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Research Article

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Load-measurement method for floating offshore wind turbines based on a LSTM neural network

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Abstract: Complicated loads encountered by floating offshore wind turbines (FOWTs) in real sea conditions are crucial for future optimization of design, but obtaining data on them directly poses a challenge. To address this issue, we applied machine learning techniques to obtain hydrodynamic and aerodynamic loads of FOWTs by measuring platform motion responses and wave-elevation sequences. First, a computational fluid dynamics (CFD) simulation model of the floating platform was established based on the dynamic fluid-body interaction technique and overset grid technology. Then, a long short-term memory (LSTM) neural network model was constructed and trained to learn the nonlinear relationship between the waves, platform-motion inputs, and hydrodynamic-load outputs. The optimal model was determined after analyzing the sensitivity of parameters such as sample characteristics, network layers, and neuron numbers. Subsequently, the effectiveness of the hydrodynamic load model was validated under different simulation conditions; aerodynamic load calculation was completed based on the D'Alembert principle. Finally, we built a hybrid scale FOWT model, based on the software in the loop strategy, in which the wind turbine was replaced by an actuation system. Model tests were carried out in a wave basin and the results demonstrated that the root mean square errors of the hydrodynamic and aerodynamic load measurements were 4.20% and 10.68%, respectively.

Key words: Floating offshore wind turbine; Long short-term memory neural network; Machine learning technique; Load measurement; Hybrid scaled model test

1 Introduction

As the world increasingly prioritizes renewable energy sources, wind energy has emerged as a prominent contender, offering a clean and sustainable alternative. Floating offshore wind turbines (FOWTs) represent an innovative technology in wind-energy utilization, and offer numerous advantages such as the ability to operate in deepwater regions, enhanced wind-energy harnessing potential, and minimal impact on marine ecosystems (Barooni et al., 2023). Consequently, they have become a focal point of research in the wind-energy industry. Unlike conventional fixed-base wind turbines, FOWTs encounter complicated load conditions in wind and wave environments (Micallef and Rezaeiha, 2021). Within a floating wind-turbine system, the rotor blades are subjected to aerodynamic loads induced by the wind, and the floating platform experiences hydrodynamic loads induced by waves and constraints from mooring line loads. Furthermore, platform motion in turn has complex coupled impacts on the load conditions of the FOWT (Yang et al., 2023). Such complicated and coupled loads present significant challenges for platform structural design and safety control. Therefore, obtaining real operational data on these aerodynamic and hydrodynamic loads is of paramount importance for structural health assessment and cost-effective design optimization (Li et al., 2020).

The substantial aerodynamic and hydrodynamic loads on FOWTs, in addition to their huge size, make it challenging to measure these loads directly using traditional methods such as strain gauges and load cells (Li et al., 2020). Subsequent maintenance is also extremely difficult. According to the author's under-

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standing, there is a scarcity of literature on direct load measurements for large wind turbines and platforms. In the absence of real load data, researchers predominantly rely on numerical model simulations to acquire load data for structural design. Presently, approaches for calculating aerodynamic loads based on blade-element momentum theory and calculation of hydrodynamic loads based on potential flow theory rely heavily on empirical formulas and hypotheses, leading to certain deficiencies in calculation accuracy (Feng et al., 2023). On the other hand, computational fluid dynamics (CFD) methods, which offer higher calculation accuracy, incur high time costs and are not suitable for real-time load-measurement or calculation. Consequently, there has been a growing focus on model-based indirect load-measurement methods. Pahn et al. (2017) developed the inverse load model of a 5MW fixed offshore wind turbine (OWT). The dynamic and static thrust measurements were achieved by measuring the tower's acceleration and strains. Maes et al. (2016) evaluated the tower load of a monopile OWT based on acceleration and stress signals and compared the effects of several filter algorithms. However, the influence of wind load was not taken into account. Song et al. (2022) used acceleration data and strain data to predict wind loads on the offshore FINO3 platform with an extended Kalman filter algorithm (though wave-load effects were neglected). Currently, the literature available regarding indirect load-measurement methods for FOWTs in wind and wave conditions remains sparse, as it involves highly complicated and nonlinearly coupled aero-hydrodynamic characteristics (Dai et al., 2018; Wen et al., 2018; Chen et al., 2021), making load identification through mathematical models difficult.

Machine learning is a powerful nonlinear modeling technique which has achieved significant success in various engineering fields. Consequently, many scientists have begun considering its application in the area of FOWTs. By learning from a large amount of real or high-fidelity data, artificial neural network models can better capture the complex relationship between marine environments and the loads or responses of FOWTs, thereby improving prediction accuracy and reliability. Noppe et al. (2018) developed a neural network model utilizing wind speed, rotor speed, and blade-pitch angle as inputs to predict the axial thrust of the turbine. The model achieved an average error of less than 15% compared to actual strain measurements. Jiang et al. (2019) employed an extensive set of simulation data to construct a neural network model, outputting thrust based on wind speed, platform heave, and pitch-motion inputs. The study findings showed that the calculated thrust closely matched the reference, indicating a high level of consistency. Chen et al. (2021) proposed a SADA method based on artificial intelligence technology to predict the dynamic response of the Hywind floating wind turbine. This method intelligently and dynamically adjusted the numerical FOWT model by integrating measured ocean environmental data (wind and wave) and platform motion data, leading to more accurate load calculation and tower-deformation prediction. Wang et al. (2022) created a multi-layer perceptron neural network model that utilized the tower's acceleration and platform motion responses to predict the tower root loads; the root mean square error was approximately 5.4%. Ma et al. (2023) employed a long short-term memory (LSTM) neural network model to predict the mooring-line tension of a floating production, storage, and offloading unit (FPSO) and investigated the impact of factors such as time windows, grid layers, and neuron numbers on the model's accuracy. Yang et al. (2023) trained a reservoir computing (RC) machine learning model using platform-motion data from experimental results, and demonstrated its efficacy in predicting platform heave, sway, and pitch motion. Li et al. (2019) devised a neural network model with two perceptron layers, utilizing wave-height data to forecast the vertical load of a wave-energy buoy device, with a curve fitting degree of 84.84%. This prediction result was subsequently applied for wave-energy control, yielding favorable control outcomes.

Currently, big-data training for aerodynamic loads relies on accurate wind-speed-distribution information within the rotor plane as well as operational data on the turbine (such as rotor speed and blade-pitch angle). In practical applications, measuring the entire plane's wind-speed field can be quite challenging, as it requires extremely reliable radar devices. Moreover, the sampling frequency of the wind turbine's operational data is typically too low (e.g. the SCADA system's sampling frequency of 1 Hz) to meet the requirements for high-frequency

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aerodynamic load calculation (Noppe et al., 2018). Therefore, directly training aerodynamic load models often leads to computational accuracy issues. Although there is considerable research on predicting the dynamic response of floating platforms, a machine learning modeling for hydrodynamic loads on floating offshore wind platforms is still in the exploratory stage. Due to the fluid memory effect, a moving floating wind turbine platform experiences radiation damping forces, which are determined by past platform motion (Roddier et al., 2010). Traditional simple multi-layer perceptron models often struggle to capture such load characteristics with historical memory effects. However, these load characteristics precisely align with the features of the LSTM neural network. Therefore, this paper introduces a novel method for measuring aerodynamic and hydrodynamic loads based on an LSTM neural network model. Initially, the LSTM hydrodynamic load model, with platform motion and wave states as input and hydrodynamic load as output, was trained on high-fidelity data from CFD simulation results. Then, the aerodynamic load on the wind turbine was computed with the D'Alembert principle. This approach circumvented the traditional challenges of directly measuring aerodynamic loads or training aerodynamic-load neural network models.

The content of this study is as follows: section 1 introduces the current status of load-measurement techniques, section 2 describes the load-measurement model, section 3 details the establishment of the LSTM hydrodynamic load model, section 4 covers the operational analysis of the load-measurement model, section 5 discusses the application of the load-measurement method in the scaled model tests, and section 6 provides a summary of this study.

2 Load-measurement model

2.1 Load-measurement method

In the complex marine environment, FOWTs are subject to the combined excitation of wind and wave loads, which mutually influence each other. Constrained by the mooring system, the platform encounters motion with six degrees of freedom (DOFs). Assuming that the FOWT is a rigid body, according to the D'Alembert principle, the dynamic equilibrium relationship can be expressed as follows:

$$\boldsymbol{F}_{\text{Aero}} + \boldsymbol{F}_{\text{Hydro}} + \boldsymbol{F}_{\text{Moor}} + \boldsymbol{F}_{\text{Inertia}} = 0 \tag{1}$$

The aerodynamic load $\boldsymbol{F}_{\text{Aero}}$ and hydrodynamic load $\boldsymbol{F}_{\text{Hydro}}$ can be regarded as the system's active forces, while the mooring load $\boldsymbol{F}_{\text{Moor}}$ can be seen as the system's constraint force, and $\boldsymbol{F}_{\text{Inertia}}$ represents the inertial force opposite to acceleration. At any given moment of rigid-body motion, the active force, constraint force, and inertial force constitute a balanced force system. The inertial force of the system can be directly calculated from the acceleration signal, and the mooring constraint force can be directly measured by load sensors or indirectly calculated from the platform-motion signals (Ren et al., 2022). Then, the remaining aerodynamic load and hydrodynamic load form a complementary relationship, so that knowing one leads to knowledge of the other.

We propose the novel load-measurement method shown in Fig. 1 to achieve sequential calculation of hydrodynamic and aerodynamic loads. A well-trained neural network model is applied to calculate the platform's hydrodynamic load based on the platform-motion and wave-elevation signals in the sensor system. Simultaneously, the mooring-line loads and inertial loads can be measured or calculated based on the load cells and acceleration signals. Finally, the aerodynamic load is calculated through the D'Alembert principle.

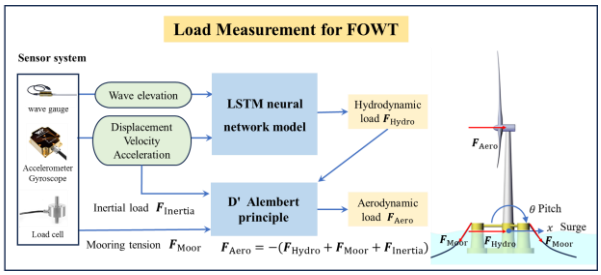

Fig. 1 Illustration of the load measurement.

The hydrodynamic load can be obtained by integrating the hydrodynamic pressure on the platform. One can conclude easily that the hydrodynamic loads are closely related to the platform's geometry, wave conditions, and platform-motion states. Therefore, when constructing a neural network hydrodynamic load model with a known geometric shape, platform motion and wave conditions serve as model inputs. In

this study, we primarily considered the case in which wind and waves align consistently and maintain a constant direction. Furthermore, only the surge and pitch DOFs were taken into account. Thus, the wave conditions could be directly described by the wave elevation collected by a wave gauge in front of the platform, and the platform motion states could be described by the surge and pitch displacement, velocity, and acceleration signals collected by kinematic measurement systems such as DGPS, a real-time kinematic (RTK) system, and inertial navigation systems (INSs). The model output was the hydrodynamic load aligned with the wave-propagation direction (i.e., the total force in the X direction).

As one of the hydrodynamic load components, the radiation damping force is caused by the memory effect of the fluid and is obtained through the convolution calculation of the past platform motion. In other words, the radiation damping force at a given moment is determined by the platform motion at every past moment, with the influence of motion from more distant moments diminishing over time. Such characteristics of load data precisely align with the features of LSTM neural network models, which effectively remember and select past information.

2.2 Structure of the LSTM model

The LSTM neural network is a variant of recurrent neural networks (RNNs) and is widely used for processing and predicting time-series data such as text, audio, and video. Compared to traditional RNNs, the LSTM is designed with a special gating mechanism to address issues such as long-term dependencies, gradient explosion, and gradient vanishing (Wang et al., 2022). These gating mechanisms enable LSTM to selectively remember or forget some information while maintaining and propagating important information over long periods. By learning the weights and biases of these gating mechanisms, LSTM can capture long-term dependencies within the data. The internal structure of a LSTM cell is illustrated in Fig. 2. The cell state c(t) acts as a conveyor belt, transmitting information throughout the time-sequence process and allowing the addition or removal of information through input and forget gates. The output h(t) is determined by the output gate and cell state. The relevant data-transmission equations for the LSTM neural network are detailed in the ESM.

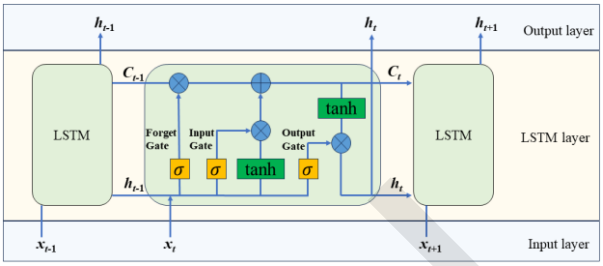

Fig. 2 The structure of a LSTM cell.

2.3 Model calculation process

In this study, we developed a sequence-to-sequence LSTM model to predict the hydrodynamic load. The model inputs were wave elevation, acceleration, speed, and displacement of platform surge and pitch (sensitivity analysis of input dimensions will be discussed later). The process is illustrated in Fig. 3.

(1) Sample data preparation. To accurately reflect the relationship between inputs and outputs, an elaborated CFD simulation model of the floating platform was created in STAR-CCM, and platform motion, wave elevation, and platform hydrodynamic loads under various conditions were extracted.

(2) Sample data preprocessing. Data normalization was performed to address the significant differences in magnitude between input and output data.

(3) Model creation and training. An appropriate model was constructed based on the characteristics of the sample data, with initial parameters chosen from experience. Then, the model was trained iteratively until the best model parameters were determined.

(4) Target load calculation: The trained LSTM model was employed to calculate the hydrodynamic load based on ‘measured’ input data. Then, the aerodynamic load calculation was conducted.

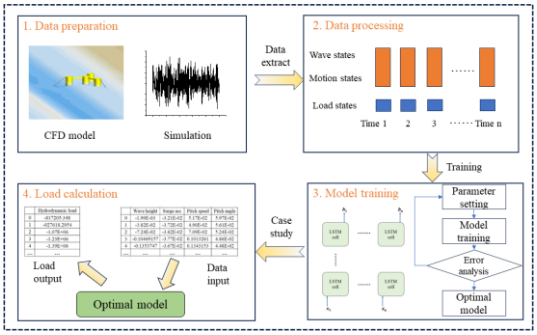

Fig. 3 The process of load-model calculation.

3 LSTM model construction

3.1 Data preparation

Currently, the majority of research on the hydrodynamics of floating offshore wind platforms relies on either the Morison formula (based on the empirical coefficients) or potential flow theory analysis methods (based on the inviscid assumption) (Liu et al., 2016). In contrast, the CFD method offers the advantage of considering fluid viscosity and all nonlinear physical effects, accurately describing the hydrodynamic loads, and effectively simulating the dynamic behavior of the floating platform under real sea conditions (Ciuriuc et al., 2022). Therefore, we employed STAR-CCM+ software to conduct the CFD simulation analysis and obtain accurate sample data.

3.1.1 Geometry model

The subject in this study was a 10-MW floating wind turbine system, consisting of the wind turbine, floating platform, and mooring system. As the training sample data only focused on waves, platform motion, and platform hydrodynamic loads, only the floating platform and mooring system were considered in the CFD model in order to reduce simulation complexity. The influence of the wind turbine was substituted by prescribed aerodynamic loads on the tower top. Even so, the parameters for the simulation model, such as mass, center of mass, and moments of inertia, were set to be the same as those of the whole system. The floating platform is depicted in Fig. 4. A detailed description can be found in the ESM.

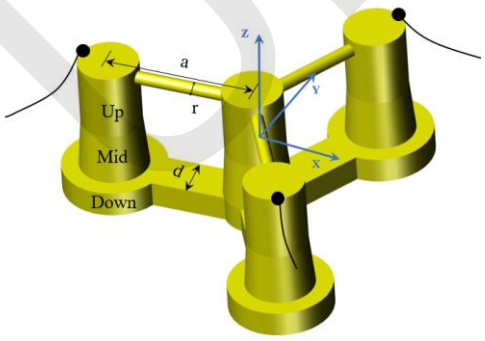

Fig. 4 The ZJUS10 semi-submersible floating platform.

3.1.2 CFD model

We constructed a numerical CFD model of the floating platform in STAR-CCM+. Dynamic fluid body interaction (DFBI) technology was adopted for fluid-field simulation under platform motion, as shown in Fig. 5. We applied the k-ω SST turbulence model to close the RANS equations, and established the volume of fluid (VOF) model to capture the motion of the free surface. The piecewise extrapolating method (PEM) was applied to calculate the tensions of the three elastic, quasi-stationary catenaries, which were modeled by the catenary coupling element technique. In addition, we applied aerodynamic loads, precalculated by OpenFAST software, at the virtual hub position through the user-defined function. Under the excitation of aerodynamics load, hydrodynamic load, and mooring-line load, the platform motion was calculated by the 6 DOF solver using the Runge-Kutta method.

The entire fluid domain consisted of a background domain that described the wave motion and a motion domain that described the floating-platform motion. The data interaction between the two domains was achieved through overset grid technology, which is particularly suitable for complex motion. The background domain spanned a rectangular prism measuring 1500×1000×500 meters, while the motion domain covered a rectangular prism measuring 200×200×100 meters. The inlet boundary, upper boundary, and bottom boundary of the background domain were all set as velocity inlets, while the two sides of the background domain were set as symmetric planes and the outlet was set as a pressure-outlet boundary. Additionally, a damping zone spanning two wavelengths was created at the outlet boundary to dissipate wave kinetic energy and minimize wave reflection. Fig. 6 shows the wave elevation at two different locations, where x1 represents the wave zone in front of the platform and x2 represents the damping zone far behind the platform. It was evident that the VOF model accurately reproduced wave results compared to theoretical values, and the damping zones effectively mitigated wave-particle motion. The validation of the mesh convergence and time-step convergence can be found in the ESM.

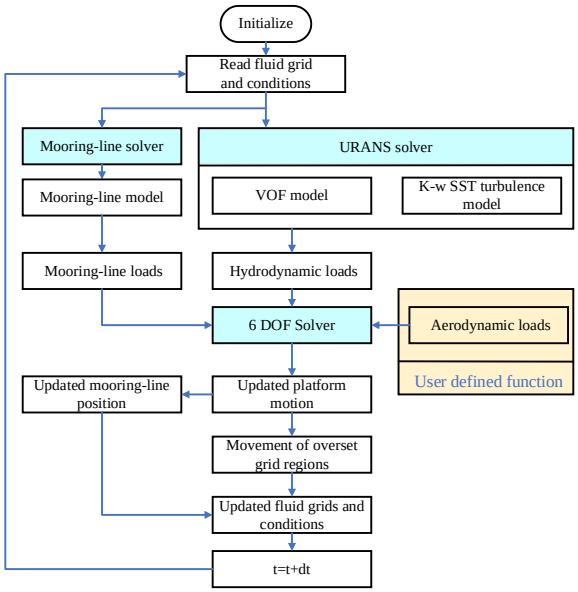

Fig. 5 The DFBI calculation process.

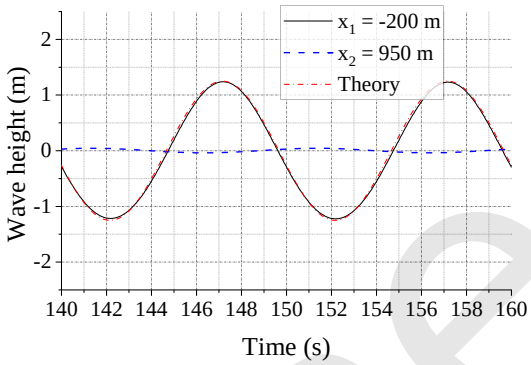

Fig. 6 The verification of the VOF model.

3.1.3 Simulation analysis

The simulation results for the hydrodynamic load along the X-axis direction in four different cases are plotted in Fig. 7. The dashed black line represents the hydrodynamic load of a fixed platform with a regular wave with a height of 2.5 m and a period of 8.5 s, which exhibits a sinusoidal periodic variation. The solid black line indicates the load of a floating platform under the same wave conditions, showcasing a noticeable reduction in amplitude which we attribute to platform motion. The red line signifies the hydrodynamic load of the floating platform when subjected to both regular waves and wind loads. A comparison reveals that the presence of aerodynamic loads alters the periodic variation of hydrodynamic loads because it shifts the platform's equilibrium position, thereby altering the system's stiffness characteristics and the underwater platform shape. The blue line represents the hydrodynamic load of the floating platform with an extremely irregular wave that has a significant height of 10.6 m and a peak period of 16 s; it demonstrates a substantial increase in amplitude variation. In summary, platform hydrodynamic loads are closely related to the wave conditions and platform motion, as mentioned before. Fig. 8 illustrates the distribution of the free surface in the case of irregular waves, and clearly shows the diffraction phenomenon that occurs as waves pass the platform. Additionally, due to fluid viscosity, a small amount of fluid adheres to the platform surface. These phenomena are difficult to produce using traditional hydrodynamic calculation methods.

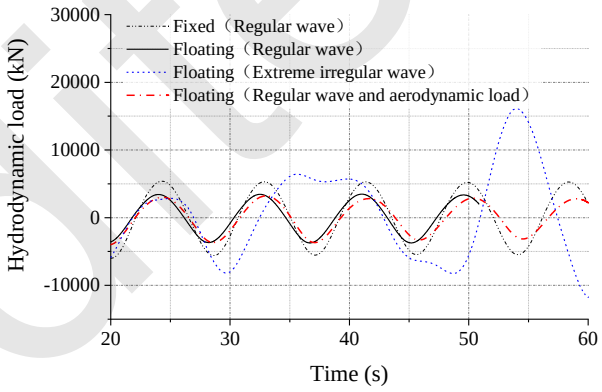

Fig. 7 Hydrodynamic load results for four cases.

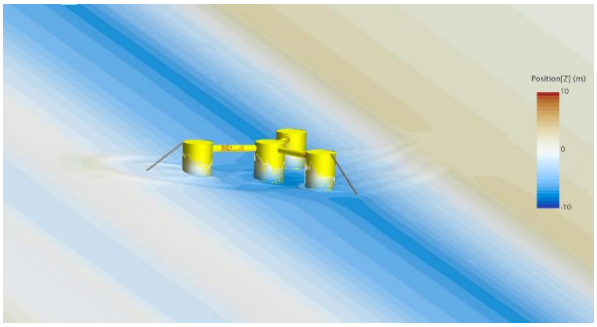

Fig. 8 Wave elevation near the platform.

3.2 Data processing

The data on platform motion, wave height, and hydrodynamic load are different in units and orders of magnitude. In order to ensure the accuracy and stability of the training process, the training data was preprocessed by regularization. We set the maximum and minimum values in the sample data as the upper and lower limits of the interval [0,1] respectively,

and the processing formula is as follows:

$$x_{\mathrm{p}} = (x - x_{\min}) / (x_{\max} - x_{\min}) \tag{2}$$

where x represents the original sample data, $x_{\min}$ and $x_{\max}$ represent the maximum and minimum values in the sample data, and x_{p} represents the normalized data. This operation ensured that each sample datum fell within the unit range and that there were no negative values. Correspondingly, after training the model to generate the output, a denormalization process was required for the data.

During the model training process, various statistical parameters were employed to evaluate learning performance. For a neural network model, the average value error E_{mean}, extreme value error $E_{\max}$, curve-fitting degree R_{fit} and root mean square error E_{rmse} are usually adopted. The detailed expression can be found in the ESM.

3.3 Determination of the optimal model

During the construction of the LSTM neural network model, it was important to avoid unreasonable model design, as this can lead to increased training time and poor fitting results. Neural network models typically have certain design spaces that allow for achieving the best fitting effect on the sample data by selecting appropriate model parameters. In this study, we determined the optimal model using the control variable method, in which each parameter of the model was adjusted individually while other parameters remained the same. The optimal model was considered to be reached when the error became stable without further reduction. Fig. 9 shows the determination process of the optimal model, which involved conducting sensitivity analyses on sample characteristics, model structure parameters, and training parameters in turn. The sample data used for training were generated from simulation results under a set of irregular sea conditions. The simulation time duration was one hour, with 90% used for training and 10% used for verification. The initial model parameters were 2 LSTM layers and 64 neurons in each layer. The configuration of the workstation used for training the LSTM model is given in Table 1 and the detailed determination process can be found in the ESM.

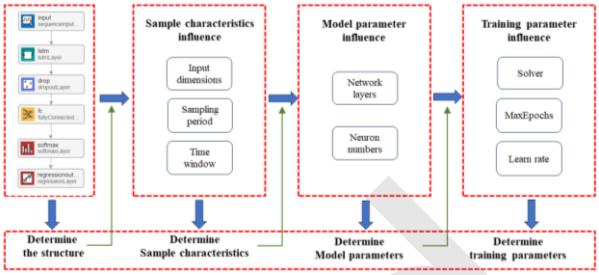

Fig. 9 Determination process of the optimal model.

Table 1 Configuration of the workstation.

Configuration	Parameter
CPU	Intel Xeon E5–2678
GPU	NVIDIA GeForce RTX 2060
RAM	256 G
Parallel logic processor	64

4 Simulation verification

After identifying the optimal LSTM model, we further validated the effectiveness of the hydrodynamic load model in several simulated cases. The verification processes were divided into two parts: verification in identical cases and verification in different cases. ‘Identical cases verification’ means that the training and verification data sets were all from simulation results obtained under the same sea-state conditions but at different time points. ‘Different cases verification’ refers to training and verification data sets from simulation results obtained under different sea-state conditions. After this stage, we carried out special-case and aerodynamic verification.

To accurately capture the internal relationship between wave elevation, platform motion state, and hydrodynamic load, we considered a variety of simulation cases based on the real sea conditions in the Gulf of Maine (Pegalajar-Jurado et al., 2018). These cases encompassed four wind conditions (low wind speed, rated wind speed, high wind speed, and extreme wind speed) and sixteen irregular wave conditions, defined based on the significant wave height and peak period. Detailed simulation cases and the special cases verification can be found in the ESM.

4.1 Identical cases verification

Under the same environmental conditions, sample data often exhibits a strong correlation. To

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validate the model, we carried out verifications for four designed cases which were most likely to represent the real operating sea state. Fig. 10 illustrates the model calculation results (red line) alongside ideal reference results (blue line), and the calculation errors are summarized in Table 2. It can be observed that the calculation curves closely align with the reference curves, with all curve fitting degrees exceeding 94%. Of the four cases, the calculation result for case 64 demonstrated the highest fitting degree (98.43%) and the smallest E_{rmse} (0.83%). In contrast, the prediction performance for case 22 was poorer, with the E_{rmse} exceeding 3%. This discrepancy arose from the influence of aerodynamic load. The aerodynamic load reached the maximum in case 22, but dropped to near zero in extreme sea-state case 64. In the absence of aerodynamic loads, the hydrodynamic loads were solely determined by the wave height, as the platform motion was also determined by the wave. Therefore, the reason for the inferior calculation results in case 22 compared to case 64 was the neglect of certain motion states mentioned previously. Even so, the model's accuracy remained acceptable.

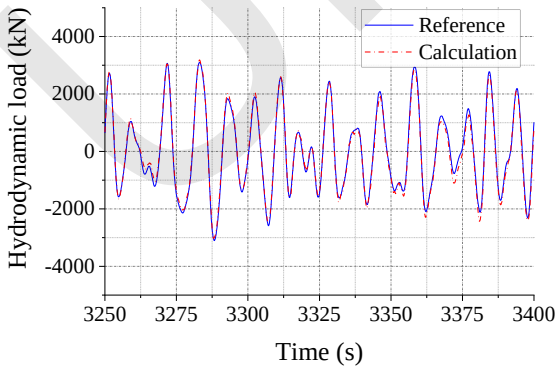
Table 2 Model performance for identical cases verification

Case	E_{mean}	E_{max}	R_{fit}	E_{rmse}
1	0.74%	3.03%	95.41%	2.71%
22	1.51%	4.77%	94.29%	3.10%
43	0.72%	3.10%	95.30%	2.54%
64	0.10%	1.51%	98.43%	0.83%

4.2 Different cases verification

In order to assess the adaptability of the LSTM model across various operating conditions, we conducted a comprehensive analysis of model performance considering three environmental variables: wave height, period, and wind speed, as shown in Table 3. Validation under different operating conditions was categorized into two groups: a partially different group and completely different group. 'Partially different group' refers to situations where the training and testing sets differed in one environmental variable while the others remained the same. 'Completely different group' indicates that all environmental variables were entirely distinct.

All operating-condition data had a duration of one hour. The comparison between the calculated and reference hydrodynamic loads is plotted in Fig. 11, and the model calculation error is summarized in Table 4. Two curves exhibited good consistency, with all curve fitting degrees exceeding 93% and root mean square errors below 4%. However, these results were slightly inferior to those obtained in the identical cases verification. Of the three variables, the model exhibited the best adaptation to wind speed, as this variable indirectly influenced hydrodynamic load through platform motion. In case 68, the model calculation accuracy was overall better than in case 65 and case 66, as there were more training samples; but lower than in case 67, which involved more environmental variables. Overall, the model demonstrated the ability to adapt to different environmental conditions.



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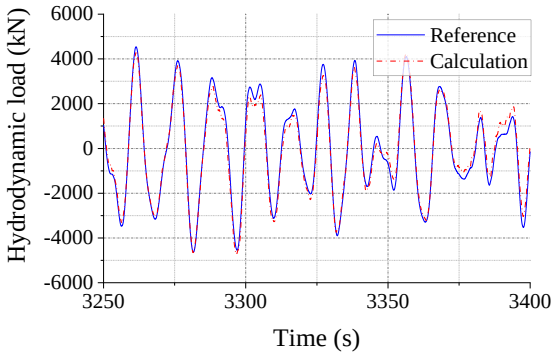

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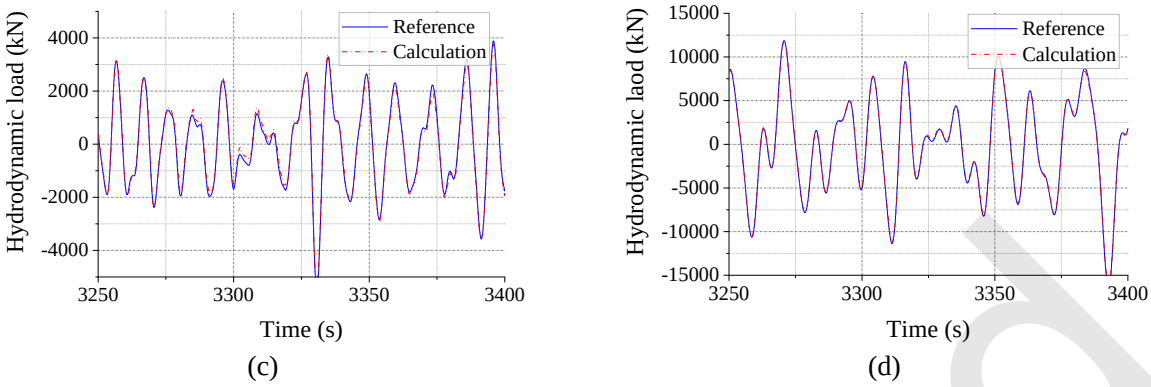

Fig. 10 Model verification for identical cases: (a) case 1; (b) case 22; (c) case 43; (d) case 64.

Table 3 Verification cases.

Verification type	Training cases	Test case	Test conditions		
			Wave height	Wave period	Wind speed
Different wave height	18, 22, 26, 30	65	3.04 m	8.5 s	11.4 m/s
Different wave period	21, 22, 23, 24	66	2.5 m	9.5 s	11.4 m/s
Different wind speed	2, 18, 34, 50	67	2.5 m	8.5 s	13.9 m/s
Fully different	1~64	68	3.04 m	9.5 s	13.9 m/s

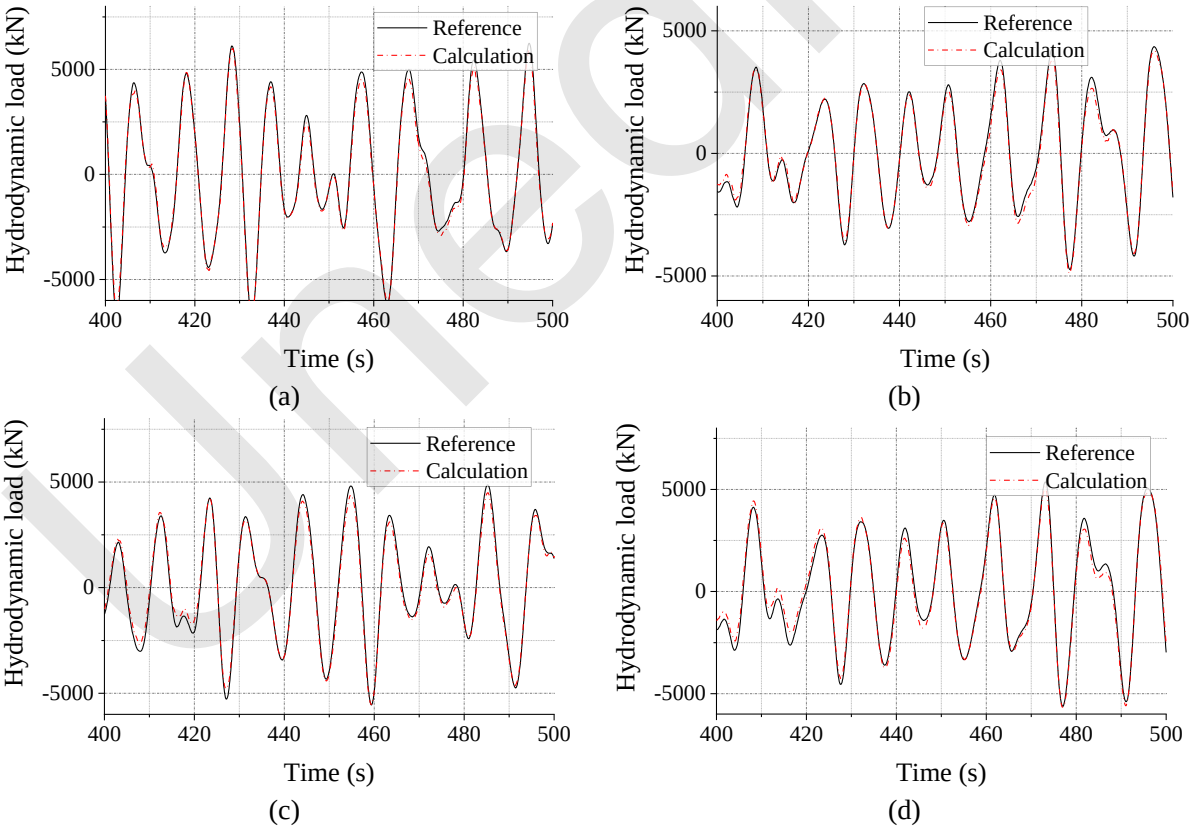

Fig. 1 Model verification in different cases: (a) different wave height; (b) different wave period; (c) different wind speed; (d) completely different

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Table 4 Model performance in different cases verification

Verification case	E_{mean}	E_{max}	R_{fit}	E_{rmse}
65	3.63%	5.56%	93.29%	3.91%
66	3.53%	6.19%	93.11%	3.85%
67	0.88%	1.60%	96.98%	1.67%
68	2.53%	4.89%	94.95%	2.95%

4.3 Aerodynamic verification

Once the hydrodynamic load calculation was completed, the axial aerodynamic load could be obtained using formula (3), which is as follows:

$$F_{aero}^{x} = M\ddot{x} - F_{hydro}^{x} - \sum T\cos(\alpha)\cos(\beta) \qquad (3)$$

where M is the mass of the FOWT, $\ddot{x}$ is the platform-acceleration signal, F_{hydro}^{x} represents the axial hydrodynamic load calculated by the LSTM model, T signifies the mooring-line tension, and α and β indicate the azimuth and inclination angle of the mooring line. Based on the hydrodynamic load calculation result for case 68, the aerodynamic load calculated by the proposed method is depicted in Fig. 12, and the aerodynamic load calculation errors are recorded in Table 5. It is obvious that the variation frequency of aerodynamic load was higher than that of hydrodynamic load. The average error was 1.96%, the curve fitting degree was 93.35%, and the root mean square error was 3.43%, validating the effectiveness of the proposed load-measurement method to a considerable extent. For the simulation verification, the calculation error for aerodynamic loads primarily stemmed from the calculation error for hydrodynamic loads.

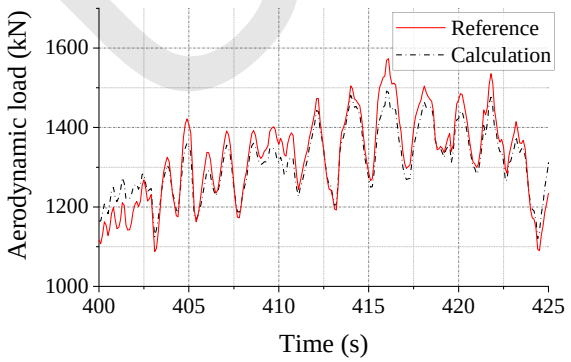

Fig. 12 Aerodynamic-load calculation results.

Table 5 Model performance for aerodynamic verification.

E_{mean}	E_{max}	R_{fit}	E_{rmse}
1.96%	2.15%	93.35%	3.43%

3 Experimental verification

To further evaluate the validity of the proposed load-measurement method, we constructed a scale model of the 10 MW FOWT, and carried out two model tests in the wave basin at Zhoushan Campus of Zhejiang University.

5.1 Experimental setup

5.1.1 Experimental scheme

Froude number similarity was adopted to ensure the similarity of hydrodynamic characteristics. In order to overcome the aerodynamic similarity problem induced by the reduced Reynolds number, we propose a hybrid model strategy, as illustrated in Fig. 13. The physical wind turbine is replaced by the actuation system, whose goal is to generate the real-time aerodynamic loads calculated by the numerical software OpenFAST. For a more comprehensive understanding of the hybrid model, one can read our previous publication (Feng et al., 2023).

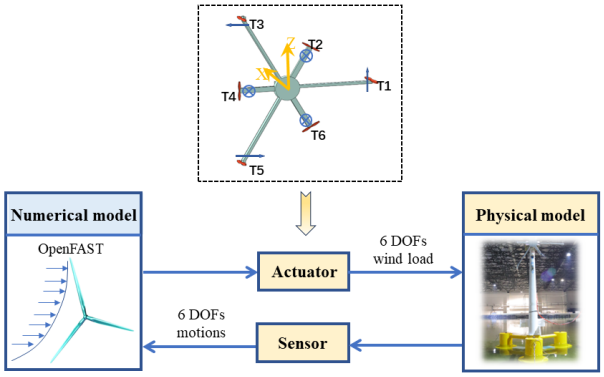

Fig. 13 Illustration of the hybrid model.

5.1.2 Hybrid scale model

Fig. 14 shows the 1:50 scale model of the 10 MW FOWT, comprising the actuation system, tower, platform, and mooring lines. Ballast water was distributed inside the platform to ensure a designed draft depth. The sensor system mainly consisted of the environmental state measurement system (a wave-height meter); the load-measurement system, including a tower-top thrust cell and mooring-line

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tension cells; and the platform-motion measurement system, including an accelerometer and attitude sensors. All sensors were connected to the host computer with the CAN communication protocol.

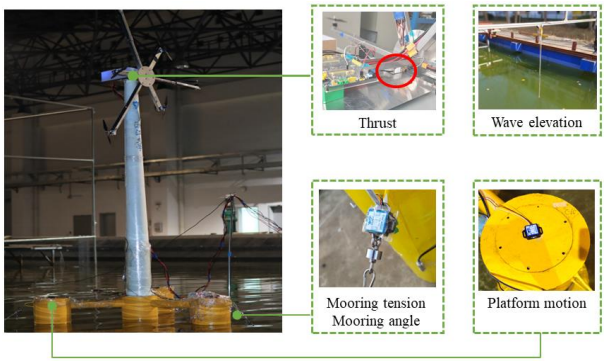


Fig. 14 Scale model and sensors.

5.2 Results

Two experimental cases were considered in model testing to verify performance of the load-measurement model under steady and unsteady conditions, as shown in Table 6. Exp 1, which represents a steady case with uniform wind and regular waves, was mainly used to train the LSTM model and validate the hydrodynamic calculation. Exp 2, which represents an unsteady case with turbulent wind and irregular waves, was mainly used to validate the aerodynamic calculation. One should keep in mind that the LSTM model was trained by the model test data in consideration of differences between the simulation model and experimental model.

Table 6 Environmental conditions of the experimental cases.

Cases	Environmental type	Wind speed (m/s)	Wave height (m)	Wave period (s)
Exp 1	Steady	11.4	2.5	8.5
Exp 2	Unsteady	11.4	2.5	8.5

The load histories of the inertial load, constraint load, aerodynamic load, and hydrodynamic load in Exp 1 can be found in the ESM. Figs. 15 and16 show the wave height and platform motion. The platform oscillates around the equilibrium position, which is dominated by the wind load. The acceleration signal represents the values in the inertial coordinate system, obtained through coordinate transformation from the original body-fixed acceleration data. Fig. 17a shows the hydrodynamic load calculation results of the LSTM neural network model after training on experimental data. The calculation curve maintained good consistency with the reference one, with a curve-fitting degree of 95.57%. Fig. 17b shows the scatter diagram of the two loads. In general, the two lines are close enough to demonstrate good load-measurement accuracy. The root mean square error of the load calculation results was 2.54%.

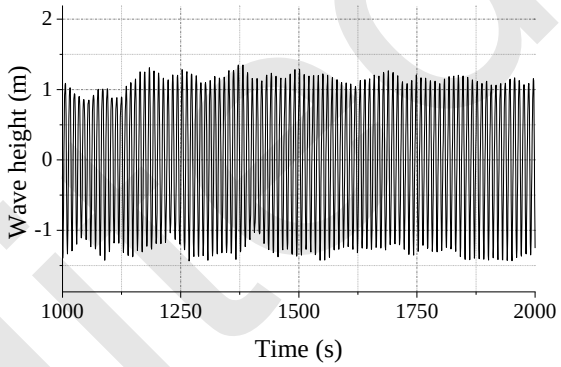


Fig. 15 Wave height sequences.

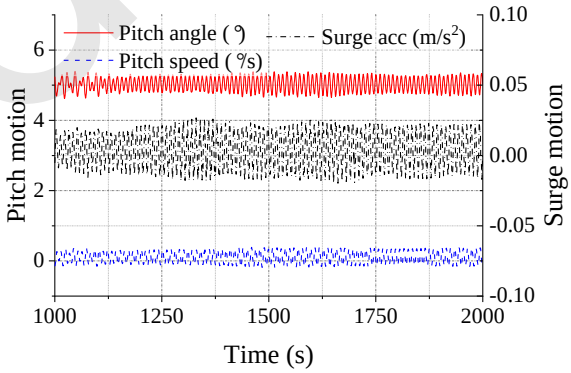
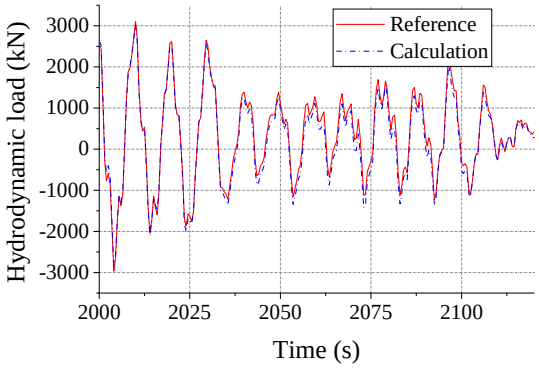
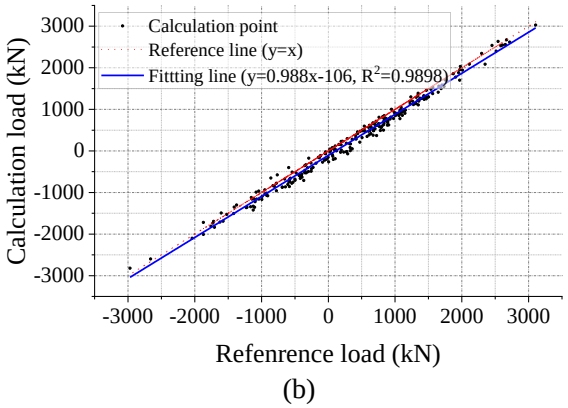


Fig. 16 Platform motion.



(a)



(b)

Fig. 17 Hydrodynamic load-measurement results for Exp 1: (a) hydrodynamic load curve; (b) load scatter diagram. The red curve represents the ideal results and the blue line represents the fitted results.

The hydrodynamic load-measurement results for Exp 2 are plotted in Fig. 18 and the load-measurement performance is displayed in Table 7. The error in Exp 2 was clearly larger than that in Exp 1 due to the influence of irregular waves. Compared to the simulation results, the experimental results from Exp 2 exhibited lower accuracy, partly due to insufficient training data. In addition, the measurement error induced by the hardware influenced the model's calculation accuracy. Even so, the LSTM model exhibited good hydrodynamic load calculation ability. The comparison between the calculated aerodynamic load and the reference one is plotted in Fig. 19. The calculation results still closely followed the reference results. The extreme value error was 5.89%, the average value error was 0.88%, and the root mean square error was 10.68%. It is worth noting that the calculation error for aerodynamic load was higher than that for hydrodynamic load. The disparity lies in the fact that the fluctuation range of the aerodynamic load is relatively small compared to that of the hydrodynamic load. Consequently, even minor relative error in hydrodynamic load calculation can lead to significant error in aerodynamic load calculation. When the error in the hydrodynamic load fluctuates sharply, the aerodynamic load calculation results may even fail to follow the trend of the reference values. To enhance the accuracy of aerodynamic load calculations, it is crucial to improve the precision of hydrodynamic load calculation. This can be achieved by increasing the amount of experimental training data and improving the quality of the experimental data. In general, engineers are more concerned about overall measurement error during a period than the error at a certain time point. Therefore, an accurate assessment of the measurement error depends on the purpose of the load data (Pahn et al., 2017).

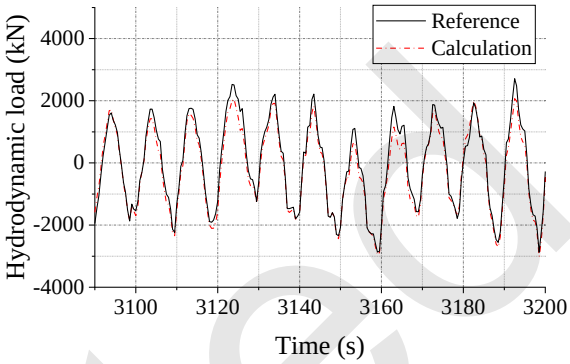


Fig. 18 Hydrodynamic load-measurement results from Exp 2.

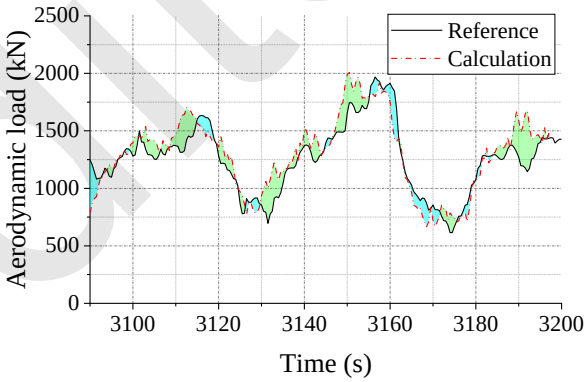


Fig. 2 Aerodynamic load-measurement results from Exp 2.

Table 7 Load-measurement performance in model testing.

Cases	E_{mean}	E_{max}	R_{fit}	E_{rmse}
F^x_{hydro} in Exp 1	1.83%	1.30%	95.57%	2.54%
F^x_{hydro} in Exp 2	2.00%	2.83%	92.44%	4.20%
F^x_{aero} in Exp 2	0.88%	5.89%	79.83%	10.68%

6 Conclusions

In this paper, we propose an aero-hydrodynamic load-measurement method for FOWT, based on the LSTM neural network model. First, we established a CFD simulation model of a floating platform, using DFBI and overset grid technologies. Then, we created and trained the LSTM model of hydrodynamic load

calculation through platform motion and wave-elevation sequences, based on the simulation results. Finally, we verified the validity of the load model under various simulation conditions and with hybrid scale-model tests. The main conclusions are as follows:

● The hydrodynamic load of the platform was closely related to wave states and platform-motion states. For the floating wind-power platform, we found that the optimal model structure for the LSTM neural network consisted of 2 layers, 128 neurons, and a time window of 1620 seconds.

● The simulation verification results show that the LSTM model can accurately calculate the hydrodynamic load of the platform, with the curve-fitting degree exceeding 93% and a root mean square error of less than 4%. For the aerodynamic load calculation, the average value error is 1.96%, the extreme value error is 2.15%, the curve-fitting degree is 93.35%, and the root mean square error is 3.43%.

● The experimental verification results show that the calculation accuracy in the experimental case is lower than in the simulation case. For the hydrodynamic load measurement, the curve fitting degree is 92.44% and the root mean square error is 4.20%. For the aerodynamic load measurement, the curve-fitting degree is 79.83% and the root mean square error is 10.69%.

It is important to note that this study only considered the surge and pitch DOFs. Additionally, only surge acceleration, pitch speed, pitch angle, and wave elevation were selected as the model inputs. The ignorance of other platform motions will certainly import in model errors. In the future, we envision this method being applied to actual full-scale FOWTs in real sea states. This would involve using more measurement equipment with high accuracy and high sampling frequency. Load-measurement accuracy would be improved by high-quality data and more input dimensions (up to 18 platform motion dimensions with displacement, speed, acceleration in 6 DOFs).

Acknowledgments

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Author contributions

Yonggang LIN designed the research. Xinagheng FENG processed the corresponding data. Xinagheng FENG wrote the first draft of the manuscript. Hongwei LIU and Yong SUN revised and edited the final version.

Conflict of interest

Yonggang LIN, Xinagheng FENG, Hongwei LIU and Yong SUN declare that they have no conflict of interest.

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Electronic supplementary materials

Table S1-S13, Figs. S1–S6

中文概要

题　目：基于长短周期记忆神经网络的浮式风电机组载荷测量方法

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目　的：浮式风电机组在实海况环境下的载荷数据对于结构降成本优化设计至关重要，但难以直接测量获取。本文旨在采用机器学习方法建立载荷黑箱模型，通过测量平台运动状态、波浪状态和系泊张力，实现对平台水动载荷、机组气动载荷的计算。

创新点：1. 基于 CFD 仿真数据，训练了一套以波高序列、平台运动为输入，平台水动载荷为输出的长短周期记忆神经网络模型；2. 建立浮式风电机组缩比模型，完成机组载荷测量实验。

方　法：1. 通过理论分析，推导出机组气动载荷和平台水动载荷之间的关系，得到机组载荷测量方案（图 1）；2. 通过 CFD 仿真模拟，分析平台水动载荷影响因素，并获取大量样本数据（图 7）；3. 通过模型实验，运用传感器对波高序列、平台运动和塔顶气动载荷进行测量，验证所提方法的可行性和有效性（图 14）。

结　论：1. 最佳神经网络模型参数是两层网络单元，每层

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128 个神经元；2.模型实验测量中，水动载荷测量误差均方根是 4.20%，机组气动载荷测量误差均方根是 10.69%。

关键词：浮式风电机组；长短期记忆神经网络；机器学习技术；载荷测量；缩比模型实验

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