closely with simulated ones, indicating minimal dispersion and high consistency.

This framework offers a practical and efficient tool for engineers and scientists working with offshore wind turbine support structures, particularly when estimating loads under varying wind conditions. The developed polynomial equations strike an optimal balance between complexity and accuracy, with polynomial degrees ranging from 2 to 4, minimizing computational demands while ensuring precise load estimation. The utility of the framework is evident in its ability to model non-linear interactions between wind

parameters and structural responses, making it highly applicable for structural analysis, load monitoring, and the design optimization of offshore wind turbine support structures. By providing accurate load predictions, the framework significantly aids in designing more reliable and efficient support structures, ultimately enhancing the operational safety and longevity of offshore wind energy systems.

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Abbreviations

OWT	Offshore Wind Turbine	M_x	Moment around x -axis
M_y	Moment around y -axis	M_z	Moment around z -axis
M_{xy}	Bending moment in x - y plane	M_{xz}	Bending moment in x - z plane
M_{yz}	Bending moment in y - z plane	M_{xyz}	Resultant moment in x - y - z space
EWS	Extreme Wind Speed	TI	Turbulence Intensity
α	Shear Exponent	θ	Flow Inclination Angle
R^2	Coefficient of Determination	RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error	GBR	Gradient Boosting Regression
AI	Artificial Intelligence	CNN	Convolutional Neural Network
MATLAB	Matrix Laboratory (software)	BLADED	Wind Turbine Simulation Software
LHS	Latin Hypercube Sampling		

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