Proceedings of the Thirty-fifth (2025) International Ocean and Polar Engineering Conference **www.isope.org**
Seoul/Goyang, Korea, June 1-6, 2025

ISBN 978-1-880653-74-6; ISSN 1098-6189

A Comparative Study of Kriging and ANN Surrogate Models in the Optimization Design of FOWT Platforms

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ABSTRACT

This paper presents a comparative study of different surrogate models, i.e. the Kriging and artificial neural network (ANN), in the optimization design of a floating offshore wind turbine (FOWT) platform. In order to solve the contradiction between the hydrodynamic performance of FOWT platforms and their steel consumption, this paper proposes a lightweight optimization design method based on surrogate models coupled with the multi-objective genetic method. Firstly, a sample set is constructed by Sobol sequential sampling, and the numerical simulation of the sample set is carried out using the potential flow method to obtain the hydrodynamic response of the FOWT platform in the sampling space. Then, two different surrogate models, i.e. a Kriging model and a multilayer perceptron (MLP) model are developed, and the models are trained using the structural parameters of the FOWT platform as inputs, while the outputs include the hydrodynamic response and the quantity of steel utilized in the platform. The two-parameter Pareto frontier solutions, i.e. the hydrodynamic response and steel consumption, are obtained using the established surrogate models by utilizing a multi-objective genetic algorithm. Both of the solution exhibit reasonable trends along the input parameters. The results from the two different surrogate models are then compared and their differences are discussed.

KEY WORDS: Surrogate Model; Multi-objective optimization; Floating Offshore Wind Turbine

INTRODUCTION

As the global demand for renewable energy grows, the development of offshore wind is spreading from shallow to deep-sea. High costs of traditional fixed offshore turbine bases in deep-sea have prompted the industry to seek more cost-effective solutions. Floating offshore wind turbines have become an industry consensus due to their advantages in developing deep-sea wind resources. Floating wind turbine commercialization faces challenges, chiefly cost. Optimizing the overall steel consumption can reduce construction costs and enhance project competitiveness, which is significant both theoretically and practically.
The computation of the hydrodynamic response of floating wind turbine platforms is generally performed using either potential flow theoretical methods that do not take fluid viscosity into account (Li et al., 2018) or computational hydrodynamics methods that do take into account fluid viscosity (Liu et al., 2017)(Wang et al., 2022), both of which involve iteratively solving the expression of a set of linear equations for some primitive system of partial differential control equations. Therefore, even the potential flow methods, which are already significantly less computationally intensive than the computational fluid dynamics methods, the computational resources required for their direct use in the optimal design of floating wind turbine floater structures are usually unaffordable. Therefore, scholars generally need to use some kind of surrogate model for the optimization problem which is less accurate than solving the partial differential equation system directly but with substantially higher solving efficiency, and this kind of method for solving the optimization problem is known as surrogate model optimization method(Han, 2016).
Wang et al.(2018) used the Kriging method, which is commonly used in constructing surrogate models, to calculate the data points required for the construction of the surrogate model using the nonlinear potential flow theory and the three-dimensional frequency-domain surface element method, and then combined with the non-dominated sequential genetic algorithm (NSGA-II) to carry out a multi-objective optimization for the wave making resistance, vertical and longitudinal oscillation motion amplitudes. The optimization results are compared with those obtained from a high-precision computational fluid dynamics model to verify their reliability. Liu et al.(2020) proposed a reliability optimization strategy based on a dynamic surrogate model to ensure global approximation accuracy and computational efficiency in the traditional reliability-based design optimization of ship structures . The optimization results show that the method can effectively reduce the calculation cost while obtaining the global optimal solution of the analysis model. Zhang et al.(2020) constructed the mapping relationship between the total body mass and the first-order torsional modes through the 3rd-order response surface proxy model, and combined with the multi-objective particle swarm algorithm to optimize the dimensions of the key body-in-white

parts, so as to design the lightweight body-in-white total mass, and the data used for the construction of the proxy model in this study are from the finite element numerical calculation. The final optimization results in a mass reduction of 11.5kg. Du Wenjie et al.(2023) developed a radial basis function neural network model to establish a nonlinear mapping relationship between artificial seabed design parameters and drag forces, utilizing data derived from computational fluid dynamics (CFD) simulations for neural network training. Subsequently, by integrating a multi-objective genetic algorithm, they optimized the design parameters of the artificial seabed. The optimization results demonstrated that the refined design exhibited significant improvements in key performance metrics such as drag force reduction, structural mass minimization, and metacentric height enhancement compared to the initial design configuration. Kang et al.(2024) took a direct sea-river vessels as the research object, and used artificial neural network combined with oversampling technology to construct a surrogate model of ultimate limit state for ship hull compartment structure, and then combined with the simulated annealing algorithm to optimize the design of the hull section structure, and the optimized structure resulted in the weight reduction of the hull section by 3.199%.
The afore-mentioned research has already applied surrogate models to a variety of optimization problems. However, there are still few instances of their application in the support platforms of floating wind turbines. Nevertheless, as floating wind turbines venture into deeper and more remote seas, the size of their floating platforms markedly increases in tandem with the length of the blades. Consequently, the conflict between their hydrodynamic response and manufacturing cost becomes increasingly acute.
In the present work, our goal is to proposes a lightweight optimization design method based on surrogate models coupled with the multi-objective genetic method. This paper first derives the formula for calculating the steel consumption of a floating wind turbine foundation. Then, it selects relevant design variables and uses Sobol sequence sampling to design examples. The hydrodynamic response of the floating platform is calculated using potential flow theory. Subsequently, using the obtained numerical results, a Multi-Layer Perceptron (MLP) artificial neural network and a kriging model is employed to establish a neural network mapping relationship between the design variables and the overall steel consumption and hydrodynamic response of the floating platform, thereby obtaining a steel consumption prediction neural network surrogate model. Finally, in combination with NSGA-II, a multi-objective genetic algorithm, the steel consumption of the floating wind turbine platform is optimized, and the Pareto optimal front is obtained.

METHODS

Hydrodynamic Response and Steel Consumption Calculation of Floating Wind Turbine Platforms

This paper presents an optimization design for a floating wind turbine platform, which consists of three cylindrical vertical columns, with circular heave plates attached to the bottom of the columns. The structures are interconnected by circular hollow struts, as shown in the figure below. To account for the interference between the mooring lines and the power cables, the outer side of the heave plate is subjected to edge trimming.

The optimized structural parameters are the radius of the vertical columns, the radius of the heave plates, and the width of the lower connecting beams. The optimization objectives are the steel consumption of the platform structure and the heave angle of the hydrodynamic response.

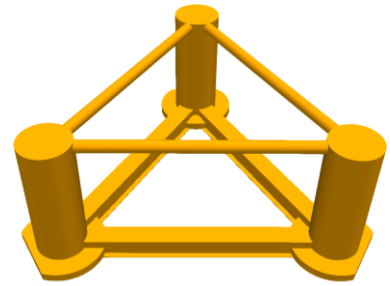

Figure 1. A three-column floating wind turbine platform model

To achieve lightweight design of floating wind turbine platforms, this paper introduces a method to quickly estimate steel quantity and structural parameters using equivalent plate thickness. The plate thickness for each platform section is determined from the original platform's main model parameters. A new sample platform shell model is built with 3D modeling software to calculate the steel consumption, center of gravity, and moment of inertia under empty conditions. Additionally, the ballast water height in each compartment can be adjusted as per design needs, allowing for the calculation of the platform's overall center of gravity and displacement.

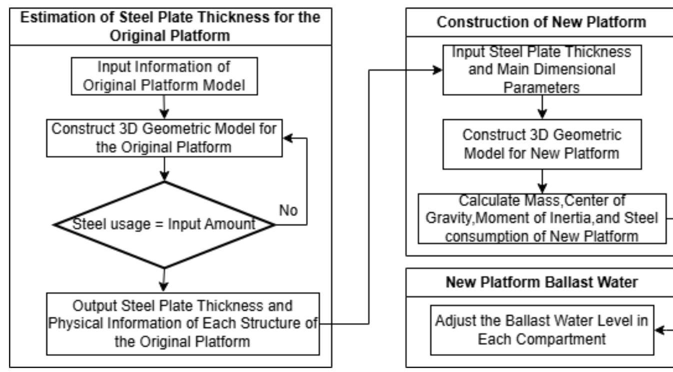

Figure 2. Calculation Process for Steel Usage of the New Sample Platform

Kriging Model and Multi-layer perceptron (MLP)

The MLP structure includes an input, output, and multiple hidden layers, adaptable to different problems. Networks with several hidden layers are deep networks. The input layer's size matches the number of design variables, and the output layer's size matches the number of target variables. This MLP model, as shown in Fig.3, is primarily designed for prediction tasks.

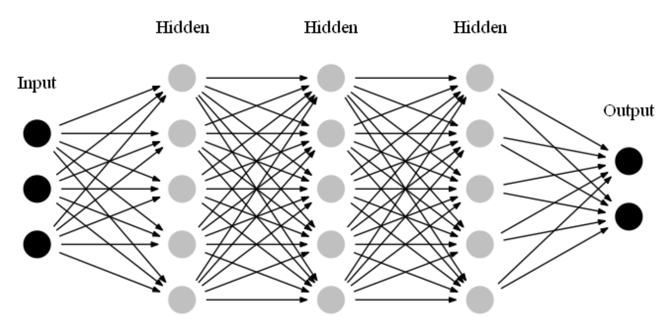

Figure 3. MLP Architecture Schematic Diagram

The MLP consists of fully connected layers, activation layers, and regularization layers.

Optimization Algorithm

Non-dominated Sorting Genetic Algorithm (NSGA-II) was proposed and improved(Deb et al., 2002).It is an optimization algorithm that simulates biological evolution. This algorithm utilizes a non-domination sorting method, which increases the likelihood of superior individuals being passed on to the next generation and reduces the complexity during the optimization iteration process. As a powerful and widely applied global optimization method, NSGA-II is one of the most influential optimization methods today.

DATASET PREPARATION

Sampling method

This paper is based on Sobol sequences for sampling, which are sequences with the smallest prime number 2 as the base, characterized by uniform distribution and rapid convergence. A random number $X_i(0 < X_i < 1)$ can be expressed as

$$X_i = i_1V_1 \oplus i_2V_2 \oplus \cdots\ i = (\cdots i_3i_2i_1)_2$$

Where V_i represents the direction numbers:

$$V_i = \frac{m_i}{2^i}\ \ i = 1,2,\cdots,n$$

$$V_i = a_1V_{i-1} \oplus a_2V_{i-2} \oplus\cdots\oplus a_{n-1}V_{i-n+1} \oplus V_{i-n} \oplus [V_{i-n}/2n] \qquad (i > n)$$

$a_1, a_2,\cdots, a_{n-1} = \{0,1\}$ are related to $m_1, m_2,\cdots, m_n$ as follows:

$$m_k = 2a_1m_{k-1} \oplus 2^2a_2m_{k-2} \oplus\cdots\oplus 2^na_nm_{k-n} \oplus m_{k-n} \qquad (1 \le k \le n)$$

Sampling Result

Within the sample space where the column radius ∈[5.5m，9m] , the heave plate radius ∈[10m，16m], and the lower connecting beam width ∈[4m，8m] , 42 sample points are selected as shown in the figure.

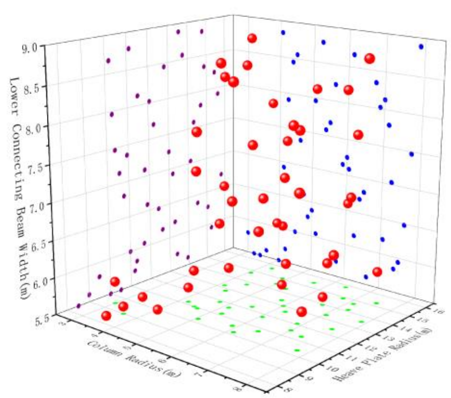

Figure 4. Based on Sobol Sequence Sampling Results

CONSTRUCTION OF SURROGATE MODEL

Dataset Classification

The complete dataset consists of 42 sample points, and the model will be trained by utilizing the first 36 points while the last 6 points is reserved for testing purposes.

Construction of Kriging Model

The process of establishing an Kriging model using can be represented as a stochastic process:

$$y(x^i) = \mu + \varepsilon(x^i)$$

In the equation, μ represents the mean of the stochastic process, and $\varepsilon(x^i)$ is a random variable used to approximate local deviations, which is normally distributed as $N(0,\sigma^2)$, with a non-zero covariance value. The correlation of the deviation can be expressed as:

$$Cor[\varepsilon(x^i),\varepsilon(x^j)] = \sigma^2R([Corr[\varepsilon(x^i),\varepsilon(x^j)])$$

$$[Corr[\varepsilon(x^i),\varepsilon(x^j)] = \exp[-d(x^i,x^j)]$$

$$d(x^i,x^j) = \sum_{h=1}^{k}\theta_h\left|x_h^{(i)} - x_h^{(j)}\right|^{P_h}\ (\theta_h \ge 0, P_h \in [1,2])$$

A series of observations can be used to construct an n-dimensional vector *I*, and the likelihood estimation function can be expressed as:

$$\frac{1}{(2\pi)^{n/2}(\sigma^2)^{n/2}|R|^{1/2}}\exp[-\frac{(y - \mathrm{I}\mu)'R^{-1}(y - \mathrm{I}\mu)}{2\sigma^2}]$$

After specifying the parameters P_h and θ_h, the values of μ and σ^2 can be obtained by solving the maximum likelihood function:

$$\hat{\mu} = \frac{\mathrm{I}'R^{-1}y}{\mathrm{I}'R^{-1}\mathrm{I}}$$

$$\hat{\sigma}^2 = \frac{(y - \mathrm{I}\hat{\mu})^TR^{-1}(y - \mathrm{I}\hat{\mu})}{n}$$

For any numerical fitting prediction point x*, let r denote its n-dimensional correlation vector with all sample point error terms: $r_i(\mathrm{x}^*) = Corr[\varepsilon(\mathrm{x}^{*(i)}),\varepsilon(\mathrm{x}^{*(j)})]$ where $\varepsilon(\mathrm{x}^{*(i)})$ *and* $\varepsilon(\mathrm{x}^{*(j)})$ are the error terms for the $i-th$ and $j-th$ sample points, respectively. The response value and variance of the prediction point can be obtained as follows:

$$y(\mathrm{x}^*) = \hat{\mu} + r'R^{-1}(y - \mathrm{I}\hat{\mu})$$

$$\mathrm{s}^2(\mathrm{x}^*) = \sigma^2[1 - r'R^{-1}r + \frac{(1 - \mathrm{I}'R^{-1}r)^2}{\mathrm{I}'R^{-1}\mathrm{I}}]$$

Construction of ANN

This paper will focus on the impact of different inflow conditions on the wake of wind turbines, and therefore sets up the following four cases in Table 2 for discussion and study. The MLP network model used in this paper is a custom architecture designed based on a fully connected network, which is widely used for a wide variety of tasks. In this paper, the design variables are the width of the lower connecting beam, the radius of the heave plate, and the radius of the column, while the platform's steel consumption and the maximum pitch angle are the objective variables.

Firstly, normalize the input data through the following equation to enhance the training efficiency of the neural network:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

The main components in the network are: the fully connected nonlinear layer, dropout layer, and output layer. The activation function for the MLP networks is set to be “tanh”. The specific neural network parameters are shown in the following table.

Table 1. MLP Artificial Neural Network Parameters Table

Layer	**Input Shape**	**Output Shape**	**Trainable Parameters**	**Activation Function**
FC1	3	32	99	tanh
Dropout				
FC2	32	32	1056	tanh
Dropout				
FC3	32	32	1056	tanh
FC4	32	1	32	tanh

All the training is performed by using the machine-learning package Pytorch. The "Adam" algorithm is adopted as the optimizer with a learning rate of 0.0001 to train the ANNs, and the mean-square error (MSE) is selected as the loss function to be minimized in the training processes. Explained as follows.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Train the two MLP networks separately to obtain the loss curves, which are shown in the figures below.

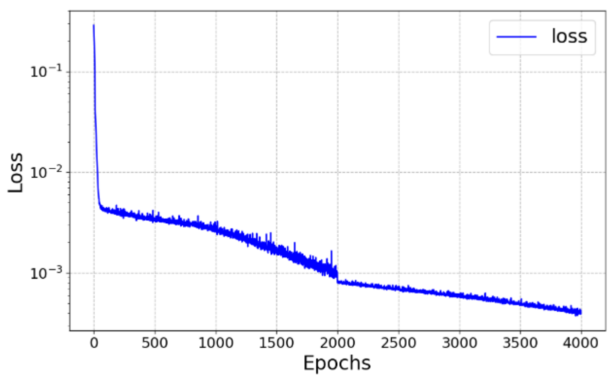

Figure 5. Steel Consumption Loss Curve

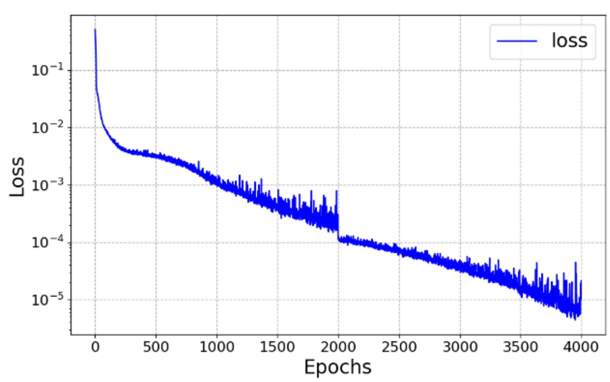

Figure 6. Maximum Pitch Angle Loss Curve

After training, the loss function curves for both steel consumption and maximum pitch angle have converged.

OPTIMIZATION

During the iteration of the optimization algorithm, in order to generate more effective samples and evolve the offspring sample group in the desired direction, it is necessary to constrain the objective function. The constraints are shown in the table below:

Table 2. Optimization Constraints

Constraints	**Constraint Parameters**
Lower Connecting Beam Width	[4m, 8m]
Column Radius	[10m, 16m]
Steel Consumption	[5500000t, 9000000t]

The proposed optimization strategy is offline, all the training data are generated upfront using Sobol sampling and numerical simulations (potential flow theory). The Kriging and ANN models are trained *once* on this precomputed dataset. No real-time updates or iterative data collection occur during optimization. The NSGA-II algorithm operates entirely on the pre-trained surrogate models, requiring no additional simulations or experimental data during Pareto frontier exploration.

In the genetic algorithm, after 2000 iterations, 10,000 design sample points were obtained. The Pareto front solutions are plotted in the figure below. The horizontal coordinate represents the steel consumption of the floating wind turbine, and the vertical coordinate represents the pitch angle. The red dots in the figure represent the Pareto front solutions obtained by the optimization method proposed in this paper, the blue dots represent the original sample points, and the cross marks represent the training sample points, which correspond to the dataset shown in Figure 7. It can be seen that the trend of the solutions obtained based on the artificial neural network is reasonable.

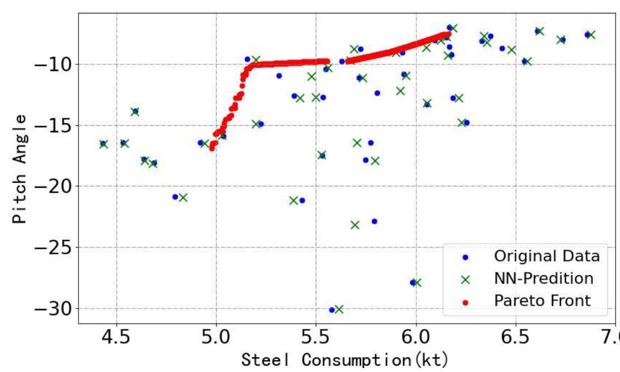

Figure 7. NSGA-II Optimization Result

Direct optimization using high-fidelity simulations is computationally prohibitive. For example, a single hydrodynamic simulation might take 4–6 hours, and optimizing with 1,000 iterations would require 4,000–6,000 CPU hours. Surrogate models (Kriging/ANN) reduce computational cost by 90–95% after initial training.

CONCLUSIONS

This paper takes the base platform structure of floating wind turbines as the research subject and proposes an optimization strategy based on artificial neural network surrogate models, applying it to the lightweight design of floating wind turbine base platforms. The paper first derives the formula for calculating the steel consumption of floating wind turbine foundations, then selects relevant design variables, uses Sobol sequence sampling for design examples, and calculates the hydrodynamic response of the floating platform using potential flow theory. Subsequently, using the obtained numerical results, two surrogate model i.e. a kriging model and a multi-layer perceptron artificial neural network is to establish a neural network mapping relationship between the design variables and the overall steel consumption and hydrodynamic response of the floating platform, thus obtaining a steel consumption prediction neural network surrogate model. Finally, combining multi-objective genetic algorithms, an optimization study on the steel consumption of the floating wind turbine platform is conducted, yielding Pareto optimal front solutions. The trends of these solutions are reasonable, verifying the feasibility of the proposed optimization method. The proposed surrogate-based strategy effectively balances computational efficiency and accuracy, enabling rapid identification of cost-performance trade-offs. This approach advances FOWT design by reducing material costs while maintaining hydrodynamic integrity, directly supporting the offshore wind industry's transition to deep-water deployments. Future work will integrate high-fidelity CFD corrections and multi-physics constraints to enhance robustness.

ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China (52131102), to which the authors are most grateful.

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