



Research paper

Data-driven prediction of wave response for a modular floating solar array

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ABSTRACT

Floating photovoltaic (FPV) systems in coastal and nearshore regions are subjected to complex wave loads that significantly influence their hydrodynamic performance. In the future, industrial scale FPV projects can consist of numerous floating bodies that are too large to be modeled using existing modelling methods such as Computational Fluid Dynamics. Therefore, there is a need to develop data-driven rapid prediction approaches. This study presents a data-driven framework to predict the heave and pitch response amplitude operators (RAOs) of FPV arrays under different wave conditions. A verified simulation model is developed, generating a dataset that incorporates the key influencing factors, including incident wave angle, wavelength-to-floater-dimension ratio, and mooring type. Random Forest (RF) and Multilayer Perceptron (MLP) models are trained and optimized through grid search cross-validation, demonstrating that both models accurately capture the spatial distribution and magnitude of RAOs, with the MLP model showing superior generalization capability. Interpretability analysis further reveals that the wavelength-to-floater-width ratio is the dominant factor driving RAO responses, while appropriate mooring strategies can effectively suppress motions under extreme conditions. Compared with conventional hydrodynamic simulations, the proposed approach significantly reduces computational cost and enables rapid evaluation of FPV dynamic responses, which provides a potentially workable approach to facilitate various purposes of large-scale ocean solar projects, such as design, monitoring, and digital twins.

1. Introduction

Solar energy, an inexhaustible clean energy source, possesses enormous potential and has attracted extensive attention (Kabir et al., 2018). Approximately 5×10^4 EJ of solar energy per year is considered relatively accessible for collection and utilization. In theory, with sufficient technological development, harnessing these resources could alleviate the global energy shortage (Blaschke et al., 2013). Currently, solar panels are primarily installed on land, as well as on some freshwater lakes and reservoirs. In regions with geographical constraints, such as the coastal areas of Southeast Asia, coastal and offshore floating photovoltaic (FPV) systems have emerged as an important approach for utilizing marine space and enhancing energy production (Hooper et al., 2021; Trapani and Redón Santafé, 2014; Wei et al., 2025). However, complex sea conditions pose significant challenges for the design of FPV systems (Liu et al., 2018), necessitating further research to develop structures capable of adapting to such conditions.

Traditional FPV systems utilize an integrated large-platform design; however, such structures are costly and exhibit limited wave resistance,

making them unsuitable for complex sea conditions (Li et al., 2023). In recent years, the trend in FPV system development has shifted from single large floaters to modular floaters. For instance, the “Hydrelion” platform in France employs a polyethylene structure that is lightweight and corrosion-resistant, assembled with plastic bolts (Cazzaniga et al., 2018). Modular platforms offer strong scalability, ease of assembly, and straightforward maintenance, yielding multiple advantages (Essak and Ghosh, 2022). However, modular design introduces more nonlinear hydrodynamic effects, complicating vibration responses (Cao et al., 2021). Consequently, during the design stage, understanding these nonlinear characteristics and accurately predicting design outcomes becomes increasingly challenging, particularly when multiple excitation sources and different mooring conditions are considered.

Potential flow theory has been widely applied in the field of fluid-structure interactions, with its application tracing back to the 1970s. Numerous studies have employed 2D or 3D potential flow methods (Hong et al., 2005; Ikhennecheu et al., 2022; Li and Liu, 2022; Zhu et al., 2008), and their results demonstrate good consistency with physical model tests, confirming that potential flow theory is an effective tool for

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predicting hydrodynamic interactions of various structures. For photovoltaic arrays comprising dozens or even hundreds of floaters, conducting direct numerical simulations of the entire array is computationally prohibitive. Previous studies have suggested that computational resources can be conserved by introducing a “cut-off radius” to select only interacting modules (Zhang et al., 2022). Further research using the “MHydro” program indicated that, for hinge-connected floater arrays, small-scale tests with 5–7 units can reproduce the array's hydrodynamic behavior. (Zhang et al., 2023a). Song et al. (2023) utilized potential flow theory to develop a numerical model in ANSYS-AQWA for examining dynamic responses under the combined effects of wave, current, and wind loads. Their results indicated that wave loads contributed up to 99 %, serving as the dominant factor, while wave height did not affect the system's internal transmission mechanism. Xu et al. (2024) investigated different FPV array layouts under both normal and extreme sea states using ANSYS-AQWA simulations. Their findings revealed that rectangular arrays exhibited the highest stability, with reduced mooring line tension, smaller motions, relatively low sensitivity to wave direction, and consequently, greater safety. Besides, Wei et al. (2024) examined FPV array motions under different sea states and introduced the wavelength-to-structure-length ratio for approximate predictions. These studies demonstrated that 3D potential flow theory, in conjunction with specific wave conditions and array layouts, can significantly enhance FPV system design and address several challenges currently faced in both theoretical and engineering practices.

Emerging machine learning approaches have become a research focus in fluid mechanics, primarily aimed at improving the efficiency of traditional fluid-mechanics analyses through data-driven methods. Unlike conventional approaches, machine learning does not require a comprehensive analysis of the complex physical mechanisms underlying problems. Instead, it relies on training with large historical datasets to extract latent patterns. Once trained, these models can rapidly and accurately predict target outputs based on input variables. Currently, machine learning is widely applied across various engineering domains, demonstrating strong adaptability and playing a crucial role in fluid-related state assessment, prediction, design optimization, and safety control.

Brunton et al. (2020) proposed a predictive framework combining fluid mechanics and machine learning, employing supervised methods (e.g., LSTM) for temporal flow-field data and unsupervised methods (e.g., PCA/POD) to extract flow features. This framework provides algorithmic adaptation schemes for fluid-related prediction tasks and emphasizes incorporating physical constraints into data-driven models to prevent violations of conservation laws. Yang et al. (2023), addressing anchor-line tension prediction for offshore floaters, employed a reservoir computing (RC) model that decomposes tension into low- and high-frequency components and integrates heave time-series for modeling. This model serves as a tool for early warning of tension overload and rupture. Alhousni et al. (2025), focusing on FPV hydrodynamics and operational-state prediction, developed a machine-learning-based bidirectional feedback framework to predict vortex-induced vibration risk and floater attitude changes, calibrating models with CFD and field observations to maintain anchor-line rupture prediction errors within 5 % and reduce operational uncertainty. Mousavi et al. (2024) combined digital-twin technology with deep convolutional LSTM (DCLSTMNN) to improve damage prediction and localization for floating wind turbines. Evro et al. (2025) proposed a multi-scale coupled modeling approach that uses LSTM to forecast wind-wave conditions and adjust control angles, while utilizing reduced-order models (ROM) to reduce traditional CFD runtimes from about 24 h to a few hours, providing an efficient solution for design and control optimization. Bae et al. (2024), addressing long design cycles caused by expensive and slow CFD, used active learning combined with Gaussian-process regression and neural networks to optimize CFD invocation strategies. Their findings revealed that, in several cases, only

a small number of samples are required to reach near full-simulation accuracy, which suits iterative design workflows. Huang et al. (2022) implemented an end-to-end optimization by coupling deep learning with CFD, accelerating the screening of optimal designs. Saghi et al. (2021) employed RF model to improve wave-impact prediction and convolutional neural networks to enhance damage detection, thereby improving the wave-resistance safety and economic efficiency of mooring/breakwater systems. Lim (2024), addressing the difficulty of early-warning for offshore floater failures, applied LSTM to improve precursor detection and combined gradient-boosting decision trees to refine failure-cause diagnosis and localization, offering an effective approach for offshore structural safety inspection.

Large modular FPV systems exhibit unique dynamic characteristics, including strong multi-body coupling, wave shielding, and gap resonance. These features introduce new challenges for modeling and prediction due to the system's large scale and structural connectivity. In this study, a machine-learning-based framework is developed to investigate the dynamic responses and design optimization of FPV arrays under various wave conditions and layouts. High-fidelity potential-flow simulations are combined with Random Forest (RF) and Multi-Layer Perceptron (MLP) models to analyze the sensitivity and contribution of key parameters such as wave incidence angle, wavelength-to-width ratio, and mooring configuration. The trained models accurately predict the heave and pitch response amplitudes across multiple scenarios using dimensionless RAOs as unified indicators, which enhance generalization and support engineering design and safety evaluation. Furthermore, SHAP-based interpretability analysis is employed to elucidate the physical influence of input features, providing explainable insights for FPV design optimization and operational monitoring. Overall, this study establishes a rapid surrogate modeling framework specifically tailored for large-scale FPV arrays and extends the applicability and interpretability of data-driven hydrodynamic modeling.

2. Hydrodynamic simulation and dataset construction

Heave and pitch motions are typically the two most critical degrees of freedom in FPV systems. When the heave amplitude increases, the relative distance between the modules and the water surface changes, potentially inducing spray and splashing phenomena, which can affect the long-term reliability and insulation performance of FPV modules. Since heave is synchronized with waves, it readily excites high-frequency dynamic tension in mooring lines, particularly under resonance conditions where the mooring system is vulnerable to impact loads. Pitch motion, on the other hand, directly alters the incident angle of sunlight, causing fluctuations in power generation and potentially leading to local hot-spot effects. Excessive pitch vibration not only accelerates structural fatigue but can also result in repeated bending damage of cables and connectors. When modules are linked by hinges or flexible joints, excessive pitch further amplifies bending moments and shear forces at connection points, increasing the risk of fatigue failure.

As demonstrated in the studies of Song et al. (2023) and Xu et al. (2024), wave loads are the dominant forcing mechanism for the dynamic response of floating structures, primarily exciting heave and pitch motions. This explains why this study selects heave and pitch RAOs as the predictive targets. Regarding mooring configurations for FPV systems, existing research shows that multiple types of mooring lines (e.g., taut or catenary) can be employed; however, studies on how different layouts of the same mooring type affect hydrodynamic behavior remain limited. Therefore, while considering the dominant influence of wave loads, this study also incorporates different configurations of taut mooring lines into the analysis.

Due to the high cost of experiments, obtaining datasets for training and testing machine learning models through laboratory tests is impractical. To ensure the reliability of the data sources, this study relies on FPV modules validated in Refs. (Wei et al., 2024; Chen et al., 2021; Zou et al., 2024), and innovatively incorporates the effects of different

mooring configurations into their structural framework. Numerical hydrodynamic modeling and simulations are then performed. Based on the simulation results, a dataset comprising a training set for model fitting, a validation set for hyperparameter tuning, and an independent test set for evaluating the generalization capability of models is constructed.

2.1. Model of a floating solar farm

Since the simulations in this study involve a large number of floating bodies, directly applying high-order CFD would be excessively costly and impractical. Therefore, the ANSYS-AQWA software based on potential flow theory is adopted to perform the simulations and obtain the required dataset. The coordinate system used is illustrated in Fig. 1. The global system is defined as O-XYZ, where the O-Z axis points upward, the overall framework extends along the X-Y plane, and the plane at $Z = 0$ denotes the undisturbed free surface.

The array is composed of 7×11 individual floating bodies, as illustrated in Fig. 2(a). Along the O-X direction, the floats are connected by hinges, with the hinge joints oriented vertically and aligned with the O-Y axis, restricting adjacent floats to pitch motion only. In the O-Y direction, linear mooring ropes and fenders are employed as soft connections to prevent local collisions. It is assumed that these mechanical connections do not introduce additional mass, and only their dimensionless geometric properties are considered. The incident wave direction θ is defined as the angle between the wave propagation direction and the positive X-axis, where $\theta = 0$ corresponds to head waves along the positive X-axis. Each floating body has a length of 1.6 m, a width of 1.1 m, and a fixed draft of 0.1 m. The modeling process focuses on the floating structures at the free surface, excluding the specific supporting components used to secure the photovoltaic panels.

The gap between adjacent floats is designed by considering the float dimensions, the wave field induced by array effects, and potential resonant responses (Li and Liu, 2022), and is set to 0.1 m. The FPV system is moored using tensioned linear elastic steel cables, in which the cable tension is directly proportional to its elongation, with the proportionality constant representing the cable stiffness. Two mooring schemes are adopted in this study. The first is the conventional four-corner mooring (Wei et al., 2024; Zou et al., 2024; Yang et al., 2024), where the projection of each cable on the X-Y plane forms an angle of $\pm 45^\circ$ with the X-axis. This configuration is widely regarded as a reasonable and effective mooring scheme. The second scheme builds upon the first by adding four additional tensioned cables at the mid-points of the array along the O-X and O-Y directions, oriented perpendicular to the respective coordinate axes. These cables are anchored to fixed vertical piles on the seabed ($Z = -5$ m), as shown in Fig. 2(b). To maintain the structural symmetry of the platform and avoid unnecessary torsion and offset, the anchoring points in the second scheme are placed at the center of the rectangle defined by the anchors of the first scheme. To ensure the reliability of the simulations, and with reference to previous experimental and numerical studies (Wei et al., 2024; Zou et al., 2024; Yang et al., 2024), the specific parameters of the mooring cables and floats are summarized in Table 1.

2.2. Fluid solution

In this study, the fluid is assumed to be incompressible and inviscid, and potential flow theory is employed to describe the hydrodynamic problem (Peregrine, 2006). Under this assumption, the velocity potential can be expressed as a scalar function $\varphi(x, y, z, t)$, whose spatial distribution satisfies the Laplace equation:

$$\nabla^2 \varphi = 0 \quad (1)$$

The velocity potential can be further decomposed into incident, diffraction, and radiation components:

$$\varphi(x, y, z, t) = \varphi_I(x, y, z, t) + \varphi_D(x, y, z, t) + \varphi_R(x, y, z, t) \quad (2)$$

Here, φ_I denotes the incident wave potential, describing the wave energy propagating along the free surface; φ_D is the diffraction potential, reflecting the disturbance induced by fixed structures; and φ_R is the radiation potential, representing the wave energy radiated outward due to forced motion of the structure. These three components are solved jointly by applying free surface, solid boundary, and radiation conditions.

For the incident waves, linear Airy wave theory is adopted, assuming single-frequency, unidirectional regular waves. The incident velocity potential can be expressed as:

$$\varphi_I = \frac{ig\xi_A}{\omega} \frac{\cosh k(z+H)}{\cosh kH} \exp[-ik(x\cos\theta + y\sin\theta)] \quad (3)$$

where ξ_A is the wave amplitude; θ is the wave propagation angle relative to the X-axis; H is the water depth; k is the wave number satisfying the dispersion relation $\omega = gk \tanh kH$.

The diffraction potential φ_D satisfies the solid boundary condition on the body surface S_B :

$$\frac{\partial \varphi_D}{\partial n} = -\frac{\partial \varphi_I}{\partial n}, x \in S_B \quad (4)$$

where $\partial/\partial n$ denotes the derivative along the outward normal of the body surface. By numerically solving this system while applying free surface and Sommerfeld radiation conditions, the wave excitation force $F^{\text{exc}}(\omega)$ and its amplitude and phase can be obtained.

For a unit-amplitude harmonic motion along the j -th degree of freedom, the boundary condition on the body surface is:

$$\frac{\partial \varphi_R^{(j)}}{\partial n} = -i\omega(n \cdot e_j), x \in S_B \quad (5)$$

where e_j is the unit vector in the j -th degree of freedom; ω is the wave frequency; i is the imaginary unit. By solving this boundary value problem using the boundary element method (BEM), the radiation potential $\varphi_R^{(j)}$ can be obtained, and the frequency-domain hydrodynamic coefficients, the added mass matrix $A(\omega) = [a_{ij}(\omega)]$ and radiation damping matrix $B(\omega) = [b_{ij}(\omega)]$, can be calculated through pressure integration.

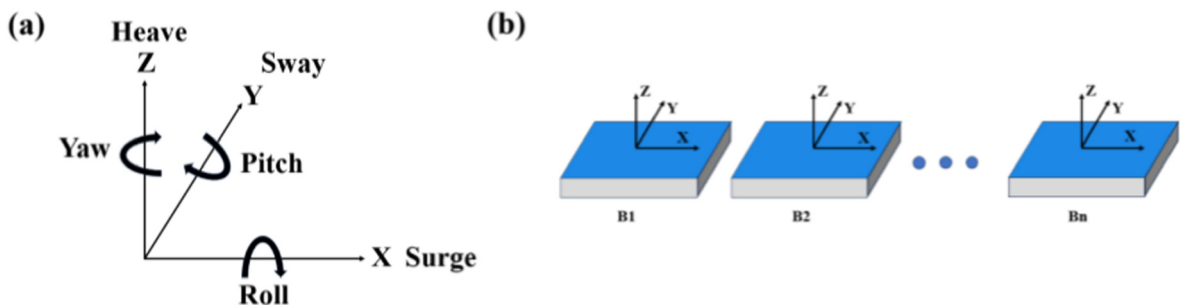


Fig. 1. Coordinate systems of the FPV array (a) Global coordinate system (b) Row arrangement diagram.

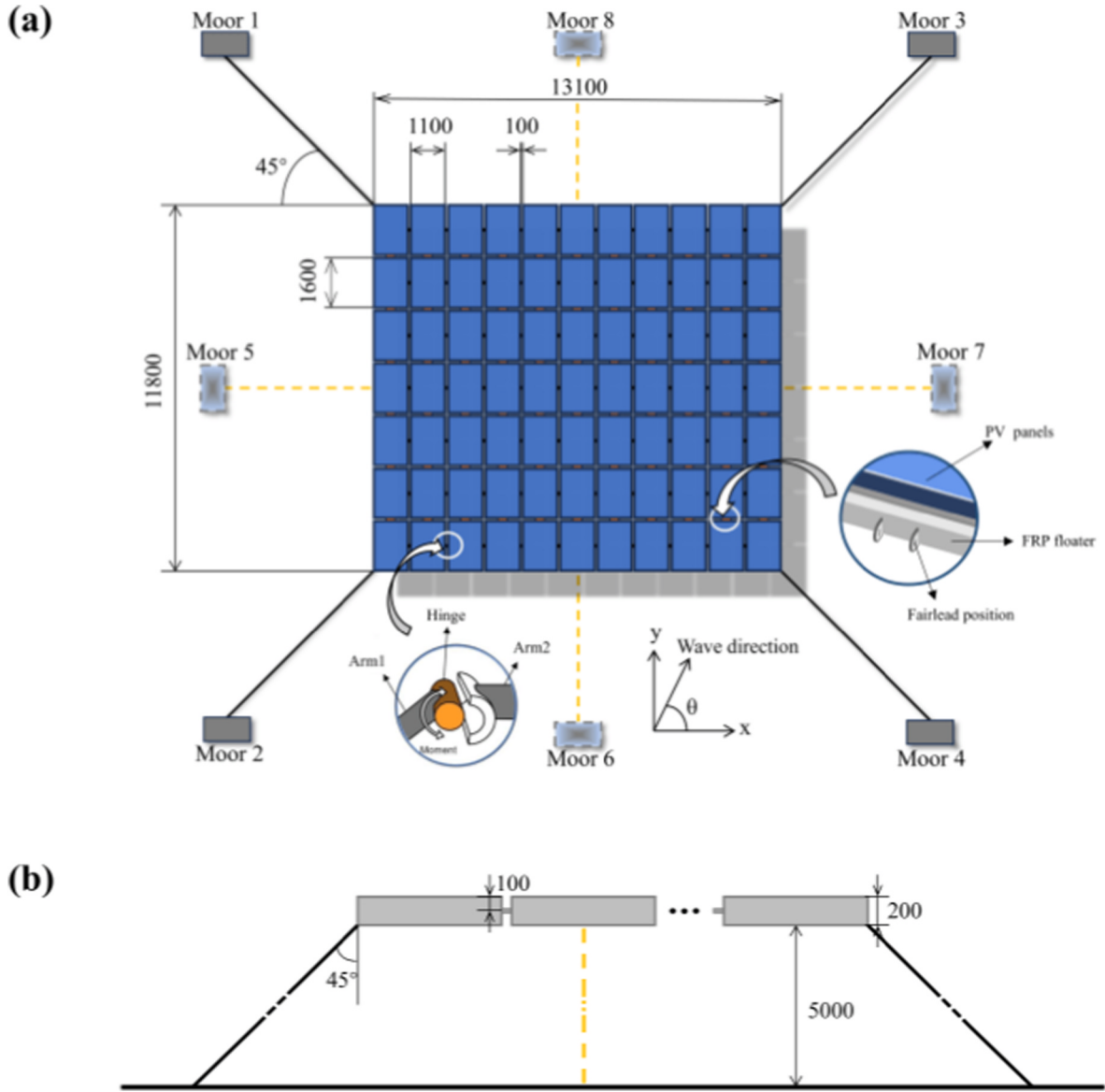


Fig. 2. FPV numerical models under two mooring types (a) Top view (b) Side view. Unit: mm.

Table 1

Physical properties of the selected floater and mechanical connections.

Floater	Unit	Value	Mechanical connections	Unit	Value
Length	(m)	1.6	Mooring stiffness	(N/m)	1e7
Width	(m)	1.1	Cable stiffness	(N/m)	5e6
Height	(m)	0.2	Fender stiffness	(N/m)	5e6

The diffraction force, added mass, and radiation damping are incorporated into the frequency-domain equation of motion (Qu and Yao, 2022):

$$[-\omega^2(M + A(\omega)) + i\omega B(\omega) + C]\xi(\omega) = F_{exc}(\omega) \quad (6)$$

where M is the structural mass matrix; C is the hydrostatic restoring matrix; $F_{exc}(\omega)$ is the frequency-domain wave excitation force vector. The frequency-domain analysis is primarily performed to obtain the hydrodynamic coefficients, including the frequency-dependent added mass $A(\omega)$, radiation damping $B(\omega)$, and wave excitation force $F_{exc}(\omega)$. These coefficients are then used as inputs for the subsequent time-domain simulations.

2.3. Structural solution

The motion prediction of multi-connected floating bodies must simultaneously account for the wave excitation, connecting elements between structures (hawsers and fenders), and external mooring system. The time-domain dynamic equation is given by:

$$\sum_{j=1}^N M_{kj} \ddot{\xi}_j(t) = F_{k,wave}(t) + F_{k,line}(t) + F_{k,moor}(t) + F_{k,fender}(t) \quad (7)$$

where M_{kj} is the mass matrix, $\xi_j(t)$ is the displacement vector of the j -th degree of freedom; the four terms on the right-hand side denote the wave excitation force, hawser force, mooring force, and fender force, respectively. Equation (7) omits the convolution term in Cummins's equation, which represents the transient radiation or "memory" effect. This simplification corresponds to an instantaneous steady-state assumption, which is appropriate for regular-wave analyses but may neglect short-duration transient components under irregular wave excitations.

Adjacent floats are connected by hinges to allow relative motion in specified degrees of freedom. In this study, a single-degree-of-freedom

hinge constraint is applied in the O-Y direction, which can be written as:

$$\begin{bmatrix} E^T & E^T R_k \\ 0 & G^T \end{bmatrix} U_k - \begin{bmatrix} E^T & E^T R_{k+1} \\ 0 & G^T \end{bmatrix} U_{k+1} = 0 \quad (8)$$

Here, $U_k = (u_k, \theta_k)$ denotes the generalized displacement of the k -th rigid body, comprising translational displacement u_k and rotation θ_k ; E is the Euler rotation matrix; R is the skew-symmetric matrix from centroid to connection point, and G is the hinge matrix:

$$E = \begin{bmatrix} e_{11} & e_{12} & e_{13} \\ e_{21} & e_{22} & e_{23} \\ e_{31} & e_{32} & e_{33} \end{bmatrix}, R_k = \begin{bmatrix} 0 & z_k & -y_k \\ -z_k & 0 & x_k \\ y_k & -x_k & 0 \end{bmatrix}, R_{k+1} = \begin{bmatrix} 0 & z_{k+1} & -y_{k+1} \\ -z_{k+1} & 0 & x_{k+1} \\ y_{k+1} & -x_{k+1} & 0 \end{bmatrix}, G = \begin{bmatrix} e_{12} \\ e_{22} \\ e_{32} \end{bmatrix} \quad (9)$$

The connection-point position vectors are defined as:

$$r_k = X_p - X_{gk} = (x_k, y_k, z_k), r_{k+1} = X_p - X_{g,k+1} = (x_{k+1}, y_{k+1}, z_{k+1}) \quad (10)$$

with X_p the position of the connection point in the global coordinate system, and X_{gk} , $X_{g,k+1}$ the centroids of adjacent rigid bodies.

The hawser force $F_{k, \text{line}}$ and fender force $F_{k, \text{fender}}$ are modeled as linear springs that activate only when stretched or compressed:

$$F_{k, \text{line}} = \begin{cases} K_l(l - l_0), l > l_0 \\ 0, l \leq l_0 \end{cases}, F_{k, \text{fender}} = \begin{cases} K_f(\delta - \delta_0), \delta > \delta_0 \\ 0, \delta \leq \delta_0 \end{cases} \quad (11)$$

where l is the instantaneous length; l_0 the unstretched length, K_l the hawser stiffness; δ the instantaneous gap; δ_0 the initial clearance, and K_f the fender stiffness. In this study, since K , l_0 , and δ_0 are identical for the hawser and fender, their behavior is effectively linear. The activation form is retained only for generality and consistency with future nonlinear cases.

The mooring system provides additional constraints and restoring forces to keep floats within the operational region. This study considers Tension Leg Platform (TLP), assuming mooring lines behave as extensible elastic cables. The mooring force is expressed as:

$$F_{k, \text{moor}} = \begin{cases} K_m(L_m - L_{m0}), L_m > L_{m0} \\ 0, L_m \leq L_{m0} \end{cases} \quad (12)$$

where K_m is the equivalent stiffness; L_m the instantaneous line length, and L_{m0} the initial slack length. Line elongation not only provides restoring forces but also introduces nonlinear effects that play an important role in suppressing low-frequency drift.

Gap resonance commonly occurs in narrow regions between adjacent floats in multi-float systems. When the incident wave frequency approaches the natural frequency of the gap water, surface oscillations are significantly amplified, resulting in pronounced resonance responses (Zhao et al., 2017). Studies indicate that the second-order harmonic components of gap responses may even exceed the primary harmonic, primarily due to nonlinear coupling between incident waves and structures (Zhang et al., 2023b). If both the floats and the gap water resonate simultaneously, the free-surface amplitude may be diminished, particularly on the windward side, an effect influenced more by float stiffness and water depth than by spacing.

In potential-flow-based numerical simulations, neglecting fluid viscosity often overestimates gap surface elevations, producing unrealistic “shock-wave” solutions. To address this issue, artificial damping is commonly introduced. Chen et al. (2024) proposed the damping-lid method, which adds a velocity-proportional term to the hydrodynamic equations, effectively introducing a damping term in the free-surface

boundary condition, to suppress excessive surface elevation. This study adopts the empirical parameter $\varepsilon = 0.15$. The modified Bernoulli equation is given by:

$$\frac{p}{\rho} + gz + \frac{\partial \varphi}{\partial t} + \frac{1}{2}(\nabla \varphi) \cdot \varepsilon \cdot \omega \cdot \varphi = 0 \quad (13)$$

where ω is the natural frequency of the array and ε is the artificial damping coefficient. The modified free surface boundary conditions are as follows:

$$-(1 + i\varepsilon) \frac{\omega^2}{g} \varphi_D + \frac{\partial \varphi}{\partial z} \varphi_D = 0, z = 0 \quad (14)$$

2.4. Verification and wave loading

Before conducting potential-flow analysis on the complete FPV system, a hydrodynamic validation of multiple unconnected floats is performed to ensure the accuracy of structural motion characteristics under wave conditions, following the approach of Wei et al. (2024) and Zou et al. (2024). It should be noted that the existing validation is only a simplified model used in simulation to confirm the consistency of the model in the overall trend. The validation, subsequent computations, and dataset generation are all carried out in ANSYS-AQWA, using the 3D potential-flow method described earlier. The configuration of the validation model is consistent with the experiments of Chen et al. (2021) and Chen et al. (2023). The model consisted of several laterally arranged floats, as shown in Fig. 3, with specific parameters listed in Table 2. The floats are symmetrically arranged, with their centers of gravity located at the geometric centers and their mass uniformly distributed.

To verify the accuracy of the numerical computations, the heave and pitch RAOs of three configuration models are compared with the results of Chen et al. (2023), as shown in Fig. 4(a) and (b). The hydrodynamic coefficients are first obtained from the frequency-domain potential-flow analysis, and then used in the time-domain simulations to compute the motion responses under regular waves. The steady-state responses are analyzed to extract the corresponding RAOs for comparison. To clearly reveal the hydrodynamic coupling effects among multiple floats, different curve styles and symbols are used to illustrate the influence of float number on the response amplitude. In the low-frequency range

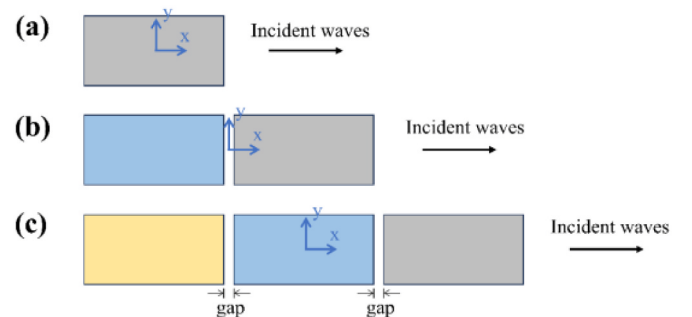


Fig. 3. Plan view of three configurations (a) 1 module (b) 2 modules (c) 3 modules.

Table 2
Geometrical parameters of a single floater.

Module characteristics	Unit	Value
Length	m	100
Width	m	50
Depth	m	5
Centre of gravity above base, KG	m	2.5
Draught	m	2
Moment of inertia, I_{xx}	m^4	14.5
Moment of inertia, I_{yy}	m^4	28.9
Moment of inertia, I_{zz}	m^4	32.3

($f < 0.5 \text{ rad/s}$), the heave RAOs of all three configurations remain at high levels, with good agreement between the reference (ref) and validation (val) curves, and only minor differences among different float numbers. As the frequency increased to $0.5 - 1.5 \text{ rad/s}$, the heave RAO exhibits a rapid decline, with almost no difference across configurations. In the validation model, the number of floats has a significant effect on the pitch peak: the single-float case shows the highest peak, followed by decreasing peaks for the two-float and three-float cases. It should be noted that potential-flow theory assumes an inviscid, ideal fluid; therefore, an additional damping factor is introduced, as discussed earlier. The empirical damping coefficient ε is introduced by adding a velocity-proportional term into the linearized Bernoulli equation and modifying the free-surface boundary condition. This damping is reflected in the potential-flow solution through the altered free-surface boundary (Zou et al., 2024), and the frequency-domain added mass and radiation damping obtained from the potential-flow analysis therefore include this free-surface damping effect. The specific response errors between the present model and the experimental results are listed in Table 3. The pitch response exhibits a resonance peak near the rotational natural frequency, whereas the heave response attains its maximum at a longer wave period. This behavior agrees with the expected physical trend that pitch motion is more sensitive to damping effects. The present conclusions may vary with different damping levels.

The numerical simulations are extended to a 7×11 FPV array under different wave conditions and mooring configurations. The results are expressed as dimensionless Response Amplitude Operators (RAOs), which are independent of specific scales and thus possess stronger generality, allowing extrapolation to various system sizes. For the incident wave, the wave height is set to $H = 0.1 \text{ m}$, and the ratio of wavelength λ to the wave-facing dimension W in the O-X direction is defined as the dimensionless parameter $R = \lambda/W$. The RAOs for heave and pitch are defined as (Huang and Thomas, 2019):

$$RAO_{heave} = \frac{A_z}{A} \quad (15)$$

$$RAO_{pitch} = \frac{\beta_z}{kA} \quad (16)$$

where $A = H/2$ is the incident wave amplitude; $k = 2\pi/\lambda$ is the wave

number, and A_z and β_z denote the amplitudes of heave and pitch, respectively.

The simulation setup is illustrated in Fig. 2. Under Quadrilateral mooring with $R = 5$, Fig. 5(a)–(b) show the contour map of $RAOs_{heave}$ and the heat map of $RAOs_{pitch}$ at $\theta = 0^\circ$. Similar to the findings of Ou et al. (Wei et al., 2024), the heave response is generally larger than the pitch response, though both exhibited consistent spatial distributions. The strongest response occurs in the directly wave-facing modules, followed by a rapid decay along the propagation direction, with two secondary peak regions emerging inside the array. This results from the interference of scattered, incident, and radiated waves during wave propagation within the array, forming standing-wave patterns and producing secondary peaks at the center. Toward the rear of the array, phase superposition of scattered and reflected waves causes RAOs to rise again. In multi-float systems, the internal floats exhibit both energy attenuation and potential local energy concentration.

For nearshore FPV systems, wave incidence is typically between 0° and 60° . To save computational resources and reflect realistic conditions, the maximum incident angle θ is set to 60° . Fig. 5(c)–(d) present the $RAOs_{heave}$ contour map and $RAOs_{pitch}$ heat map for Quadrilateral mooring with $R = 5$ at $\theta = 60^\circ$. Consistent with Zou et al. (2024), larger incident angles significantly alter the heave and pitch responses, and the spatial uniformity disappears.

The heave response becomes concentrated in the lower-right region, with high-response areas becoming more localized, while the pitch response is concentrated in the upper-right region with a peak exceeding that of the head-on wave case. Notably, although oblique waves intensify local pitch responses, the overall number of high-response modules decreases. Oblique incidence concentrates energy along the diagonal channel of the array, resulting in asymmetric distributions. Furthermore, due to asymmetric wave pressure, the lower-right floats experience greater longitudinal rotational excitation, shifting the pitch peak toward the upper right. These local floats absorb most of the rotational energy, which may significantly increase fatigue loads at specific positions.

2.5. Dataset generation

Considering the nearshore deployment conditions of the tension-leg FPV system, the incident wave angle is set to $0^\circ - 60^\circ$, covering typical oblique wave directions in such environments. The wavelength ratio

Table 3
Uncertainty evaluations on structural motions.

Different combinations	Uncertainty level (%)	
	Mean heave RAOs	Mean pitch RAOs
One floater	1.4 %	9.5 %
Two floaters	5.2 %	9.5 %
Three floaters	6.74 %	14.4 %

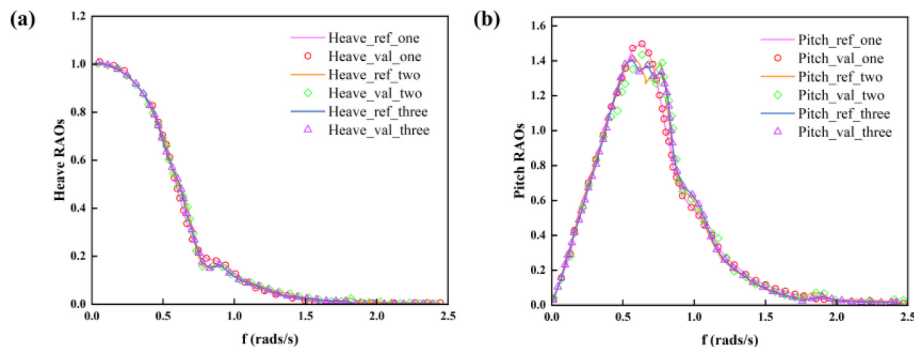


Fig. 4. RAOs of the multi-floaters under various wave conditions (a) Heave (b) Pitch.

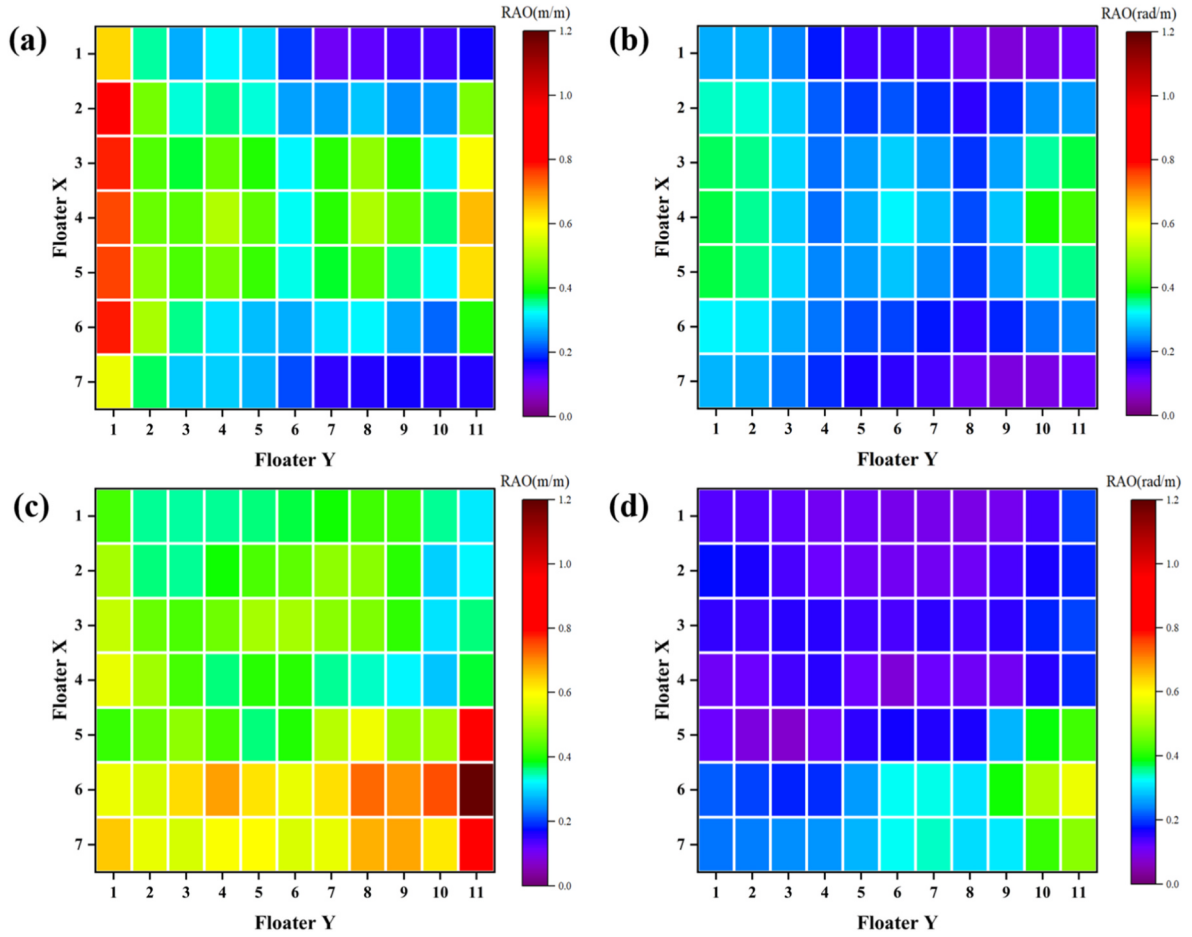


Fig. 5. RAOs under different weave loads using quadrilateral mooring (a) $RAOs_{heave}$ under $\theta = 0^\circ$, $R = 5$ (b) $RAOs_{pitch}$ under $\theta = 0^\circ$, $R = 5$ (c) $RAOs_{heave}$ under $\theta = 60^\circ$, $R = 5$ (d) $RAOs_{pitch}$ under $\theta = 60^\circ$, $R = 5$.

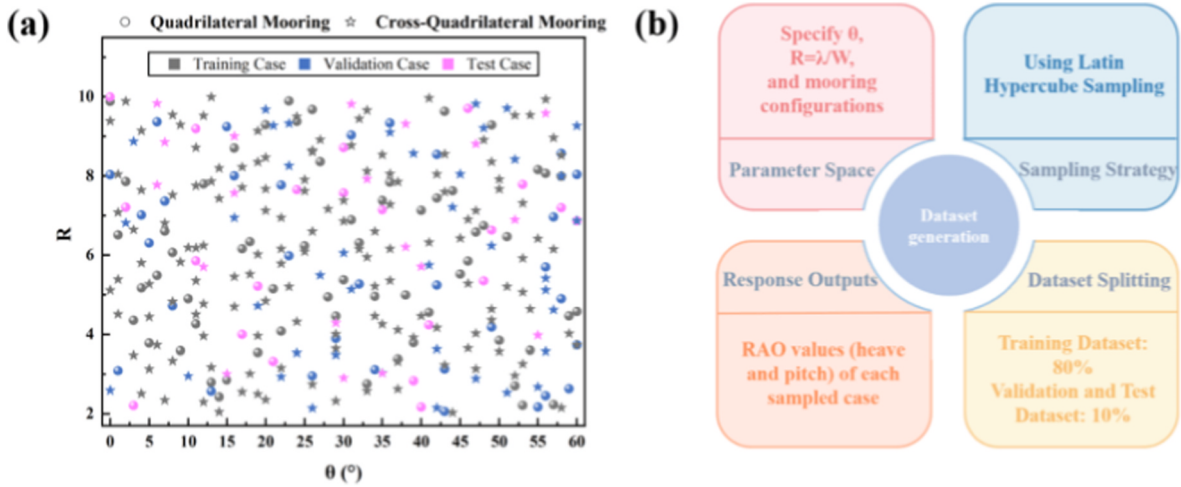


Fig. 6. Dataset construction (a) Latin hypercube sampling (b) Datasets for training and validation of deep learning models.

$R = 2 - 10$ is chosen following Refs. (Zou et al., 2024; Yang et al., 2024), representing short-to-long wave conditions commonly observed near-shore. Meanwhile, to facilitate subsequent machine learning modeling, the two mooring types, Quadrilateral Mooring and Cross-Quadrilateral Mooring, are encoded using One-Hot representation as 0 and 1, respectively. Using Latin hypercube sampling, 400 combinations are selected within the three-parameter input space. As displayed in Fig. 6,

the 400 samples are divided into 80 % for training the machine learning model, 10 % for validation to tune hyperparameters, and 10 % for testing to evaluate the final accuracy and generalization capability. Subsequently, numerical simulations are conducted in ANSYS-AQWA for all 400 cases, yielding the $RAOs_{heave}$ and $RAOs_{pitch}$ of 77 modules in each case to construct the complete dataset.

3. Machine learning framework

3.1. Random forests model

A decision tree serves as the base learner of the RF, with its training comprising the construction of a tree structure. The algorithm recursively partitions the training set by identifying the optimal feature and split point, aiming to minimize the mean squared error (MSE) of sample labels within each node, until the predefined stopping criterion is satisfied (De'ath and Fabricius, 2000).

If the training set is ultimately divided into N leaf nodes, denoted as $LeafNode_{i=1}, \dots, LeafNode_{i=N}$, then for a new input x , its prediction can be expressed as

$$f(x) = \sum_i^N avg_i I(x \in LeafNode_i) \quad (17)$$

Here, avg_i represents the average of the sample labels within $LeafNode_i$; and I is an indicator function that equals 1 if x belongs to the corresponding $LeafNode_i$, and 0 otherwise.

The RF is an ensemble learning method built upon the Bagging framework (Breiman, 1996). Its core lies in training a large number of mutually independent decision trees and aggregating their predictions to determine the final output, thereby achieving good generalization performance and strong resistance to overfitting. The training mechanism consists of two key components: (1) bootstrap sampling draws samples with replacement from the original training set, generating unique training subsets for each tree and forming base learners with distinct structures; (2) feature randomness (Breiman, 2001) is introduced by selecting a subset of features at each node split to determine the optimal split point, which significantly enhances model diversity even when trained on identical sample subsets.

As exhibited in Fig. 7, if the random forest contains B decision trees, with the prediction of the j -th tree denoted as $f_j(x)$, then for a new input x , its prediction is expressed as:

$$g(x) = \frac{1}{B} \sum_{j=1}^B f_j(x) \quad (18)$$

3.2. Multilayer perceptron

Fig. 8 illustrates the structural composition of a MLP, which is

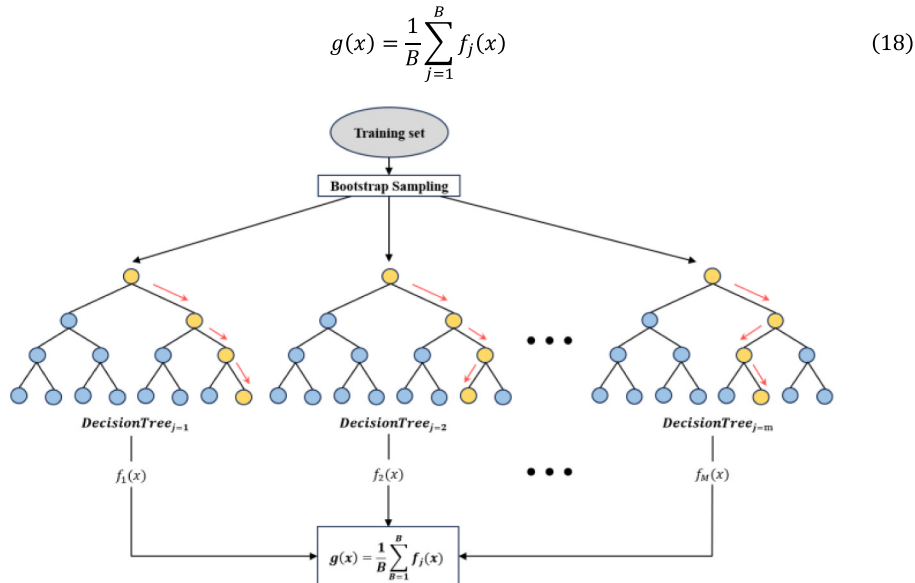


Fig. 7. Structural diagram of the random forest model.

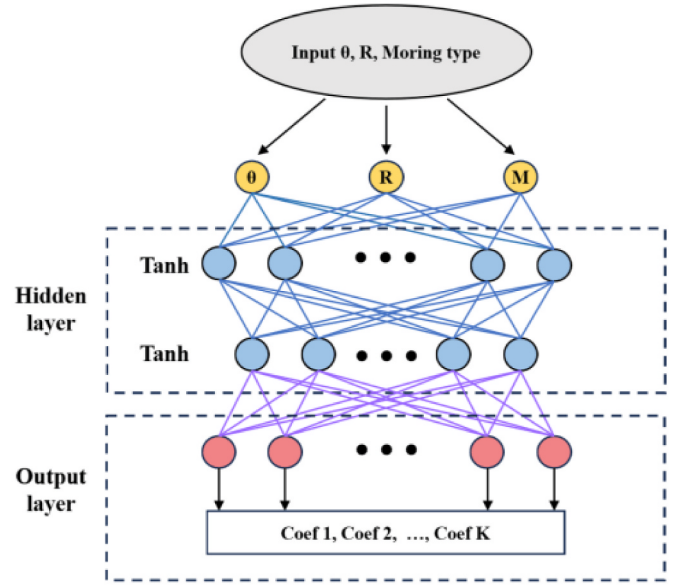


Fig. 8. Structural diagram of the multilayer perceptron model.

essentially a typical feedforward neural network. It consists of an input layer, one or more hidden layers, and an output layer, with neurons in each layer are connected through weighted links to achieve information transmission and nonlinear transformation. The key concept is that nonlinear activation functions in the hidden layers (e.g., Tanh, ReLU) map input features into a higher-dimensional representation space, theoretically allowing the approximation of any continuous function and thereby enabling complex nonlinear modeling capabilities (Hornik et al., 1989).

For an L -layer MLP model, the propagation function can be expressed as:

$$\mathbf{h}^{(0)} = \mathbf{x} \quad (19)$$

$$\mathbf{h}^{(l)} = \alpha(\mathbf{W}^{(l)} \mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}), l = 1, 2, \dots, L-1 \quad (20)$$

$$\mathbf{y} = \gamma(\mathbf{W}^{(L)} \mathbf{h}^{(L-1)} + \mathbf{b}^{(L)}) \quad (21)$$

Here, $\mathbf{x}$ denotes the input vector, $\mathbf{y}$ the output vector; $\mathbf{W}^{(l)}$ and $\mathbf{b}^{(l)}$ represent the weight matrix and bias vector of the l -th layer, respectively; α is the nonlinear activation function in hidden layers, while γ is the activation function of the output layer.

The training process of the MLP is based on the backpropagation (BP) algorithm, combined with gradient descent or advanced optimizers to iteratively update parameters and minimize the error between predicted outputs and ground truth values (Erwin, 1986). During backpropagation, gradients are computed layer by layer using the chain rule. For instance, the gradient of the weight matrix in the l -th layer can be written as:

$$\mathbf{z}^{(l)} = \mathbf{W}^{(l)} \mathbf{h}^{(l-1)} + \mathbf{b}^{(l)} \quad (22)$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(l)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{h}^{(l)}} \frac{\partial \mathbf{h}^{(l)}}{\partial \mathbf{z}^{(l)}} \frac{\partial \mathbf{z}^{(l)}}{\partial \mathbf{W}^{(l)}} \quad (23)$$

where $\mathbf{z}^{(l)}$ represents the weighted summation at the l -th layer. Through repeated iterative training, the network progressively adjusts its weights and biases, improving both its fitting capability and generalization performance.

3.3. Data preprocessing

Although a complete dataset has been obtained through numerical simulations, input features must still be standardized prior to ML model training. The purpose of standardization is to map features with different dimensions and ranges onto a unified numerical scale, thereby preventing certain features with larger magnitudes from dominating the training process, and enabling the optimizer to achieve faster and more stable convergence during gradient descent. The standardization formula is as follows:

$$X'_i = \frac{X_i - \mu}{\sigma} \quad (24)$$

where X_i denotes the raw feature, while μ and σ represent the mean and standard deviation of the training features, respectively. The standardized feature X'_i thus has zero mean and unit variance.

For each set of input features, the corresponding output target $\mathbf{Y}$ is a 154-dimensional high-dimensional vector sequence, representing the $RAOs_{heave}$ and $RAOs_{pitch}$ of 77 floaters. Directly predicting the entire $\mathbf{Y}$ may introduce redundant information and noise, impairing training effectiveness. Conversely, training each floater independently neglects the potential coupling effects between adjacent floaters. To address this issue, principal component analysis (PCA) is applied to $\mathbf{Y}$, mapping the high-dimensional data into a lower-dimensional subspace while retaining the dominant variance information.

Specifically, $\mathbf{Y}$ is first mean-centered column-wise, and the principal directions are extracted through eigenvalue decomposition of the covariance matrix. The projection matrix $\mathbf{V}_k$ is constructed from the eigenvectors corresponding to the top k largest eigenvalues. The dimensionality reduction process is expressed as:

$$\mathbf{Y}_{PCA} = (\mathbf{Y} - \bar{\mathbf{Y}}) \mathbf{V}_k \quad (25)$$

where $\bar{\mathbf{Y}}$ is the column-wise mean vector, and $\mathbf{Y}_{PCA}$ is the reduced low-dimensional representation. This procedure retains as much of the key variance as possible, eliminates redundant dimensions, and improves stability under limited-sample conditions.

It should be further noted that during prediction, since the model outputs reside in the reduced principal component space, they must be mapped back to the original feature space. The inverse transformation is given as:

$$\hat{\mathbf{Y}}_{orig} = \hat{\mathbf{Y}}_{PCA} \mathbf{V}_k^T + \bar{\mathbf{Y}} \quad (26)$$

where $\hat{\mathbf{Y}}_{PCA}$ denotes the low-dimensional prediction, and $\hat{\mathbf{Y}}_{orig}$ is the reconstructed output in the original space. This inverse mapping ensures that evaluation metrics are computed in the original space, thereby enhancing the comparability and interpretability of the model.

The linear transformation of PCA may potentially filter out local phenomena with low variance but high physical significance, particularly those corresponding to extreme responses under engineering design conditions. To quantitatively assess this possibility, several floats with the top 5 % highest peak responses in the training dataset are independently analyzed while retaining 98 % of the cumulative variance. For each selected float, the top 10 % of its largest peaks were used to calculate reconstruction errors. As summarized in Table 4, although the PCA-based dimensionality reduction is primarily governed by global variance contributions, it still demonstrates satisfactory capability in preserving the extreme responses of key structural components. However, it should be noted that in the most extreme cases, the reconstructed peak magnitudes tend to be slightly lower than the original values.

4. Results and discussion

Different ML models are designed to address various practical problems, employing distinct approaches to capture the complex nonlinear relationships between input variables and predicted outputs. In this study, RF and MLP models are trained using scikit-learn in Python (Pedregosa et al., 2011) to predict the principal motion responses (heave and pitch RAOs) of FPV systems under varying environmental loads and mooring configurations.

The model development and overall workflow are demonstrated in Fig. 9. Given the significant influence of hyperparameters on predictive performance, Grid Search cross-validation (GridSearchCV) is employed to optimize the model's hyperparameters (Adnan et al., 2022). The optimal hyperparameter set for the RF model is identified as follows: $n_estimators = 200$, $max_depth = 12$, $min_samples_split = 2$, $min_samples_leaf = 1$. For the MLP model the best hyperparameters are: activation = 'tanh', L2 regularization (alpha) = 0.01, hidden_layer_sizes = (100, 50), initial learning rate = 0.001, solver = 'lbfgs'. The MLP model is ultimately selected for further and in-depth analysis of predictive performance and results.

4.1. Qualitative analysis of prediction results

To intuitively evaluate the predictive accuracy of the two machine learning models, two samples are randomly selected from the test set and their predicted values are compared with the ground truth. Specifically, the 77 floating modules are sequentially numbered from left to right and top to bottom as the x-axis, while their corresponding RAO_{heave} or RAO_{pitch} values are plotted along the y-axis. Two sets of input parameters are selected: $\theta = 55$, $R = 3.98$, $moring_type = 1$ and $\theta = 38$, $R = 9.31$, $moring_type = 1$, as described in Fig. 10.

Both machine learning models successfully captured the overall trend of RAOs, though differences in predictive performance are evident. In Fig. 10(a)–(b), the RF model yields consistently larger predictions than the MLP model, deviating more from the ground truth. This can be attributed to the higher dynamic responses on the wave-facing side, where extreme variations induced by wave loads are

Table 4

PCA reconstruction accuracy for the top 5 % of floats (with the top 10 % peaks within each float).

Floater	AbsErr mean	AbsErr max	RelErr mean (%)	RelErr max (%)
(2,1)	0.0174	0.0468	1.8	4.94
(3,1)	0.0189	0.0525	1.77	4.78
(4,1)	0.0202	0.0591	1.83	5.47
(5,1)	0.0172	0.052	1.58	4.71
(6,1)	0.0248	0.1011	2.36	9.35

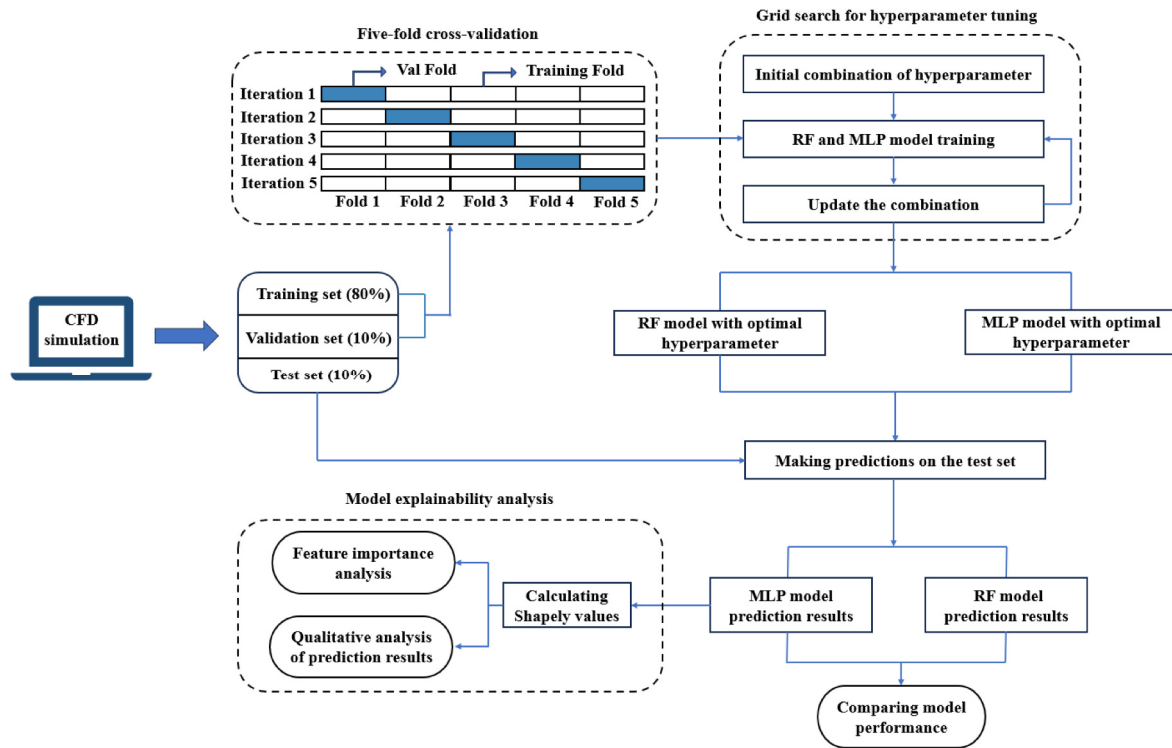


Fig. 9. Development and analysis procedure for machine learning models.

difficult for RF to capture accurately. Although the RF model is robust to non-smooth decision boundaries and outliers, its leaf-averaging mechanism tends to overestimate when only a few extreme samples are present, pulling neighboring predictions upward. For example, the existence of an exceptionally large peak in Fig. 10(a) leads to overall higher RF predictions, whereas such a phenomenon is absent in Fig. 10(b).

In contrast, the results depicted in Fig. 10(c)–(d) demonstrate that, although both models exhibit reasonable performance, the MLP model generates predictions that more closely aligned with the true curves. Since RAO fields driven by wave loads are continuous in the frequency domain and are generally formed by the superposition of dominant spatial modes (diffraction/interference modes), employing continuously differentiable functions for fitting is more physically appropriate than using piecewise-constant approximations. By utilizing joint training, the MLP model is better equipped to maintain the relative amplitudes among different modes, thereby yielding more consistent predictions at extreme points.

Overall, both the MLP and RF reproduce the principal spatial variation patterns and do not exhibit non-physical phase reversals or abrupt oscillations between adjacent floaters. Local discrepancies are observed predominantly in regions with steep RAO gradients, where a floater may be slightly under-predicted while its neighbor is slightly over-predicted. These deviations are small in magnitude and do not appear to be systematic. For connector-level force estimation or fatigue assessment, however, a dedicated analysis with higher-fidelity hydrodynamic/structural coupling or expanded targeted measurements would be required.

Both models are trained to minimize the Mean Squared Error (MSE). However, the MLP utilizes gradient-based continuous approximation in function space to distribute errors across the input domain, thereby reducing the overall squared error. After PCA removes part of the noise, this approach further enhances the preservation of the relative heights of rare peaks. Except for the 67th module in Fig. 10(a), where the absolute deviation between prediction and ground truth is relatively large, the MLP achieved good fits across all other modules. In contrast, the RF

model, constrained by its piecewise constant leaf-averaging, is susceptible to local averaging bias or staircase-like errors when extreme values are rare in the training samples. Therefore, while individual case comparisons offer valuable insight, they are insufficient for a comprehensive evaluation, necessitating further quantitative analysis of both models.

4.2. Quantitative analysis of prediction results

In regression tasks, the coefficient of determination (R^2) is one of the key metrics used to evaluate model performance, as it quantifies the extent to which the model explains the variance of the dependent variable. By comparing prediction errors with those of a baseline model, R^2 intuitively reflects the quality of the fit. Essentially, it measures the proportion of variance explained by the model, where a higher proportion indicates better performance. An R^2 value of 1 indicates perfect prediction, which is virtually unattainable in practical machine learning tasks. When $R^2 < 0$, it suggests that the model is mis-specified or the data is highly noisy. Typically, an R^2 between 0.4 and 0.8 indicates that the model captures part of the underlying pattern but still leaves much room for improvement; an R^2 between 0.8 and 0.9 implies that the model captures trends effectively; and an R^2 greater than 0.9 suggests excellent predictive accuracy.

The test set, which is not seen during training, is used to evaluate the model's generalization ability. Accurate predictions on the test set indicate practical usability. Since hydrodynamic simulations are computationally expensive, it is important to investigate the number of simulations required for a machine learning model to achieve reliable fitting. Fig. 11(a) presents the predictive performance of RF and MLP models with varying training data sizes. Overall, R^2 increases with more training samples, as the models learn trends more effectively. Remarkably, with only 10 % of the training data, both models achieved R^2 values above 0.9, indicating that they have already captured the key patterns, such as the spatial distribution and approximate magnitudes of heave and pitch responses, despite remaining deviations from the ground truth. When 60 % of the training data is used, the R^2 of the MLP model plateaued at 0.99, while the RF model's R^2 increases slightly to

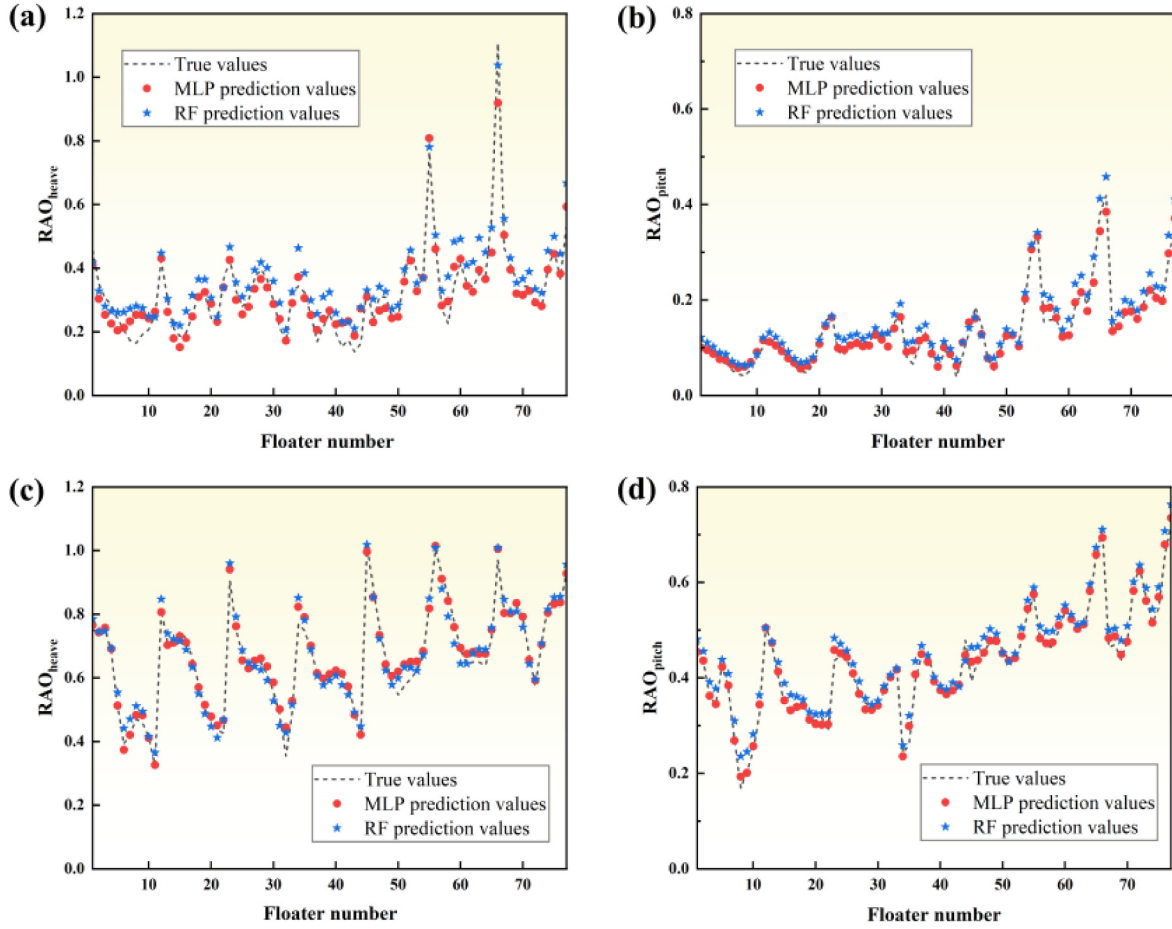


Fig. 10. Comparison of predicted values under different inputs (a) RAO_{heave} of sample one (b) RAO_{pitch} of sample one (c) RAO_{heave} of sample two (d) RAO_{pitch} of sample two.

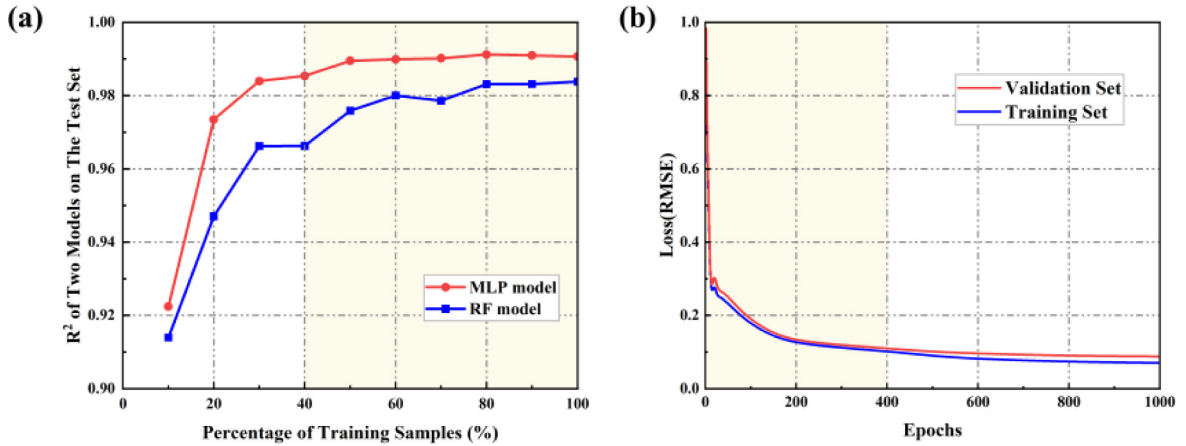


Fig. 11. Qualitative analysis of prediction results (a) R^2 of two models on the test set (b) RMSE of the MLP model.

0.98. Therefore, selecting the simulation scale based on practical needs is reasonable, as a small fraction of simulations can already reveal overall patterns, while using 60 % yields nearly the same predictive accuracy as the full dataset. In practice, 1–2 % of variance remains unexplained, which is normal and expected, as perfect fitting is nearly impossible. Overall, the MLP model outperformed the RF model in terms of training speed, stability, and final accuracy. Owing to the feedback-based learning mechanism of neural networks, the MLP demonstrates distinct advantages in predicting the motion responses of FPV systems.

Root Mean Squared Error (RMSE) is another core metric in regression tasks, measuring the deviation between predicted and true values, where smaller values indicate higher accuracy. Fig. 11(b) presents the RMSE curves for the MLP model over 1000 epochs for both training and validation sets. Both curves consistently decrease and plateau after approximately 400 epochs, indicating that the model continues to learn and eventually converges. No increase in validation error is observed, confirming that overfitting does not occur. Although the training RMSE is slightly lower than the validation RMSE, the difference is minimal,

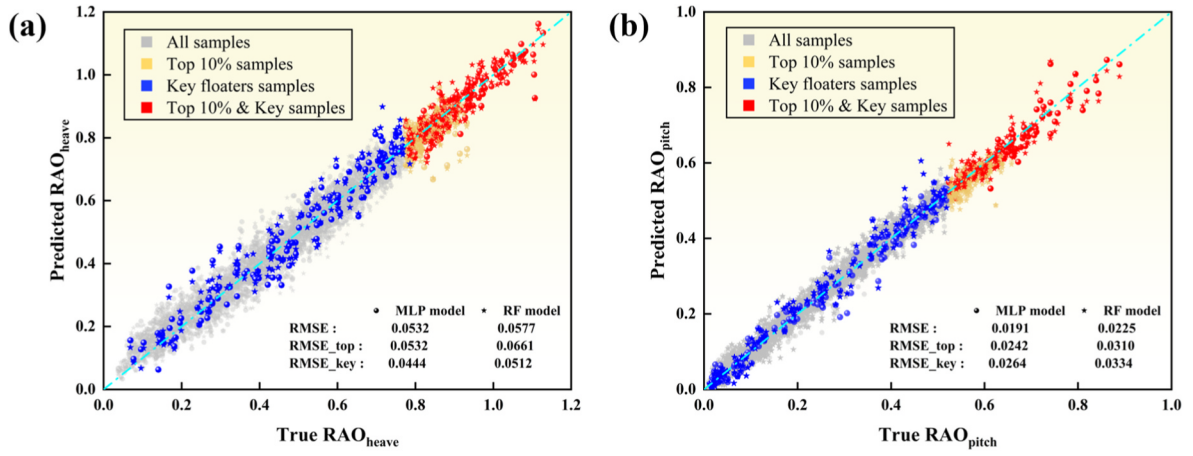


Fig. 12. Comparison between predicted and true RAO values of all floaters in the test dataset (a) heave RAO (b) pitch RAO.

suggesting that the model does not merely memorize noise and generalized well. Overall, the steadily decreasing and converging RMSE curves validate the suitability of the chosen MLP model and hyper-parameters, demonstrating that the approach is both well-suited and robust for the related problem.

The extreme RAO peaks are among the most critical parameters in engineering design. A model may achieve high overall accuracy for the majority of low-response floaters while failing to capture the few floaters experiencing the largest loads. Fig. 12 presents the comparison between the predicted and true RAOs for all floaters in the test dataset, where points closer to the 1:1 reference line indicate smaller prediction errors. Yellow markers denote the top 10 % RAO values, blue markers represent key floaters exhibiting the highest peak responses among all cases, and red markers highlight the intersection of these two subsets. The results demonstrate that both the MLP and RF models maintain strong consistency with the reference data even for extreme responses, without clear underestimation or overestimation of peaks. Overall, the MLP model outperforms the RF model. Nevertheless, a slight degradation in predictive accuracy is observed for the largest RAO values. This is likely because such extreme events occur infrequently in the dataset, providing limited samples for model training.

4.3. Model explainability analysis

4.3.1. Importance analysis of input features

Feature importance analysis aims to reveal the extent to which each input feature influences the model's predicted outputs and identifies which features have decisive effects. In the prediction of dynamic

responses for FPV systems, understanding the importance and contribution of input features is crucial for system safety design and optimization. Metrics such as MSE quantify overall prediction error from a global perspective. However, they do not indicate the contribution of individual features or reveal how variations in features affect model outputs. Therefore, this study employs the SHapley Additive exPlanations (SHAP) method (Lundberg and Lee, 2017), based on the Shapley value from cooperative game theory, to provide a deeper interpretation of the MLP model. Since both MLP and RF models exhibit highly consistent predictive trends, the SHAP-based feature importance is analyzed only for the MLP model. The dominant factor R and the relative contributions of mooring type and incident angle are verified to be consistent across both models. Therefore, the MLP-based SHAP analysis is considered representative of the overall feature-dependence characteristics.

The relative importance of an input feature can be measured by averaging its absolute Shapley values across all samples. The scale of the Shapley value corresponds to that of the feature, and a larger value indicates a greater contribution to the prediction. It should be noted that, although PCA dimensionality reduction is applied during prediction, it does not affect feature importance evaluation.

Fig. 13 presents the SHAP-based global and extreme-response feature importance for both heave and pitch RAOs. Panels (a) and (c) show the global SHAP summary plots computed over the entire test dataset, illustrating the overall distribution of feature contributions. Panels (b) and (d) correspond to the Top 20 % RAO subset, which includes the highest 20 % of predicted response amplitudes in the test set, representing near-extreme conditions. Each point represents a test sample,

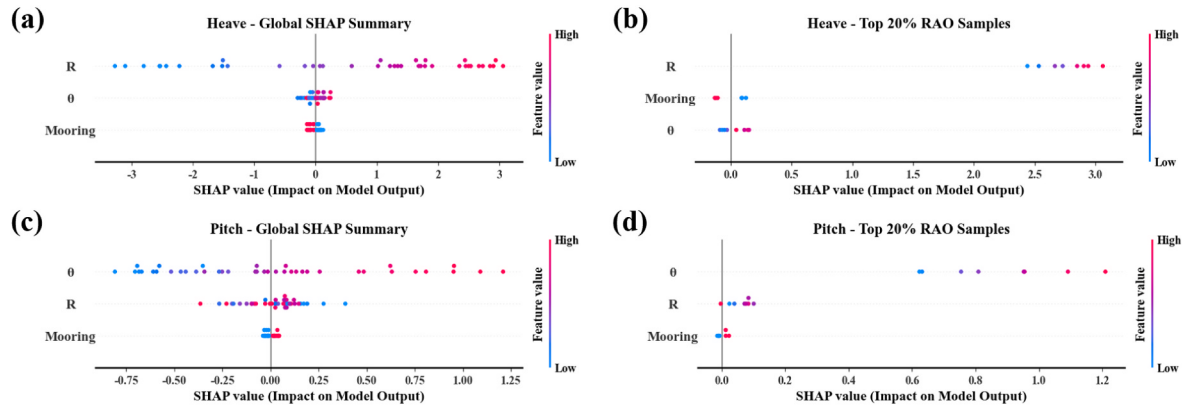


Fig. 13. SHAP-based global and extreme-response feature importance for heave and pitch RAOs (a) Heave - Global SHAP summary (b) Heave - Top 20 % RAO subset (c) Pitch - Global SHAP summary (d) Pitch - Top 20 % RAO subset.

and color denotes the normalized feature value (blue = low, red = high). In the global SHAP distribution (Fig. 13(a)), the geometric ratio R is the dominant predictor for heave RAOs, exhibiting the widest SHAP spread and the largest mean magnitude. This indicates that vertical motion is primarily governed by the wavelength-to-structure size relationship, consistent with hydrodynamic scaling laws and potential-flow predictions. The incident angle θ and mooring type contribute less on average, implying that directional and connection effects mainly redistribute wave loads spatially rather than changing the overall heave magnitude. However, when the analysis focuses on the Top 20 % high-response subset (Fig. 13(b)), the SHAP contribution of mooring type increases substantially, while that of θ becomes slightly more dispersed. This shift suggests that, under near-resonant conditions or strong multi-body coupling, mooring stiffness and connection configuration significantly affect the maximum vertical motion. Therefore, while R dominates the mean hydrodynamic response, mooring effects become critical in determining peak amplitudes relevant to design safety.

For pitch (Fig. 13(c)), the global SHAP summary shows that the incident angle θ is the most influential input variable, followed by R ; mooring type exhibits minimal contribution. This trend reflects that pitch excitation is mainly driven by wave directionality, since oblique waves induce asymmetric loading across the array. In contrast, the Top 20 % subset (Fig. 13(d)) reveals an enhanced influence of R , while θ remains dominant. This implies that the largest pitch responses occur when both a high aspect ratio (large R) and oblique incident waves coexist, promoting stronger phase asymmetry and rotational excitation. Mooring configuration still has limited impact on pitch, suggesting that rotational dynamics are primarily governed by hydrodynamic rather than structural constraints.

Fig. 14 illustrates the pairwise SHAP interaction plots for heave and pitch responses. For the heave motion, the wavelength ratio R is clearly the dominant factor, showing a nearly linear positive relationship with the SHAP value, while θ has a minor amplifying effect when R is large. The mooring type does not exhibit a systematic influence on either θ or R , suggesting that the heave motion is primarily governed by wave-structure resonance rather than mooring stiffness. In contrast, for the pitch motion, θ becomes the dominant predictor, with SHAP values increasing almost linearly with θ . The effect of R is secondary and shows noticeable interaction with θ but remains insensitive to the mooring configuration. Overall, the Cross-Quadrilateral mooring slightly broadens the SHAP value distribution but does not fundamentally alter the dominant physical dependence. These interaction plots confirm that R mainly drives the heave response through wavelength-structure

coupling, whereas θ controls the pitch response via asymmetric excitation moments. The mooring type acts only as a secondary modifier, influencing extreme cases but not changing the overall feature hierarchy.

4.3.2. Analysis under different loads

Based on the validated models and the dataset obtained from reliable simulations, the machine learning models can efficiently and accurately predict the primary motion responses of FPV systems under different wave loads and mooring types. This allows for a more intuitive and convenient analysis of how incident angle, mooring type, and the wave length-to-floating body width ratio (R) affect the floating body responses. Fig. 15(a)–(b) present the RAO_{heave} and RAO_{pitch} for each floating body under nine typical wave load and mooring scenarios, with the incident wave direction consistent with that in Section 2.4. With the trained predictive model, computations using a GTX4070 GPU take only a few seconds, whereas running the corresponding simulation model requires at least several hours from setup to computation.

From Fig. 15(a), it can be seen that RAO_{heave} exhibits clear patterns with respect to both R and θ . As R increases from 3 to 9, the overall heave response significantly intensifies. In particular, the peak and secondary peak distributions are more distinct on the wave-facing side and the trailing edge of the array. This occurs because as R increases, the combined effects of wave radiation and diffraction lead to local energy accumulation. Differences due to incident angles are also evident: at $\theta = 15^\circ$, the response distribution is relatively symmetric, similar to that shown in Fig. 5. As the incident angle increases, the response distribution gradually shifts along the wave propagation direction, with enhanced front-edge responses and weakened rear-edge responses. This shift indicates that oblique waves induce stronger phase differences and spatial interference within the array, leading to a more uneven energy distribution.

The effect of mooring type is also significant: Cross-Quadrilateral Mooring provides stronger constraint on the heave response than Quadrilateral Mooring, leading to a slightly lower overall response, particularly when R is large. Fig. 15(b) shows the variation of RAO_{pitch} . Compared to heave, pitch response is more sensitive to the incident angle. When $R = 3$, different incident angles and mooring types have minimal impact, and all floating bodies exhibit low pitch levels. As R increases, the incident angle and mooring type begin to significantly influence the pitch response.

Similar to heave, floating bodies on the wave-facing side show larger responses, while the trailing edge exhibits weakened motion.

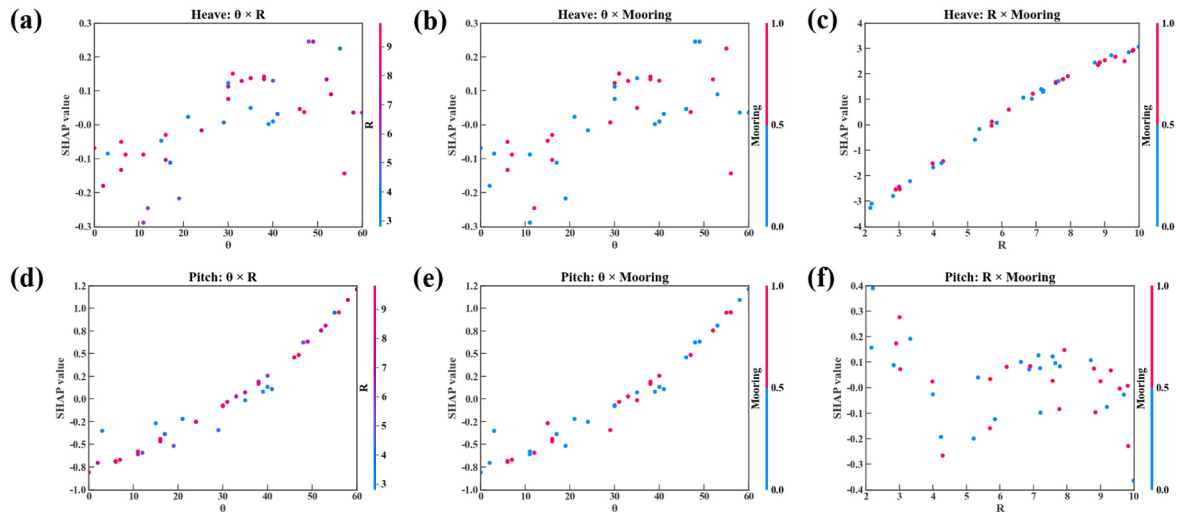


Fig. 14. SHAP-based feature interaction analysis for heave and pitch RAOs (a) Heave - $\theta \times R$ (b) Heave - $R \times$ Mooring (c) Heave - $\theta \times$ Mooring (d) Pitch - $\theta \times R$ (e) Pitch - $R \times$ Mooring (f) Pitch - $\theta \times$ Mooring.

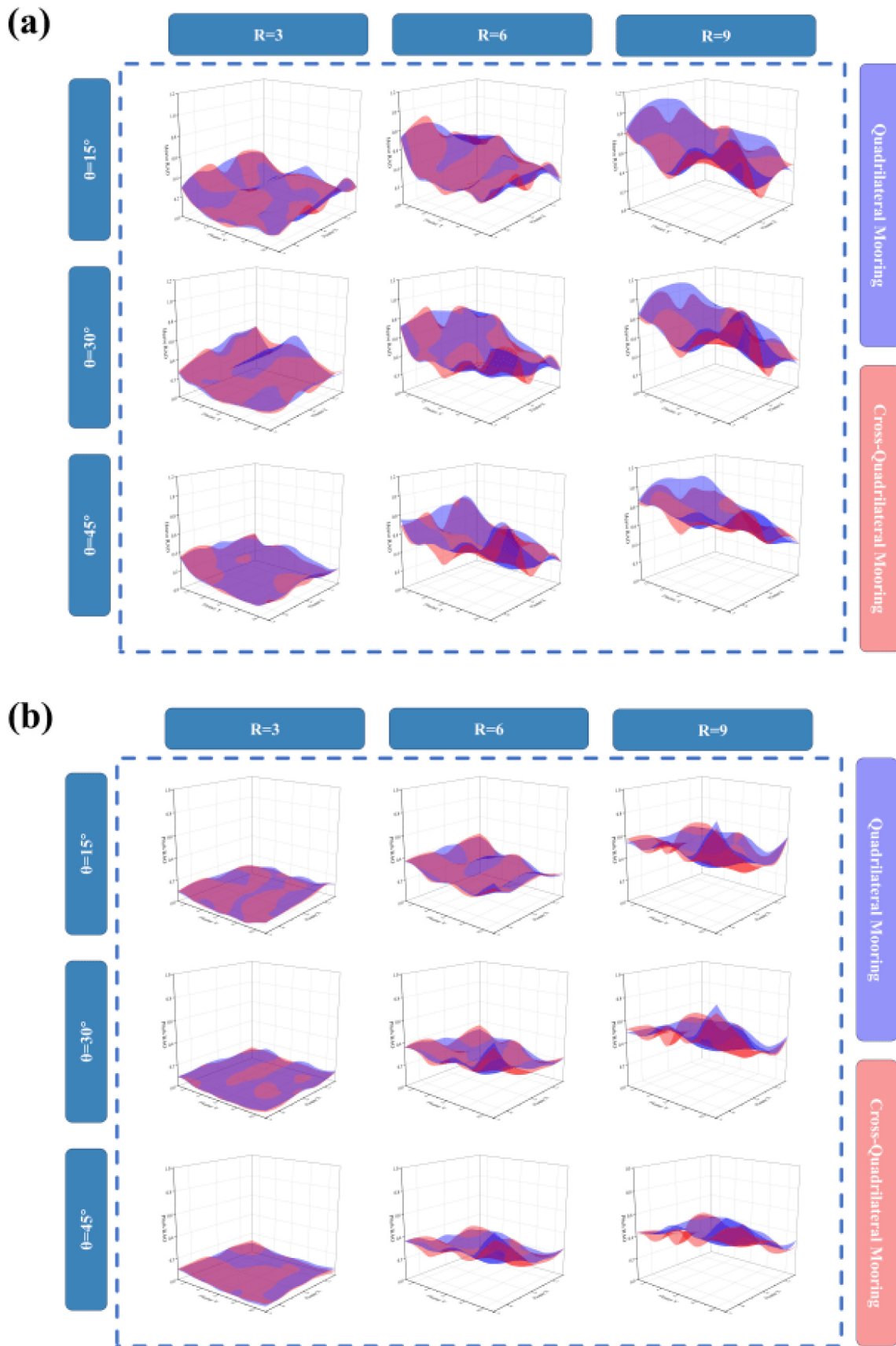


Fig. 15. Comparison of RAOs response under different loads (a) RAO_{heave} (b) RAO_{pitch} .

Interestingly, under high incident angles and large array sizes, Cross-Quadrilateral Mooring has a more pronounced pitch-constraining effect, suppressing peak pitch responses. Compared with the conventional quadrilateral mooring, the cross-quadrilateral mooring introduces additional restoring stiffness at the geometric center of the FPV array. This configuration effectively constrains the excessive responses of the internal modules, which are otherwise weakly restrained in the four-corner scheme. By redistributing wave-induced loads more uniformly across the array, the cross arrangement reduces the relative displacements between adjacent modules and alleviates local resonance phenomena. Moreover, the added symmetric constraints enhance the anti-torsional capability of the system, particularly under oblique wave incidence, thereby suppressing extreme pitch responses. As a result, both the overall RAO level and the peak responses are reduced, demonstrating that introducing central mooring lines can serve as an efficient strategy to improve the hydrodynamic stability of modular FPV systems.

5. Conclusions

Existing simulation approaches have high computational costs that are not suitable for large-scale FPV projects that have numerous floaters and wave conditions. For tasks that require extensive parameter analysis, AI-based rapid prediction approaches may be practical. This study develops two machine learning models: a tree-based RF model and a neural network-based MLP model, and evaluates their performance, serving as an alternative to traditional simulation methods. These models require only key input parameters, such as incident angle, wave length-to-floating body width ratio (R), and mooring type, to predict the primary motion responses (heave and pitch) of FPV systems under various conditions. Based on the analysis, the main conclusions are as follows:

- Machine learning models such as RF and MLP can accurately predict the RAO_{heave} and RAO_{pitch} of FPV systems. In the presence of noise in the simulation data, combining potential flow simulations with PCA-based dimensionality reduction allows efficient dataset construction without losing physical realism.
- Machine learning models trained on datasets obtained from potential-flow simulations can accurately predict most conditions across the entire parameter space, providing rapid and reliable surrogate predictions with substantially reduced computational cost compared to direct simulations.
- SHAP-based interpretability analysis reveals that R is the dominant factor for heave motion, exhibiting a clear positive contribution consistent with wave-structure resonance mechanisms. In contrast, the pitch motion is primarily governed by θ , which controls the spatial asymmetry and excitation moments of the array. The parameter R acts as a secondary factor that modulates pitch responses through its interaction with θ .
- Although mooring type is not a decisive factor, Cross-Quadrilateral Mooring can effectively reduce peak motion responses when R is large and overall system motion is high.

The study demonstrates that data-driven machine learning models have great potential for predicting multi-body motion responses, which is essential for accelerating FPV system optimization, structural design, and condition monitoring. With more industrial FPV projects available in the future, AI-based approaches should have more extensive applications based on their superior practicalities.

Although the proposed framework demonstrates strong predictive performance and clear physical interpretability, several limitations should be acknowledged. The time-domain formulation adopted in this study neglects Cummins's memory function, and thus transient wave radiation effects are not explicitly represented. In addition, while the model successfully reproduces the overall spatial patterns and mean

RAO responses, its accuracy in predicting the absolute maxima and fine-scale spatial gradients across the floater array has not been independently validated. The use of PCA introduces a linearity assumption and potential information loss, which may slightly affect the reconstruction of localized resonance peaks. Furthermore, all simulations were performed under regular-wave conditions, which may omit some effects in real-life projects. Finally, the present model was developed and calibrated for a single FPV geometry and mooring configuration, and its general applicability to other layouts remains to be further evaluated. These simplifications define the scope of the current work, and future studies will extend the framework to irregular waves and other FPV configurations to enhance generality and robustness.

CRedit authorship contribution statement

Chao Zhang: Writing – original draft, Resources, Project administration, Investigation, Conceptualization. **Yu Zhou:** Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jiaxu Li:** Software, Methodology, Investigation, Formal analysis. **Shengnan Chu:** Validation, Software, Methodology, Investigation. **Qing Qin:** Writing – review & editing, Software, Investigation. **Luofeng Huang:** Writing – review & editing, Resources, Project administration, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Luofeng Huang is a Deputy Editor of Ocean Engineering. The authors declare that they have no other known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data underlying the results are available as part of the article and no additional source data are required.

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