

Research Article

Sampling-based integrated design optimization of floating wind turbine substructures with Pywind

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Highlight

- This study develops a Pywind-based integrated design optimization framework that incorporates Latin Hypercube Sampling (LHS) strategies.
- Standard LHS yields faster results with fewer samples, while Maximin LHS offers better uniformity and reduced clustering, particularly at larger sample sizes.
- Maximin LHS improves space-filling uniformity by reducing the Voronoi coefficient of variation by 41.5%, increasing the mean Voronoi area by 46.8%.
- The study contributes to optimizing floating wind turbine design, offering a scalable, cost-effective solution for high-dimensional design spaces in offshore wind systems.

Abstract

Design optimization of floating wind turbine (FWT) substructures remains computationally demanding due to the extensive time-domain simulations required to explore high-dimensional design spaces. This study builds upon the previously developed Pywind-based integrated design optimization (IDO) framework, extending it by comparing two sampling strategies: Latin Hypercube Sampling (LHS) and Maximin LHS. A 15 MW semi-submersible FWT is employed to assess the performance of these methods in capturing design variability and coupled hydrodynamic and structural responses under stochastic environmental conditions. The analysis shows that Maximin LHS significantly improves space-filling uniformity, reducing the Voronoi coefficient of variation by 41.5% compared to Standard LHS.

Additionally, Maximin LHS shows a 46.8% improvement in the mean Voronoi area, resulting in more even parameter-space coverage. This highlights the capability of the Pywind-based IDO framework to conduct efficient, scalable, and statistically robust time-domain optimization. The findings underscore the IDO framework's potential for probabilistic design exploration, supporting intelligent decision-making for the next generation of FWT systems.

Keywords: floating wind turbine, integrated design optimization, Pywind-IDO, LHS, time-domain simulation

1. Introduction

Offshore wind energy has emerged as a cornerstone of the global renewable energy transition, offering vast untapped resources in deep-water regions where onshore and nearshore developments are constrained by spatial and environmental limitations (Obane et al., 2020). With the rapid expansion of offshore wind capacity, particularly in Europe and Asia, the industry is now moving toward deeper waters and larger turbines with rated capacity exceeding 15 MW (Barter et al., 2023). In such environments, fixed-bottom foundations become technically infeasible or economically unattractive, leading to the rise of floating wind turbines (FWTs) as a promising solution for cost-effective and large-scale offshore power generation. Their adaptability to varying water depths, enhanced access to high-quality wind resources, and potential for modular assembly make FWTs an essential enabler for future offshore wind deployment (Barooni et al., 2022).

Despite rapid technological advances, the deployment and industrialization of FWTs still face significant challenges. The coupled aero-hydro-servo-elastic interactions introduce strong nonlinearities, complicating both design and operation. The structural flexibility of large blades, the compliant motion of floating substructures, and the complex load transfer among aerodynamic, hydrodynamic, and control subsystems collectively form a high-dimensional design space with strong interdependencies (Zhao et al., 2022). Furthermore, achieving global static equilibrium while maintaining hydrodynamic stability, structural safety, and power performance requires repeated iterations under varying environmental and operational conditions. These challenges highlight the necessity of an integrated, simulation-driven design methodology that efficiently captures multidisciplinary coupling effects and guides early-stage decision-making.

The design optimization of FWTs generally follows a multi-stage process comprising conceptual configuration selection, preliminary design, and detailed structural optimization. Among these stages, the preliminary design phase plays a pivotal role in defining the overall system's feasibility by determining the platform type, principal dimensions, and ballast configuration that satisfy both hydrostatic and dynamic performance criteria (Karimi et al., 2017). It establishes the foundation for subsequent structural refinement, control tuning, and cost estimation. However, due to the strong coupling between aerodynamic loading,

hydrodynamic responses, and mooring stiffness, identifying an optimal configuration often requires extensive iterations over a wide design space and multiple environmental scenarios. Consequently, the efficiency and robustness of the preliminary design directly influence the quality and feasibility of later optimization stages (Chen and Kim, 2021).

To support such iterative analyses, existing workflows typically combine parameterized geometric modeling with frequency-domain hydrodynamic solvers, such as HydroD (Andersson and Pedersen, 2011), WAMIT (Lee, 1995), NEMOH (Kurnia and Ducrozet, 2023), or Capytaine (Ancellin and Dias, 2019), to compute added-mass, damping, and restoring characteristics of the substructure. The results are then fed into time-domain coupled simulation tools, including OpenFAST (NREL, 2023), SIMA, or OrcaFlex, to evaluate fully coupled dynamic responses under realistic environmental conditions. Optimization algorithms such as genetic algorithms (Hall et al., 2013), surrogate-assisted methods (Yildirim et al., 2025), or multi-objective search strategies have also been applied to improve local components (Wen et al., 2025), typically mooring layouts or tower stiffness, within these frameworks. Nevertheless, most of these studies remain component-oriented rather than system-integrated, lacking a unified workflow that simultaneously considers aero-hydro-servo-elastic coupling across all subsystems.

Recent studies have further explored data-driven and computationally efficient approaches for ocean engineering systems, including interpretable machine learning (Pei et al., 2026) and an efficient time-domain fatigue analysis framework for semi-submersible FWT hulls (Wang et al., 2026). These efforts reflect a broader trend toward reducing the computational burden of high-fidelity simulations in ocean engineering. However, current implementations are fragmented and labor-intensive, involving multiple software interfaces, manual data exchange, and repeated reinitialization to maintain consistency in static equilibrium. Even when simplified frequency-domain approaches are employed to accelerate early evaluations, iterative recalculations of hydrodynamic coefficients, added-mass and damping matrices, and restoring terms are still required as the platform's main dimensions evolve. These fragmented loops lead to computational inefficiency, hinder automation, and reduce reproducibility when performing large-scale parametric or optimization studies. Therefore, there is a pressing need for a unified, configuration-driven framework that seamlessly integrates parametric modeling, hydrodynamic analysis, and coupled dynamic simulation within a single workflow. Such integration would enable efficient, reproducible, and scalable preliminary design exploration of FWT substructures, thereby bridging the gap between high-fidelity analysis and automated design optimization.

To overcome the inefficiencies of fragmented workflows, our previous work proposed a time-domain integrated design optimization (IDO) framework (Li et al., 2025b). The framework was implemented in OpenFAST through a secondary development interface for dynamic response evaluation, and another was built entirely within Pywind (Dong et al., 2025), an in-house Python-based aero-hydro-servo-elastic simulation platform. This integration established

a consistent data flow from geometry generation and equilibrium initialization to dynamic analysis and post-processing, enabling automated batch simulations with minimal human intervention. In earlier studies, the IDO framework was applied to a brute-force design optimization case study, systematically evaluating hundreds of substructure configurations for a 15 MW semi-submersible FWT (Kang et al., 2026). While this exhaustive search provided valuable insights into parameter sensitivities and performance trade-offs, it remained computationally intensive for large-scale or high-dimensional design exploration.

Therefore, the present study extends the IDO framework by incorporating sampling-based strategies to enable efficient, statistically representative exploration of the high-dimensional design space. In contrast, sampling techniques offer a practical means of capturing system behavior using a limited number of well-distributed design points, thereby providing both accuracy and efficiency in early-stage design studies. Moreover, sampling analysis facilitates dimensionality reduction by identifying dominant variables governing platform stability and dynamic responses, thereby transforming high-dimensional design problems into tractable subspaces. The primary innovation of this study is the integration of Latin Hypercube Sampling (LHS) and its Maximin-enhanced variant into the Pywind-based IDO workflow to enable data-efficient time-domain optimization. A comprehensive case study of a 15 MW semi-submersible FWT (Li et al., 2025a) is conducted to systematically compare the two sampling strategies with respect to spatial coverage, convergence behavior, and predictive fidelity. Through this integration, the framework demonstrates how optimized sampling distributions can substantially reduce computational cost while preserving the physical interpretability and accuracy of fully coupled dynamic simulations, providing a foundation for future extensions toward probabilistic and intelligent design optimization.

The remainder of this paper is organized as follows: Section 2 describes the methodological framework, including the implementation of the Pywind-based IDO workflow and the integration of the two sampling algorithms. Section 3 introduces the case setup, covering the 15 MW semi-submersible configuration, the definition of design variables, and the sampling plan. Section 4 presents and discusses the comparative results of the Standard LHS and Maximin LHS strategies, focusing on space-filling performance and sensitivity representation. Finally, Sections 5 and 6 discuss and summarize the main findings, highlight the methodological contributions of sampling-based IDO, and outline future research directions.

2. Methodology

2.1. Overview of the Integrated Design Optimization Framework

The time-domain IDO framework aims to provide a unified, automated workflow for the preliminary design and performance evaluation of FWT. As illustrated in **Fig. 1**, the framework is composed of three modules: (1) Principal parameter configuration and sampling; (2) Parametric modeling and hydrodynamic analysis; and (3) Fully coupled dynamic simulation and performance evaluation. This architecture establishes a continuous data stream from the

definition of design variables to time-domain analysis, enabling both deterministic and sampling-based optimization processes within a single computational environment.

In the first stage, the framework defines a set of principal design parameters, such as column spacing, pontoon dimensions, draft, and deck height, that determine the platform's primary geometry and hydrostatic equilibrium. To efficiently explore the design space, the framework integrates Standard LHS and its Maximin-enhanced variant to generate representative design sets (Helton and Davis, 2003). These sampling strategies ensure balanced coverage of high-dimensional parameter spaces and construct a comprehensive database for subsequent evaluation, thereby supporting both sensitivity analysis and dimensionality reduction. The second stage involves parametric geometry generation, ballast optimization, and hydrodynamic analysis. Each sampled configuration is automatically meshed through the pygmsh modeling module (Schlömer, 2022). The hydrodynamic coefficients, including added mass, radiation damping, and restoring matrices, are computed using open-source boundary element solvers Capytaine (Ancellin and Dias, 2019). This process allows rapid assessment of hydrodynamic performance across multiple configurations and provides essential inputs for time-domain simulations. In the third stage, the framework performs fully coupled aero-hydro-servo-elastic dynamic simulations using Pywind (Dong et al., 2025). The simulation results, including platform motions, tower-base loads, and mooring tensions, are post-processed and stored in a database for performance and sensitivity analysis. Statistical indicators and aggregated response metrics are then used to evaluate trade-offs among stability, structural loading, and cost proxies, forming the basis for optimization and design-space refinement.

Fig. 1 Workflow of the sampling-based IDO framework for FWT substructures.

The framework consists of three main stages: (1) principal parameter configuration and sampling (Standard LHS and Maximin LHS); (2) parametric modeling, ballast optimization, and hydrodynamic coefficient computation; and (3) fully coupled time-domain simulation and performance evaluation using Pywind.

2.2. Sampling strategy

The IDO of FWT substructures involves a multidimensional design space defined by principal-scale parameters such as column spacing, draft, column and pontoon diameters, and deck elevation. To efficiently explore the design space while preserving statistical representativeness, LHS and its optimized variants are employed in the present framework.

2.2.1. Standard Latin Hypercube Sampling

LHS provides a statistically efficient means of generating representative design sets within the multidimensional parameter space of the IDO framework. The method ensures that each design variable is uniformly sampled across its admissible range while maintaining minimal overlap among samples in different dimensions. Let the design vector be:

$$X = [x_1, x_2, \dots, x_d]^T \in \mathbb{R}^d \quad \text{Eq. 1}$$

where d is the number of design parameters, such as draft, column spacing, and column diameter, and each variable x_j is bounded by $[a_j, b_j]$. The objective of LHS is to generate a set of N samples $\{x^{(i)}\}_{i=1}^N$ that uniformly populate the d -dimensional hyper-rectangle while avoiding redundancy along any single dimension. To achieve this, the range of each variable x_j is divided into N equal probability intervals. One sample is drawn from each interval, and the samples are randomly combined across all variables so that every interval along every dimension is represented exactly once. Denote by π_j a random permutation of integers $\{0, 1, \dots, N-1\}$, and by $U_{ij} \sim \mathcal{U}(0, 1)$ a uniform random perturbation within each stratum. The normalized sampling matrix $Z \in [0, 1]^{N \times d}$ is thus constructed as:

$$Z_{ij} = \frac{\pi_j(i) + U_{ij}}{N}, i = 1, \dots, N, j = 1, \dots, d. \quad \text{Eq. 2}$$

This formulation guarantees that the projection of all N samples onto any coordinate axis is uniformly distributed. Each normalized sample is then mapped to the physical domain of the design variable by a linear or probabilistic transformation:

$$x^{(i)}_j = a_j + (b_j - a_j)Z_{ij} \text{ or } x^{(i)}_j = F_i^{-1}(Z_{ij}) \quad \text{Eq. 3}$$

where $F_i^{-1}(\cdot)$ denotes the inverse cumulative distribution function if a non-uniform prior is imposed on x_j . In practice, the uniform mapping is adopted for the principal-scale geometric parameters of the FWT platform. The Standard LHS method has several desirable properties:

- **Marginal stratification:** each variable is evenly represented across its range.
- **Low discrepancy:** compared with simple Monte Carlo sampling, LHS achieves lower variance for the same sample size N .
- **Scalability:** the algorithm requires only $O(Nd)$ operations and can be implemented with negligible overhead relative to downstream time-domain simulations.

Within the Pywind-based IDO framework, the LHS module thus serves as a computationally lightweight yet statistically robust front end for generating initial design configurations. It provides balanced coverage of the feasible region and serves as the foundation for subsequent Maximin refinements.

2.2.2. Maximin Enhancements

Although Standard LHS ensures uniform stratification along each design dimension, the resulting multidimensional point set may still exhibit local clustering or void regions, particularly when the number of design parameters is high. Such uneven spatial density can lead to biased representation of the design space and reduced accuracy in identifying global trends in hydrodynamic or structural responses. To overcome this limitation and achieve a more uniform global coverage, the Maximin LHS criterion is introduced as an optimization-based enhancement to the Standard LHS method.

The Maximin criterion maximizes the minimum pairwise distance between any two sampling points in the normalized design space, thereby enforcing the largest possible uniform separation among samples. Let the normalized LHS matrix be:

$$Z = [z_1, z_2, \dots, z_N]^T \in [0,1]^{N \times d} \quad \text{Eq. 4}$$

where each row $z_i = (Z_{i1}, Z_{i2}, \dots, Z_{id})$ represents one design configuration generated by LHS. Because the physical ranges of design variables, such as column spacing or draft, may differ significantly, the coordinates are first normalized by their respective scales to prevent anisotropy. Define the scaling matrix:

$$W = \text{diag}\left(\frac{1}{b_1 - a_1}, \frac{1}{b_2 - a_2}, \dots, \frac{1}{b_d - a_d}\right) \quad \text{Eq. 5}$$

and the scaled sample points $\bar{z}_i = Wz_i$. The optimization problem for the Maximin LHS is then formulated as:

$$\max_{Z \in \mathcal{L}} \delta(Z) = \min_{1 \leq i < k \leq N} \|\bar{z}_i - \bar{z}_k\|_2 \quad \text{Eq. 6}$$

where $\mathcal{L}$ denotes the set of all Latin-hypercube-feasible designs that preserve the one-point-per-stratum constraint. The objective $\delta(Z)$ represents the minimum Euclidean distance between any two scaled samples; maximizing it yields the configuration in which samples are as far apart as possible in the multidimensional space.

In practice, this optimization problem is solved heuristically because the feasible space $\mathcal{L}$ is combinatorial. A commonly used approach, adopted in the present framework, is the random candidate (random-cd) refinement scheme implemented in SciPy. Starting from an initial Standard LHS, multiple candidate exchanges of column elements are generated at random, and each candidate is evaluated by its minimum inter-point distance. If the new configuration increases $\delta(Z)$, it is accepted; otherwise, the previous design is retained. This stochastic coordinate-descent process continues until no further improvement is achieved or a preset number of iterations is reached. The resulting Maximin LHS achieves improved space-filling uniformity, mitigates sample clustering, and enhances the representativeness of the design database for subsequent performance evaluation.

2.2.3. Summary and implementation notes

The Standard LHS method provides a fast, uniformly stratified coverage of the parameter space, ensuring that each design variable is evenly represented across its range with minimal computational overhead. It is particularly suitable for rapid preliminary studies, sensitivity analyses, and situations where the number of design evaluations is constrained by computational cost. In contrast, the Maximin LHS algorithm introduces an additional optimization layer that maximizes the minimum inter-sample distance, thereby improving the overall space-filling property of the design set. This refinement mitigates local clustering and yields a more homogeneous global distribution of sampling points, which is beneficial for nonlinear, high-dimensional design spaces where interactions among parameters strongly influence hydrodynamic and structural responses.

Within the Pywind-based IDO workflow, both sampling schemes are implemented as modular components of the pre-processing stage. The sampling module first generates a normalized Latin hypercube matrix, which is then mapped to the physical design variables and subsequently evaluated through fully coupled simulations. **Fig. 2** illustrates the visual distinction between the two methods: the Standard LHS yields uniformly stratified but partially clustered samples, whereas the Maximin exhibits greater dispersion and more balanced space coverage. The algorithmic procedure of this sampling module is summarized in **Fig. 3**, which outlines the key steps from normalized LHS construction to the Maximin refinement and scaling to physical design ranges. The Maximin refinement terminates when no further improvement in the minimum inter-point distance is achieved, or when the preset iteration budget of the random-cd solver is reached.

Fig. 2 Sampling distributions between the Standard LHS (left) and the Maximin LHS (right). Both sets contain the same number of samples distributed in a two-dimensional normalized design space. The Maximin LHS achieves improved space-filling uniformity by maximizing the minimum inter-sample distance ($\Delta_{min} = 0.026$ vs 0.019 in the example), reducing local clustering and improving parameter-space coverage.

Fig. 3 Pseudocode of the LHS-based sampling module integrated in the Pywind-IDO framework. The algorithm first constructs a stratified Latin hypercube in the normalized space and, when the maximin option is selected, refines the layout by maximizing the minimum pairwise distance. The resulting samples are then scaled to the physical design ranges and passed to the subsequent modeling and simulation modules.

2.3. Pre-processing module

Following the generation of representative design samples through the LHS-based module, each configuration is automatically converted into a fully defined three-dimensional platform geometry for subsequent hydrostatic and hydrodynamic evaluations. This stage constitutes the parametric modeling layer of the IDO framework, in which geometric construction, ballast adjustment, and hydrodynamic coefficient computation are performed before time-domain simulation.

2.3.1. Parametric geometric modeling

The platform geometry is defined by a set of principal-scale parameters, including column spacing, column diameter, pontoon diameter, and draft, which are sampled from the LHS-based design database. A parametric model generator, implemented in Python using the pygmsh library (Schlömer, 2022), constructs the geometric mesh and boundary surfaces of each semi-submersible configuration. The geometry generation routine maintains strict geometric consistency by enforcing watertight connectivity between the columns, pontoons, and deck structures. The parametric approach allows rapid regeneration of multiple platform configurations while preserving mesh quality and numerical stability in downstream hydrodynamic solvers. The meshing density is adaptively refined around the free surface and connection regions to accurately capture potential-flow interactions.

2.3.2. Ballast optimization and hydrodynamic analysis

For each generated geometry, a ballast optimization routine is executed to satisfy global hydrostatic equilibrium conditions (Li et al., 2025b). This process is particularly crucial for side-column floating wind turbines, where the complex mass and load distribution due to design asymmetry requires more careful ballast management than for central-column systems. The ballast iteration aims to determine a feasible set of ballast heights in the three columns that satisfy two coupled requirements: (i) the global mass target, given by the displaced water at the design draft, and (ii) the system center of gravity (CoG) constraint along the x-axis (set to zero in this study for symmetry). The solution must respect geometric bounds between the pontoon top and column top for each tank. At each trial fill height, the framework generates a ballast mesh representing the internal water domain by offsetting the shell thickness from the column and pontoon walls. Hydrostatic quantities of this ballast domain are then evaluated using Capytaine to obtain ballast volume, ballast mass, and ballast centroid. The system CoG is computed by combining the platform, tower, rotor-nacelle assembly (RNA), and ballast contributions and normalizing by the total mass. The ballast optimization algorithm proceeds in three phases:

- **CoG adjustment phase:** With the first column height fixed as a reference, the two side columns are updated using a symmetric binary search. The goal is to reduce the CoG discrepancy along the x-axis.
- **Mass adjustment phase:** Once the CoG constraint is nearly satisfied, all three column heights are adjusted by a common step to match the target ballast mass implied by the global displacement.
- **CoG fine-tuning phase:** If mass tolerance is met but the CoG deviates due to the global shift in phase 2, a local search is conducted around the second and third column heights while keeping the reference height unchanged.

The algorithm tracks the best intermediate solution and terminates either when both the CoG constraint and the mass tolerance are satisfied or when the maximum number of iterations is reached. Upon convergence, the framework outputs the optimal fill-height vector, ballast mass, ballast centroid, and the final system CoG. These quantities are reused to set the CoG for the complete platform mesh and to compute the final hydrostatic and inertia properties that initialize the time-domain simulation. Frequency-domain hydrodynamic coefficients are evaluated on the part mesh that isolates the submerged wetted geometry. The body is discretized for potential-flow analysis in Capytaine to obtain added-mass and radiation-damping matrices over a range of frequencies and degrees of freedom of motion, along with wave-excitation forces. Hydrostatic stiffness and waterplane properties are computed consistently from the total mesh with the converged system CoG.

2.4. Time-Domain simulation and post-processing

Each configuration generated during pre-processing is analyzed using Pywind, an in-house, fully coupled time-domain solver for FWTs (Dong et al., 2025). Pywind is implemented in Python and resolves the nonlinear interactions among aerodynamic, hydrodynamic, structural, mooring, and control subsystems within a unified set of equations of motion. Aerodynamic loads are computed using blade element momentum theory with dynamic stall corrections, hydrodynamic forces combine potential-flow radiation-diffraction loads from Capytaine with Morison-type viscous terms, and platform motions follow rigid-body dynamics extended through Kane's formulation. The mooring and control modules, respectively, provide quasi-static or dynamic cable models and variable-speed-pitch regulation.

Simulation outputs, including motions, structural responses, mooring tensions, power, and mass, are automatically post-processed and normalized against the baseline configuration. For each metric J_i , a signed relative improvement Δ_i is defined as:

$$\Delta_i = \begin{cases} \frac{J_i^{(0)} - J_i^{(c)}}{\max(\varepsilon, |J_i^{(0)}|)} & \text{if the objective is to minimize } J_i \\ \frac{J_i^{(c)} - J_i^{(0)}}{\max(\varepsilon, |J_i^{(0)}|)} & \text{if the objective is to maximize } J_i \end{cases} \quad \text{Eq. 7}$$

Where, ε is a small constant to prevent division by zero. The improvement is clipped to $\hat{\Delta}_i = \text{clip}(\Delta_i, -\delta_{max}, \delta_{max})$ with a practical $\delta_{max} \in [0, 5, 1]$ to limit the influence of rare extremes in time-domain statistics. All metrics are aggregated as:

$$R_{raw} = \sum_{i \in \mathcal{T}} w_i \hat{\Delta}_i \quad \text{Eq. 8}$$

and penalized when physical constraints are violated:

$$R_{final} = R_{raw} \prod_{i \in \mathcal{I}} \rho_c \quad \text{Eq. 9}$$

where each $\rho_c \in [0,1]$ is a penalty factor associated with constraint c (e.g., $\rho_c = 0.1$ for ballast failure). This design preserves gradient-like guidance from continuous metrics while decisively down-ranking infeasible candidates.

3. Case study setup

3.1. Floating wind turbine model description

This study considers a semi-submersible FWT system designed to support the IEA 15 MW reference turbine. The platform adopts a three-column layout with a side-mounted turbine, introducing intrinsic longitudinal asymmetry in mass and load distribution. This poses challenges in achieving hydrostatic equilibrium, especially in maintaining the longitudinal CoG alignment with the platform's geometric centerline, which is critical for static stability and dynamic performance. As shown in **Fig. 4**, the complete system consists of four major components: RNA, tower, floating platform (semi-submersible hull), and mooring system. Further specifications, including detailed properties of the tower, mooring system, and controller setup, can be found in Li et al. (2025b).

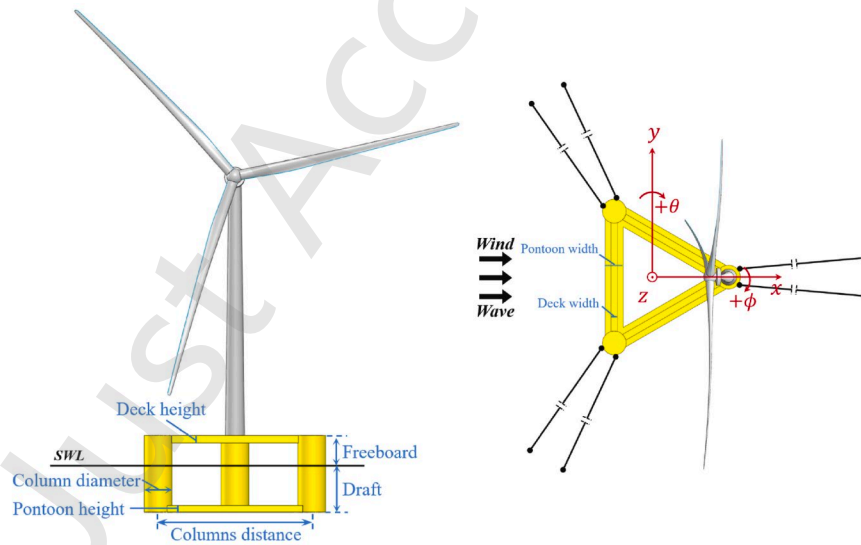


Fig. 4 Configuration of the 15 MW FWT with the three-column floater (Li et al., 2025b).

3.1.1. Wind turbine model

The upper turbine is modeled after the IEA Wind 15-MW reference turbine developed under Task 37 (Gaertner et al., 2020). This open-access model is representative of next-generation offshore turbines and has been widely adopted for research and benchmarking purposes. The turbine includes a three-bladed upwind rotor with a diameter of 240 m, a hub height of approximately 150 m, and a rated power of 15 MW. Detailed specifications for the RNA and tower, including mass properties and aerodynamic coefficients, are available in the NREL

technical report (NREL/TP-5000-75698) and the official GitHub repository (IEAWindSystems, 2025). The tower is a tapered tubular steel structure designed to resist combined wind and wave loads while satisfying fatigue, buckling, and natural-frequency constraints (Allen et al., 2020).

3.1.2. Floating platform configuration

The support structure is a three-column semi-submersible platform, with vertical columns connected by lower horizontal pontoons and upper deck beams. The selected geometry is based on Layout 1 reported by Wang and Moan (2023), as part of an initial global sizing study for large-scale floating wind platforms. The three-column semi-submersible is one of the most commercially mature floating foundation concepts, with proven hydrodynamic performance and water-depth independence, justifying its selection as the research object for validating the proposed IDO framework. **Table 1** shows the main dimensions of the semi-submersible hull. The platform's hydrostatic performance, including metacentric height and pitch stiffness, has been preliminarily validated under multiple wind directions and sea states, ensuring compliance with the criteria and suitability for further parametric exploration.

Table 1. Main dimensions of the semi-submersible hull (Wang and Moan, 2023).

Design Variable	Value	Description
Column diameter (m)	14.0	Outer diameter provides buoyancy and support.
CC distance (m)	75.0	Distance between column centers for stability.
Pontoon width (m)	11.0	Width of pontoons connecting the columns.
Pontoon height (m)	4.5	Affects submerged volume and structural integrity.
OP diameter (m)	14.0	Diameter of outer pontoons enhancing rigidity.
Draft (m)	20.0	Submerged depth affects buoyancy and stiffness.
Column height (m)	30.5	Length of each column contributing to stiffness.
Deck beam width (m)	4.0	Width of beams supporting the tower base.
Deck beam height (m)	4.0	Height of beams influencing bending resistance.
Freeboard (m)	15.0	Distance from waterline to deck ensures buoyancy.

3.2. Simulation implementation

3.2.1. Environmental and simulation setup

All simulations were performed under the rated operating condition of the IEA 15 MW reference turbine (Li et al., 2025b). The inflow wind speed at hub height was set to $U_{hub} = 10.59 \text{ m/s}$, corresponding to IEC turbulence class A with stochastic fluctuations generated by a Kaimal spectrum. The sea state was defined by a JONSWAP spectrum with a significant wave height $H_s = 2.09 \text{ m}$, peak period $T_p = 8.87 \text{ s}$, and peak enhancement factor $\gamma = 1.0$. The wind-wave alignment angle was kept at zero degree to represent the co-linear rated condition. Hydrostatic equilibrium for each sampled configuration was established through a constraint-based ballast adjustment routine, which iteratively updated the water ballast distribution until both the total mass and the CoG satisfied prescribed tolerances:

$$|M_{target} - M_{current}| \leq \epsilon_m, |CoG_{target} - CoG_{current}| \leq \epsilon_{cog} \quad \text{Eq. 10}$$

With $\epsilon_m = \epsilon_{cog} = 0.05$ as default tolerances. Each candidate design was simulated using fully coupled aero-hydro-servo-elastic dynamics under turbulent wind and irregular waves. The total simulation duration was 4100s with a fixed time step $\Delta_t = 0.0125$ s. This time step satisfies the numerical stability requirements for aerodynamic and hydrodynamic load calculations. The first 500s of each run were discarded to eliminate startup transients, leaving 3600s of steady-state data for statistical evaluation. Key response quantities, such as platform motions, tower-base bending moments, and mooring tensions, were extracted and time-averaged to compute the reward.

3.2.2. Case matrix

To compare sampling strategies, a series of 8 design sets was generated using the LHS. Each case corresponds to a unique combination of a sampling criterion and a random initialization, while sharing the same parameter bounds, environmental conditions, and baseline configuration. Specifically, both the Standard LHS and Maximin LHS criteria were evaluated under identical random number generator (RNG) keys to form paired experiments, thereby isolating the effect of the maximin refinement on space-filling performance and optimization outcomes. Two sampling densities were adopted, 100 and 300 samples, to balance statistical representativeness and computational cost. The complete case matrix is summarized in **Table 2**.

Table 2. Case matrix for LHS-based design generation and optimization studies.

Run ID	Samples N	Criterion	RNG key	Notes
LC1	100	Standard LHS	42	Paired with LC4 (same RNG)
LC2	100	Standard LHS	23	Paired with LC5 (same RNG)
LC3	100	Standard LHS	12	Paired with LC6 (same RNG)
LC4	100	Maximin LHS	42	Maximin refinement of LC1
LC5	100	Maximin LHS	23	Maximin refinement of LC2
LC6	100	Maximin LHS	12	Maximin refinement of LC3
LC7	300	Standard LHS	42	Higher sampling density, paired with LC8
LC8	300	Maximin LHS	42	Maximin refinement of LC7

3.2.3. Reward configuration and weighting

The reward function provides a scalar measure of overall design quality by aggregating multiple performance indicators derived from the coupled time-domain simulations. Each indicator represents a key physical response relevant to platform stability, structural safety, comfort, and cost. To ensure a balanced evaluation, all metrics are normalized with respect to the baseline configuration, following the formulation in **Eqs. (7)-(9)** in Section 2.4. Positive values indicate performance improvement, while negative values denote degradation. The indicators are grouped into five categories: (i) platform motions in six degrees of freedom (6-

DOF), (ii) tower-base bending and shear loads, (iii) nacelle accelerations, (iv) mooring-line tensions, and (v) power and mass metrics. Constraint handling is enforced through multiplicative penalty factors $\rho_c \in [0,1]$ that down-rank infeasible configurations. Penalties are triggered if ballast equilibrium fails, CoG constraints are violated, or motion and load thresholds are exceeded. In this study, small tolerance parameters ($\epsilon = 10^{-6}$) and clipping limits ($\delta_{max} \in [0.5,1.0]$) are adopted to maintain sensitivity while preventing domination by outliers. The weighting scheme is summarized in **Table 3**.

Table 3. Reward groups, indicators, and weighting used in the sampling-based IDO study. All statistics (mean, max, and std) are obtained from post-processed time-domain responses.

Group	Key metrics	Direction	Typical weight range
6-DOF motions	Surge, sway, heave, roll, pitch, yaw	Minimize	0.1 - 3.0
Tower-base loads	Bending moment, shear force	Minimize	0.1 - 2.0
Nacelle acceleration	Mean/max/std	Minimize	0.2 - 1.0
Mooring tension	Mean/max/std	Minimize	0.1 - 0.5
Power & mass	Avg. power ($\uparrow$), steel mass ($\downarrow$)	Mixed	1.0 - 2.0

Note: The weights are engineering-judgment-based parameters and can be adjusted according to specific design objectives.

3.2.4. Hydrodynamic computation and verification

Fig. 5 illustrates the hydrodynamic modeling and time-domain verification within the IDO framework. The left panel presents the wetted-surface mesh of the three-column semi-submersible platform, automatically generated by the parametric modeling module and discretized for potential-flow analysis in Capytaine to compute the added-mass, radiation-damping, and wave-excitation coefficients. The right panel compares the platform pitch time histories obtained from Pywind (solid line) and the commercial software SIMA (dashed line) under an operational condition. The two sets of results show good agreement and demonstrate the workflow from hydrodynamic coefficient computation to time-domain performance evaluation within the proposed LHS-IDO framework.

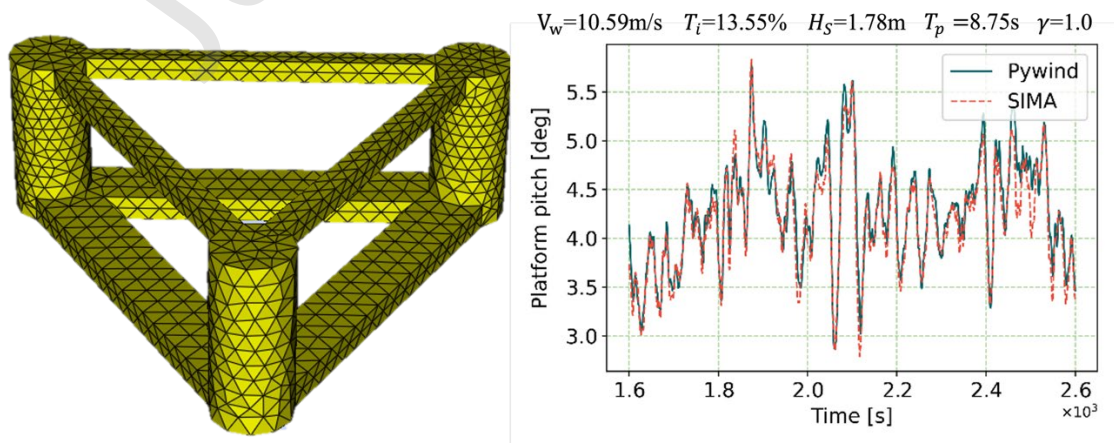


Fig. 5 Hydrodynamic modeling and time-domain verification of the IDO framework.

4. Results

4.1. Sampling analysis

In this subsection, the effectiveness of the two LHS strategies, Standard LHS and Maximin LHS, is evaluated based on their ability to provide a uniform coverage of the design space. The key metrics used to assess sampling quality are spatial coverage, clustering index, and Voronoi coefficient of variation (CV).

Fig. 6 presents the spatial coverage of the design points for both the Standard and Maximin LHS methods across multiple runs. Spatial coverage quantifies the extent to which the design points are distributed across the entire parameter space. A more evenly distributed distribution indicates greater spatial coverage, which is desirable for minimizing bias during optimization. The clustering index, as shown in the plot, provides insight into the concentration of the design points within particular regions. A lower clustering index indicates that the sampling strategy avoids excessive point clustering, ensuring a more thorough exploration of the design space. The analysis reveals that Maximin LHS outperforms Standard LHS in terms of both spatial coverage and clustering. For example, in the 100-sample configuration, Standard LHS has a mean clustering index of 1.3333, whereas Maximin LHS has 1.0000, representing a 25% reduction in clustering. This result indicates that Maximin LHS generates a more evenly distributed set of samples, with fewer regions of excessive concentration. The spatial coverage values for both methods remain near zero, indicating no significant clustering at the global scale. However, Maximin LHS clearly achieves a more uniform distribution, as evidenced by its consistently lower clustering index.

Fig. 6 Comparison of sampling distributions between Standard LHS and Maximin LHS for 100 samples: LC1 vs LC4 (left), LC2 vs LC5 (middle), LC3 vs LC6 (right). The Maximin LHS achieves improved space-filling uniformity by maximizing the minimum inter-sample distance, reducing local clustering, and improving parameter-space coverage.

Fig. 7 shows the Voronoi diagrams for both LHS strategies, providing a visual representation of how the design space is partitioned by the sampled points. The CV is used to measure the uniformity of the distribution by analyzing the variation in the areas of the Voronoi cells. The smaller the CV, the more evenly the parameter space is filled by the samples. The Voronoi analysis indicates that Maximin LHS significantly improves uniformity compared to Standard LHS. For example, in the 100-sample configuration, the mean Voronoi CV for Standard LHS is 5.1999, whereas for Maximin LHS it is 1.4633, representing a 71.9% improvement. This suggests that Maximin LHS yields a more uniform distribution of points, thereby minimizing variability in Voronoi cell sizes. Additionally, the mean Voronoi area for Maximin LHS is 0.0296, compared to 0.0556 for Standard LHS, indicating a 46.75% improvement in coverage.

Fig. 8 presents the results of the Principal Component Analysis (PCA), which assesses the dimensional efficiency of the two sampling strategies. PCA identifies the most significant dimensions of the design space and provides insight into how effectively the sampling strategies explore the parameter space. The analysis reveals that, for both methods, the number of components required to explain 90% of the variance is the same: 9 components. However, Maximin LHS demonstrates a more efficient sampling strategy by capturing a higher percentage of variance in the first principal component (PC1). For Standard LHS, PC1 accounts for 15.7% of the variance, while for Maximin LHS, it accounts for only 10.8%. This suggests that Maximin LHS provides a more efficient exploration of the design space, capturing a wider range of variations with fewer components.

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Fig. 7 Comparison of Voronoi diagrams between Standard LHS and Maximin LHS for 100 samples: LC1 vs LC4 (upper), LC2 vs LC5 (middle), LC3 vs LC6 (lower). The Voronoi diagrams illustrate the spatial distribution of the sampled points. Maximin LHS improves the uniformity of the design space coverage, as evidenced by the reduced variation in the Voronoi cell sizes ($CV = 2.9723$ vs 5.0828 for Standard LHS), minimizing clustering and enhancing the efficiency of sampling.

Fig. 8 PCA comparison of Standard LHS and Maximin LHS for 100 samples: LCs 1-3 (left) vs LCs 4-6 (right). The PCA results show the dimensional efficiency of both sampling methods. Maximin LHS requires fewer components to capture 90% of the variance (9 components for both methods), but exhibits a reduced variance in the first principal component (PC1: 10.8% for Maximin vs 15.7% for Standard LHS), indicating a more efficient exploration of the design space.

In summary, **Table 4** shows the quantitative comparison of sampling metrics. The analysis demonstrates that Maximin LHS consistently outperforms Standard LHS in terms of uniformity and efficiency. Maximin LHS provides a more evenly distributed set of samples, reduces clustering, and improves spatial coverage, as reflected in the lower Voronoi CV and clustering index. The results from the PCA analysis indicate that Maximin LHS is more efficient at exploring the design space, requiring fewer components to capture most of the variance. These findings highlight the advantages of Maximin LHS, particularly when computational resources are limited, as it ensures a more reliable optimization process with better coverage of the parameter space.

Table 4. Quantitative comparison of sampling metrics for LCs 1-6.

LCs	Min Distance (mean)	Mean Distance (mean)	Voronoi CV (mean)	Mean Area	Std Area	Improvement (%)
LC1	0.012	0.533	5.200	0.033	0.175	-
LC2	0.017	0.529	7.868	0.116	0.916	-
LC3	0.012	0.530	2.181	0.017	0.037	-
LC4	0.012	0.534	1.463	0.018	0.026	+41.5%
LC5	0.012	0.532	4.494	0.048	0.215	+41.5%
LC6	0.010	0.532	2.960	0.023	0.069	+46.8%

Note: Maximin LHS shows significant improvements in spatial coverage and uniformity. Compared to Standard LHS, it reduces the Voronoi CV by 41.5% on average. Additionally, the mean area covered by each sample increases by 46.8%, while the clustering index decreases to 1.000, which is a 25% reduction compared to Standard LHS.

4.2. Reward analysis

This subsection focuses on the analysis of reward distribution and reward change rate for the designs generated using both Standard LHS and Maximin LHS. The reward function is a key metric for evaluating the overall performance of the designs, with higher values indicating better configurations.

The histograms in **Fig. 9** (upper panel) show the distribution of reward values for each configuration. The statistical summary of the rewards reveals that Maximin LHS generally yields a lower mean reward than Standard LHS, with mean rewards of -2.164 and -2.151, respectively. Despite the lower mean reward, Maximin LHS exhibits greater consistency in results, as evidenced by a smaller standard deviation (1.812 for Maximin LHS vs. 1.558 for Standard LHS). The boxplots in **Fig. 9** (lower) further highlight this trend, with Maximin LHS demonstrating a narrower interquartile range and fewer outliers, indicating more reliable and stable performance across different design iterations. The statistical analysis of the reward distribution shows that the mean rate of change in reward for Maximin LHS is consistently closer to zero, indicating more stable optimization with fewer fluctuations. For example, the mean reward change rate for LC1 (Standard LHS) is -0.0127, whereas for LC4 (Maximin LHS) it is -0.0224, indicating that the Standard LHS is slightly more variable in its reward progression. However, the difference is not large enough to be statistically significant, as confirmed by the t-test (p-value = 0.9257).

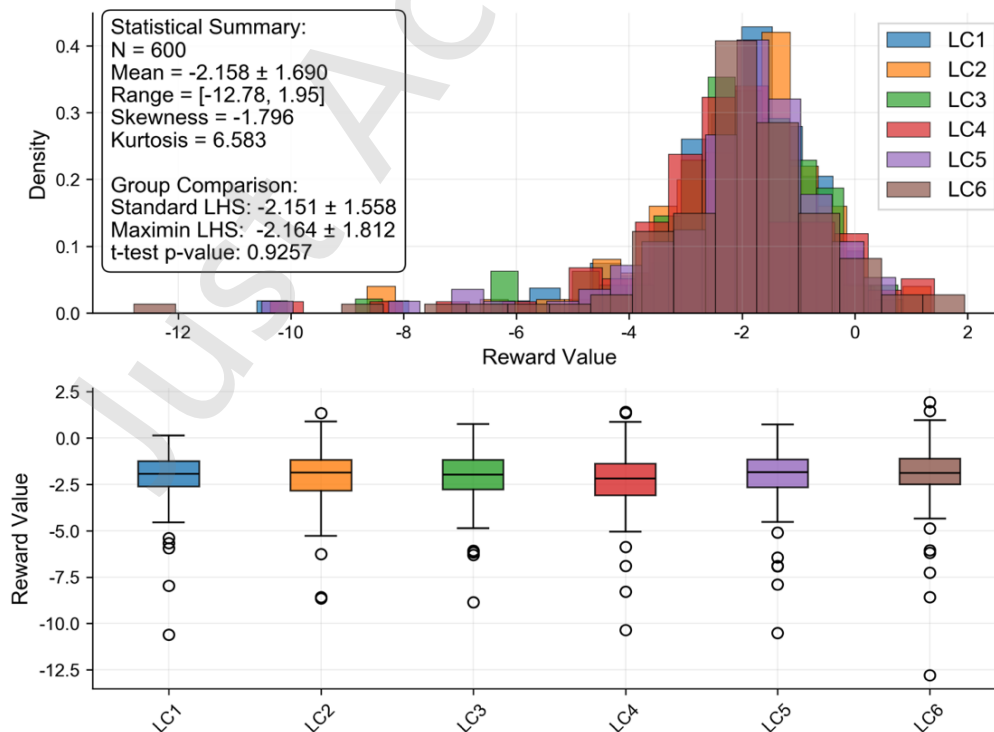


Fig. 9 Reward distribution comparison between Standard LHS and Maximin LHS for LCs 1-6. The histograms (upper) and boxplots (lower) illustrate the variation in reward values, with Maximin LHS exhibiting lower variability and more consistent performance.

Furthermore, **Fig. 10** illustrates the reward change rate dynamics over iterations for both methods. The scatter plot (left) shows that the reward change rate for Maximin LHS is more evenly distributed around zero, indicating smoother convergence, while Standard LHS exhibits more outliers and larger fluctuations. The density plot (right) further supports this observation: the distribution of reward change rates for Maximin LHS is more concentrated around zero, suggesting that Maximin LHS yields more consistent improvements toward optimal designs. In contrast, Standard LHS has a broader distribution with larger positive and negative deviations, indicating more erratic changes in the reward values throughout the optimization process. Maximin LHS demonstrates better performance in terms of stability and consistency of improvement, as evidenced by the lower variability in the reward change rates. The standard deviation of the reward change rate is smaller for Maximin LHS (2.625) than for Standard LHS (2.221), further supporting the conclusion that Maximin LHS is more reliable at generating optimal configurations.

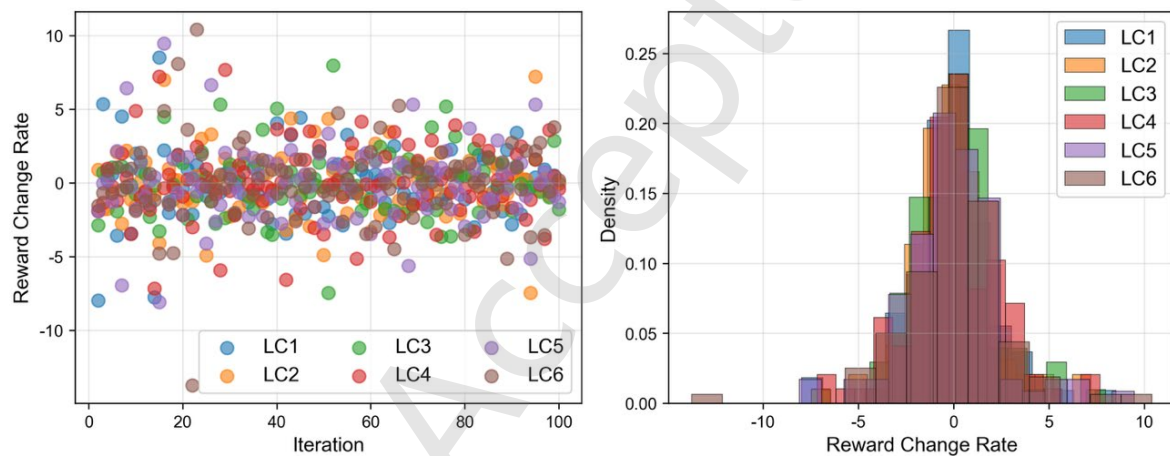


Fig. 10 Reward change rate comparison for Standard LHS and Maximin LHS (LCs 1-6). The scatter plot (left) and density plot (right) highlight the smoother and more consistent convergence of Maximin LHS, with less fluctuation in the reward change rate compared to Standard LHS.

4.3. Comparison of sample size and parameter sensitivity analysis

In this subsection, a detailed comparison of sample sizes (100 and 300) is presented to assess the impact of sampling density on reward values and to explore correlations between primary design parameters and rewards.

Fig. 11 presents the reward distribution for the 300-sample configurations of LC7 (300-Standard) and LC8 (300-Maximin), along with their statistical summaries. The distribution clearly shows that the reward values for LC7 are more consistently centered around a mean of -2.148 and have lower variance than those for LC8, which has a mean of -2.135. The range for LC7 is -8.678 to 1.911, and for LC8, it is -9.841 to 1.806, indicating that both configurations exhibit similar spread in reward values, but LC8 shows slightly more extreme values. In addition, LC7 exhibits a narrower interquartile range (IQR) and fewer outliers, suggesting a

more stable optimization process. In contrast, LC8, while also displaying a similar mean, has a broader IQR, indicating more variability in reward values. This result is further supported by the statistical test (t-test), which shows no significant difference between the two methods (p-value = 0.9257), meaning that despite the observed differences in reward variability, the two methods perform similarly in terms of reward distribution at the 300-sample level.

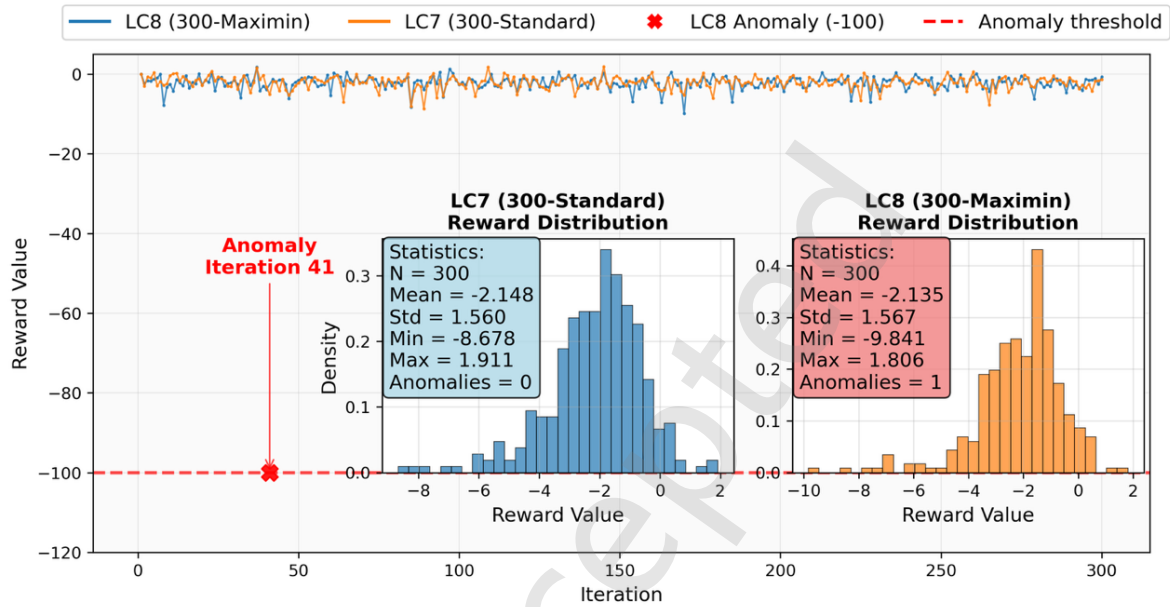


Fig. 11 Reward distribution and statistical summary for LC7 and LC8. Both LC7 and LC8 consist of 300 samples, showing the distribution of reward values over 300 iterations. LC7 exhibits a more consistent reward distribution with fewer extreme values, while LC8 shows more variation, including an extreme outlier in iteration 41, where the reward is -100. This anomaly results from the penalty applied for violating constraints such as ballast equilibrium or CoG violations. Despite the outlier, statistical analysis reveals similar overall performance between the two methods, with a p-value of 0.9257, indicating that both methods perform comparably.

Fig. 12 compares the parameter sensitivity identification efficiency for LC7. The top panel shows the correlation coefficients between each design parameter and the rate of change in reward for both sampling strategies. LC7 exhibits stronger correlations, with parameters such as Column Distance ($r = 0.49$) and Column Height ($r = 0.44$) making significant contributions to the reward. In contrast, LC8 shows weaker correlations, indicating that the Maximin LHS does not identify key parameters as effectively as the Standard LHS. This finding is quantified by the overall sensitivity identification efficiency, where LC7 achieves an average sensitivity of 0.1400, significantly outperforming LC8, which has an efficiency of only 0.0661. The bottom panel of Figure 10 further illustrates the sensitivity identification efficiency for individual parameters. LC7 demonstrates higher sensitivity across most parameters, particularly for Column Distance and Column Height, which are critical to platform stability and performance. This suggests that LC7 is more effective in identifying which parameters most influence the reward, making it a more reliable method for optimizing FWT designs.

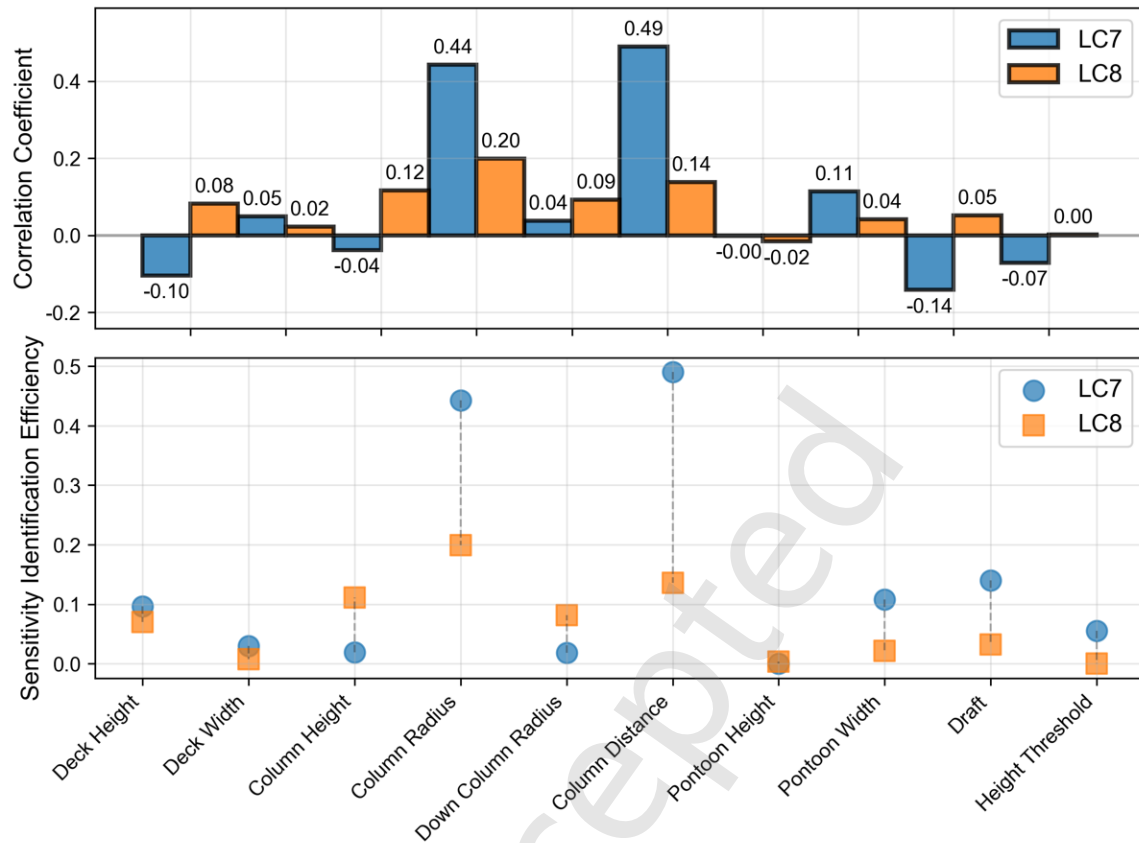


Fig. 12 Comparison of correlation between design parameters and reward change rate for LC7 and LC8. The upper plot illustrates the correlation coefficients between design parameters and reward for both sampling strategies. The lower plot displays the sensitivity identification efficiency of each parameter for both LC7 and LC8, showing that LC7 (Standard LHS) identifies key parameters with higher efficiency compared to LC8 (Maximin LHS), particularly in parameters such as Column Distance and Column Radius.

Fig. 13 compares key parameter values (top) and performance metrics (bottom) for four different configurations. The parameter table at the top displays parameter values across different configurations. For example, the Column Height increases by 1.1% for LC7 compared to LC1 (30.70 m vs. 30.36 m) and by 1.9% for LC8. Similarly, Column Radius in LC8 increases by 3.8% compared to LC1, while LC7's value is slightly reduced by 0.9%. The radar charts below compare the maximum and mean performance metrics for each configuration. In terms of Surge Max, LC1, LC4, and LC7 show small improvements over the baseline, with LC7 having the highest Surge Max value at 16.503 m (0.6% improvement). The most noticeable improvement is in Pitch Max, where LC7 achieves a 26.3% gain over the baseline. LC8 also outperforms the baseline, with a 39.4% reduction in Pitch Max. LC7 reduces the Tower Base Moment by 3.5%, while LC8 reduces it by 12.4%. These improvements indicate that LC7, with 300 samples, effectively optimizes critical responses such as Tower Base Moment and Surge compared to the baseline and other configurations. For Pitch Mean, LC7 demonstrates the most significant improvement of a 26.3% reduction compared to the baseline. LC1 shows a 6.0%

improvement in Pitch Max and a 4.0% reduction in Tower Moment Max. LC4 also shows a notable 20% improvement in Pitch Max, while LC8 exhibits a 39.4% reduction in Pitch Max, indicating the potential for more optimized aerodynamic and hydrodynamic behavior.

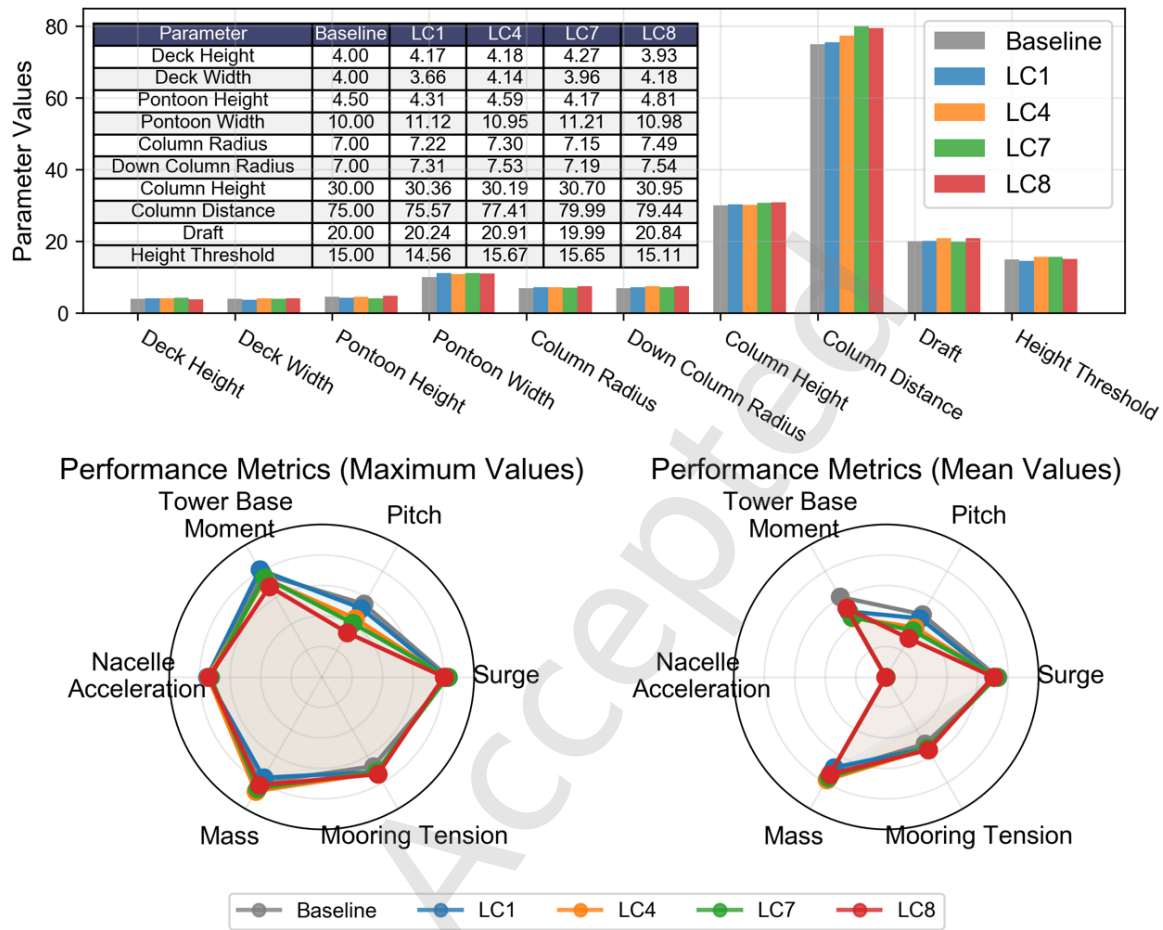


Fig. 13 Comparison of design parameters and radar plots for the best reward in LC1, LC4, LC7, and LC8. The upper plot shows the design parameter for the best-reward samples across iterations. The lower plot presents the radar charts comparing the normalized maximum and mean values of key performance metrics for the best-reward configurations.

5. Discussion

5.1. Key Innovations and Contributions

A significant contribution of this study is the comparison of two Latin Hypercube Sampling (LHS) strategies within the Pywind-IDO framework: Standard LHS and Maximin LHS. The Pywind-IDO framework offers a unified, fully automated workflow that integrates parametric modeling, ballast optimization, hydrodynamic coefficient computation, and coupled time-domain simulation into a single Python environment, eliminating the need for manual data exchange across fragmented software platforms. Its modular architecture enables scalable exploration of high-dimensional design spaces and straightforward extension to surrogate-assisted or probabilistic design methods, while retaining full physical interpretability by

evaluating every configuration through high-fidelity fully coupled simulations. Additionally, the study integrates reward functions to evaluate design performance, incorporating critical metrics such as platform motion, tower-base loads, nacelle acceleration, and power production. This reward-based approach supports more effective design optimization. The combination of Maximin LHS and reward functions within the Pywind-IDO framework improves efficiency and accuracy in FWT design, providing both quantitative and qualitative insights to optimize FWT substructures.

5.2. Comparison of Sampling Methods: Standard LHS vs Maximin LHS

Standard LHS is an efficient sampling method that requires fewer iterations to achieve reasonable space coverage, making it suitable for quick design explorations or when computational resources are limited. However, it tends to exhibit higher clustering, particularly with fewer samples, which can lead to suboptimal exploration of the design space. On the other hand, Maximin LHS improves spatial uniformity by maximizing the minimum distance between samples, resulting in a more even distribution across the parameter space. This method shows significant improvements in uniformity and coverage, especially as the number of samples increases. However, the trade-off is a slightly higher computational cost, as more iterations are required to achieve the same level of space coverage. The comparison of these two methods is summarized in the following table, highlighting key differences in their performance across several criteria. The table also guides when each method is most suitable, based on the specific needs of the optimization task. For practical engineering applications, Standard LHS is preferable for rapid preliminary screening with small sample sizes due to its negligible computational overhead, whereas Maximin LHS is better suited to detailed exploration of high-dimensional design spaces where uniform space-filling is critical. A hybrid workflow, using Standard LHS for initial screening followed by Maximin LHS for refined optimization, can also be adopted when computational budgets allow.

Table 5. Comparison of Standard LHS and Maximin LHS

Criteria	Standard LHS	Maximin LHS
Uniformity	Lower spatial uniformity compared to Maximin LHS	Provides more uniform space-filling, with lower CV values
Computational Cost	Less computational cost with fewer iterations needed for the same level of space exploration	Slightly higher computational cost, but more efficient space coverage
Clustering	Higher clustering, especially with fewer samples	Less clustering provides a more even distribution
Sample Density Impact	As the sample size increases, spatial uniformity improves significantly	Shows less improvement from 100 to 300 samples
Best Use Case	Ideal for quick results with fewer samples, less stringent uniformity requirements	Best for problems where uniform space exploration is critical, particularly with a higher sample size

6. Conclusion

This study presented a sampling-based integrated design optimization (IDO) framework for floating wind turbine substructures, built upon the in-house Pywind fully coupled solver. By integrating Standard and Maximin Latin Hypercube Sampling (LHS) strategies into a unified automated workflow, the framework enables efficient exploration of high-dimensional design spaces through fully coupled aero-hydro-servo-elastic time-domain simulations. A systematic comparison based on eight load cases with 100 and 300 samples reveals both the uniformity gains of Maximin refinement and the complementary strengths of the two sampling approaches. The key contributions and findings are summarized as follows:

- **Maximin LHS substantially improves space-filling uniformity**, reducing the Voronoi coefficient of variation by 41.5% and increasing the mean Voronoi cell area by 46.8%, while yielding more stable reward distributions with fewer outliers.
- **The two sampling methods exhibit complementary strengths**: Standard LHS achieves higher parameter-sensitivity identification efficiency (average sensitivity 0.140 vs. 0.066), making it preferable for rapid preliminary screening, whereas Maximin LHS is better suited for detailed exploration of high-dimensional design spaces.
- **The framework identifies meaningful performance gains with limited simulations**, achieving up to a 39.4% reduction in maximum pitch motion and a 12.4% reduction in tower-base bending moment using only 100–300 fully coupled evaluations, demonstrating a cost-effective approach for FWT preliminary design.

Despite these advancements, the study does have limitations. The analysis focused primarily on a specific FWT configuration and sample sizes of 100 and 300, which may not generalize to other turbine types or larger-scale studies. Future work could expand the investigation to include a broader range of sampling techniques, incorporate more diverse design configurations, and evaluate the impact of different environmental conditions. Furthermore, exploring hybrid sampling methods or integrating machine learning techniques could further enhance the optimization process by reducing computational costs while maintaining design robustness.

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Author contribution statement

P.C. wrote the main manuscript text, developed the Pywind-IDO framework, and conducted the LHS sampling comparison analysis. L.D. and R.M.F. coordinated the project and provided

engineering design specifications. Z.Y.F. and L.Y.Z. contributed floating wind engineering experience and validated the applicability of the results. Y.R.K. performed time-domain simulations and post-processed the data. Z.S.C. conceptualized the study, supervised the research, and critically revised the manuscript. All the authors have read and approved the final version of the manuscript.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of competing interest

All the contributing authors report no conflict of interests in this work.

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Use of AI generated contents and AI-assisted technologies statement

None.

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