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A Machine-Learning Approach for the Development of a FOWT Model Integrated with Four OWCs

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***Abstract*— The wind-wave excitations cause structural vibrations on the Floating Offshore Wind Turbines (FOWT) pressing the power generation efficiency and reducing the life expectancy. In particular, tower-top displacement and barge-type platform pitch dynamics are extremely sensitive to wind speed and wave elevation to the point that may even lead to structural instability in extreme conditions. Having into account that computational techniques such as Artificial Neural Networks (ANNs) are widely used in artificial intelligence because of their strong predicting and forecasting capabilities, the aim of this article is to create a deep-layer ANN model that incorporates Oscillating Water Columns (OWCs) into the barge platform. This ANN model enables to address stability issues of the hybrid floating offshore wind platform. The proposed control-oriented model has been successfully validated to achieve adequate dynamic behavior and structural performance using FAST.**

Keywords*— *Artificial neural network, barge platform, floating offshore wind turbine, oscillating water column.

I. Introduction

According to global energy forecast data, energy demand will increase by 4.6% in 203 due to climate change and the emerging and developing economies Chen et al. (2022). To address basic demands, the global market is being redirected towards sustainable energy resources. Despite the availability of multiple renewable energy sources, wind and wave generation have expanded dramatically in the recent decade, as illustrated in Figure 1. In pursue of these green policies many studies have been conducted on ocean energy resources, such as Rusu and Onea (2013).

Europe is compelled by the energy roadmap to have a marine energy infrastructure able to cover approximately 10% of its energy consumption from wave and tidal energy by 2050 Khojasteh et al. (2022). Several countries, including the UK and Spain, have already taken this approach and in this path to development, Wave Energy Converters (WEC) have gained significant importance Windt et al. (2022).

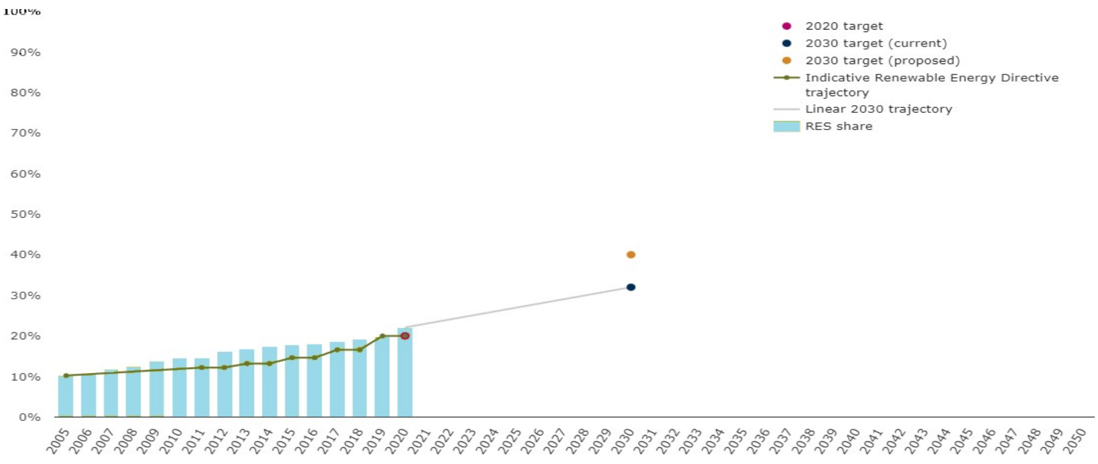


Figure 1: Renewable electricity generation growth by technology by 2050

Basque Government IT555-22, PID2021-123543OB-C21 and PID2021-123543OB-C22 (MCIN/AEI/10.13039/501100011033/FEDER, UE).

Governments are paying increasing attention to wind energy, which is a clean, abundant, and sustainable resource Zeng et al. (2022). Installing onshore wind turbines near residential areas would result in a slew of issues, including noise and aesthetics. To prevent these issues, wind turbines must be pushed way into deep water. Due to increased wind speed and lesser wind shear, FOWTs have a higher power generation efficiency than onshore/nearshore wind turbines Rudolph et al. (2004). As a result, the development of FOWT is increasingly gaining traction as a method for overcoming the energy crisis Haritos (2007).

Wave energy is a resource captured from the oscillation of the ocean surface. One of the methods used to extract this energy is known as the Oscillating Water Column (OWC), which uses the movement of waves to compress the air inside a chamber. That compressed air is used to move a turbine, which is responsible for the production of electricity Garrido et al. (2022).

Researchers recently unveiled a hybrid platform for generating energy from both wind and waves. P. Aboutalebi et al (2021) demonstrated the feasibility of integrating four OWCs systems in barge platforms. This topology appears to be a promising approach subject to active structural control as shown in Figure 2. In comparison to spar and tension leg platforms, the size and design of the barge platform makes it easier to create space for wave energy converter integration Chuang et al. (2021).

The nature of the resources that provoke vibration of the barge-type offshore wind turbine in diverse maritime situations is unpredictable, which makes reducing unwanted motion from hybrid platforms a difficult task. Hybrid FOWT-OWC control is a comparatively new but complex topic of study. The primary goal of the hybrid system is to reduce power output fluctuations while minimizing platform fatigue levels. However, new approaches are required to reduce the external disturbances, outages, and parameter uncertainty of the off-shore system that remain higher in comparison to those of an on-shore wind turbine.

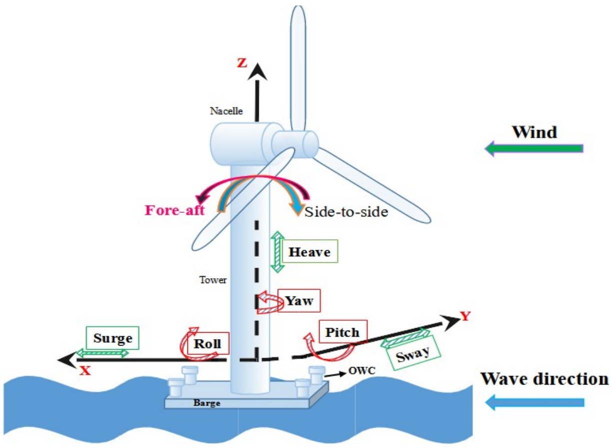


Figure 2: Barge-based FOWT with four OWCs

There have been a number of passive and active stabilization and vibration reduction approaches for FOWT. The structural dynamic properties of an offshore hybrid platform are complex but the dynamic behavior in the frequency domain is straightforward. Many researchers Amaechi et al. (2022) have investigated the response amplitude operators (RAOs) of platform motion in the frequency domain for various types of offshore wind turbines and created a floating platform to ensure the overall stability of the wind turbine system.

Furthermore, researchers have also researched on the dynamic aspects of offshore wind turbines in the time domain. Jonkman et al. [Jonkman (2009) Prowell et al. (2010)] established a time domain simulation tool named FAST that is based on the equations of Kane and have deploy it to examine the dynamic responses of various wind turbines in detail.

It is evident from published works that various researchers are working on highly nonlinear 5MW FOWT dynamics Basack et al. (2021). Their investigation on control simulations rely on linearization techniques, assumptions, and the pursuit of the desired operating points. M'zoughi et al. (2022) have created a simplified FOWT-OWC model that takes into account two DOFs and employs PID Control techniques.

In this context, this article presents a novel advanced control-oriented artificial neural model, which is able to approximate the system nonlinear dynamics, with the target to implement controllers that minimize both platform pitch and top-tower displacement. The deployment of a control oriented artificial neural network model for the hybrid wave and wind barge platform is the main key novelty in this work. Even though significant efforts have been made to develop hybrid platforms for energy generation, no investigation has been performed to control the hybrid generation and platform stability Belloli et al. (2020). This ANN based computational machine learning algorithms are frequently used in the field of artificial intelligence due to their great predictive capabilities Marugán et al. (2018). As a result, in a control-oriented framework, a novel dynamic model of the system is established to facilitate the utilization of closed control loops, which are capable of mitigating undesirable platform vibrations.

II. Proposed Hybrid Floating System

Following J. Jonkman barge platform with a single moonpool in the center and dimensions of 40mx40mx10m, we have previously integrated four OWC moonpools at each corner of the platform so that they can be used as active control of the structure. Various numerical engineering programs have been used to create such hybrid platform i.e, Multisurf, WAMIT, FAST and MATLAB.

A. Geometry Design

The geometry of the platform is created using MultiSurf. We concentrated on two different platforms, each with its

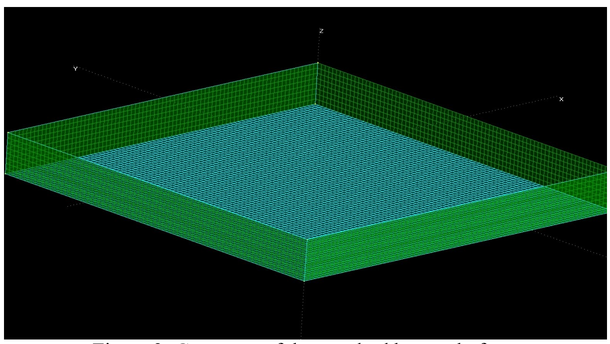


Figure 3: Geometry of the standard barge platform

own set of characteristics. The first platform is a standard barge platform, as shown in Figure 3, while the second platform is a barge platform with four OWCs in the corners, as shown in Figure 4.

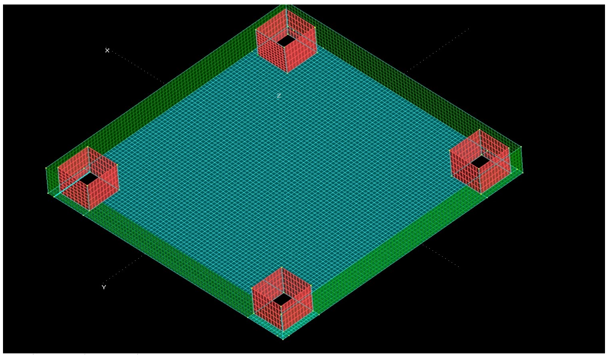


Figure 4: Geometry of the four OWC-based barge platform

B. *Advanced Hydrostatic and Hydrodynamic Computations*

The input to the FOWT model is considered as unidirectional regular waves and can be represented as

$$x(t) = A\ sin(\omega t) = A\ sin(2\pi f t) = A\ sin\left(\frac{2\pi}{\lambda}t\right) \quad (1)$$

where the speed for the wave propagation is c=λ f. λ denotes the wavelength, that measures the distance between successive crests, and A is the wave amplitude from Still Water Level (SWL) to the wave crest.

The dynamics of a barge type 5MW FOWT where four OWCs are embedded may be described in time-domain as

$$M_{ij}(x,u,t)\ddot{x}_j = f_i(x,\acute{x},u,t) \quad (2)$$

where M_{ij} is the mass inertia, t is the time, u is the control inputs, and $\ddot{x}_j$ is the second time derivative of the j^{th} Degree of Freedom (DoF).

The generalized external forces acting on the system is represented by the term on the right-hand side of (2), which includes the aerodynamic load on the blades and nacelle, hydrodynamic forces on the platform, elastic, and servo forces.

In the frequency domain, the generalized system for the linear equations of motion can be expressed as

$$I_{FOWT}(\omega)\ddot{x} + D_{FOWT}(\omega)\acute{x} + S_{FOWT}x = \vec{f}_{FOWT}(\omega) + \vec{f}_{PTO}(\omega) \quad (2)$$

where I_{FOWT}, D_{FOWT}, and S_{FOWT} may be represented as inertia, damping, and stiffness matrices, respectively. $\vec{f}_{FOWT}$ and $\vec{f}_{PTO}$ represented as the drag of waves and hydrodynamic forces imposed by Power-take-off (PTO).

WAMIT is a diffraction panel program for linear analysis of surface wave interactions with various types of floating and submerged structures. This software can be used to assess a variety of traits. The matrices were obtained using the Multisurf file directly into WAMIT to retrieve the hydrostatic and hydrodynamic coefficients. WAMIT can be coupled to MultiSurf to use the geometric floating model to calculate the hydrodynamic loads caused by water pressure on wetted surfaces.

III. ANN-BASED FOWT MODEL

An Artificial Neural Network (ANN) is a biologically inspired framework that can mimic and perform tasks as closely as possible to the human brain. ANNs are used to learn from data in order to make future predictions and are capable of recognizing patterns and making judgments based on previously stored information. A basic structure has been given in Figure 5.

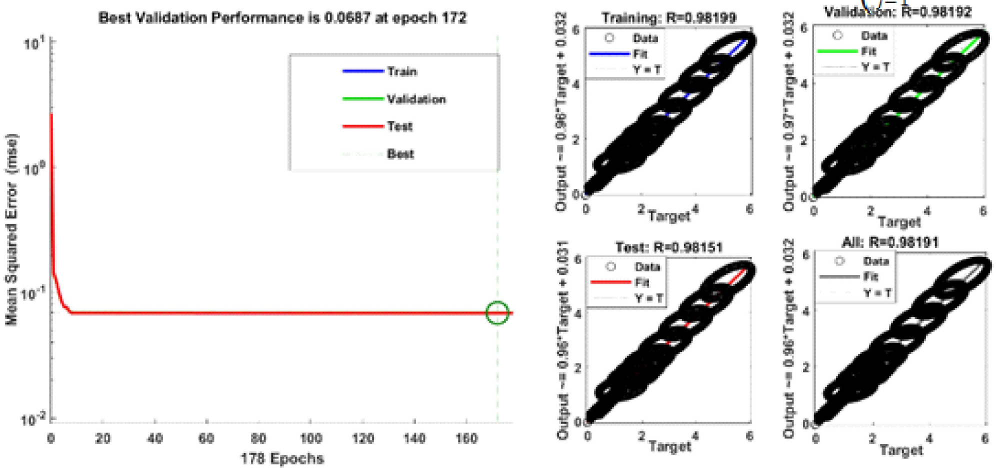
The data transfer from the input layer to the output layer is the so called feedforward network. The sum function stablish the connection between the j^{th} neuron in the current layer and all N neurons in the previous layer as

$$s_j = \sum_{j=1}^{N} w_{jk}x_k + b_j \quad (5)$$

through the weights $w_{jk}$where s_j is the sum, b_j is the bias, and N is the total number of neurons in the previous layer.

Then, this sum s_j is passed through an activation function as

$$v_j = \sigma_j(s_j) = \sigma_j\left\{\sum_{j=1}^{N} w_{jk}x_k + b_j\right\} \quad (5)$$



(a) (b)

Figure 5: Training performance of ANN1. (a) Convergence history.(b) Regression curves

where v_j is output of neuron and σ_j is the activation coefficient for the j^{th} neuron.

For the linear and nonlinear functions, Multi-Layer Perceptron (MLP) is a commonly used feed-forward ANN network. For the selection of the best model, the network that has the lowest Mean Squared Error (MSE) is usually chosen M'zoughi et al. (2020). The expression for the MSE can be defined as

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(v_k - \hat{v}_k)^2 \qquad (6)$$

where n is the total number of observations, v_k is target output, and $\hat{v}_k$the estimated output by ANN. For best results, the Levenberg-Marquardt algorithm (LMA) is used and is responsible for updating the weights and reducing the MSE. LMA is an iterative minimization algorithm that employs an average between the Gauss-Newton and the gradient descent method M'zoughi et al. (2020) approximating the Hessian as

$$H = J^T J \qquad (7)$$

and its gradient can be calculated using the jacobian matrix

$$g = J^T e \qquad (8)$$

where the Jacobian is the matrix that contains the first derivatives of the network errors with respect to weights and biases as

$$J(x) = \begin{bmatrix} \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\ \frac{\partial e_2(x)}{\partial x_1} & \frac{\partial e_2(x)}{\partial x_2} & \cdots & \frac{\partial e_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_n(x)}{\partial x_1} & \frac{\partial e_n(x)}{\partial x_2} & \cdots & \frac{\partial e_n(x)}{\partial x_n} \end{bmatrix} \qquad (9)$$

and the gradient of performance may be defined as

$$\nabla f(x) = 2J^T(x)e(x) \qquad (10)$$

The LMA uses this approximation to the Hessian matrix in the following newton like update

$$x_k = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (11)$$

The ANN model has five hidden layers, each of which has a linear activation function (ReLU) in the output layer and a sigmoid activation function for the neurons in the hidden levels. ANN is created using a number of different steps and with several software. Multisurf is used to define the structural geometry of the platform. The hydrodynamic, elastodynamics, and added masses are then calculated using WAMIT. This data from WAMIT has been introduced to FAST to perform the aerodynamics computations. Finally, the computational design of ANN is done in MATLAB/Simulink after incorporating the data from FAST.

IV. Simulation and Results

The "NREL offshore 5MW baseline wind turbine" mounted on a floating barge is tested and simulated in this part using FAST and MATLAB/Simulink. Simulations have been performed to identify the optimal ANN model using a multi-layer perceptron to achieve the best performance. 70% of the data was used for training, 15% for validation, and 15% for testing. Multilayer networks can perform almost any linear and nonlinear computation and can arbitrarily approximate any acceptable function. The ANN model presents five hidden layers, each with a sigmoid activation function for those neurons in the hidden levels, and a linear activation function (ReLU) in the output layer. The lowest MSE is chosen to achieve satisfactory results as shown in Figure 5

TABLE I. Model Performance Characteristic

Performance	*Observations*	*MSE*	*R*
Traning	17925	0.0692	0.98199
Validation	3841	0.0691	0.98192
Test	3841	0.0694	0.98151

A. Validation Results

The validation has been carried out once the ANN model has been designed and trained. The ANN-based model is represented by the red (solid) curve, whereas the FAST model is represented by the blue (dashed) curve. Simulating the nonlinear model for a long enough time to dampen out the transient state yielded a periodic steady state condition for this type of system. The first 500 runs were omitted to avoid transients. The network's inputs are waves with 5 meters amplitude and wind speed with step-wise increment from 8 to 15m/s.

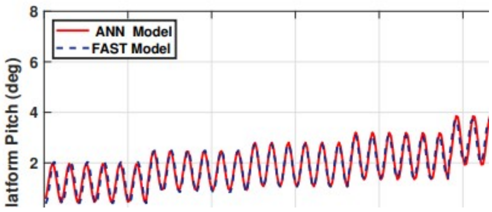


Figure 6: Platform Pitch from FAST and ANN platform

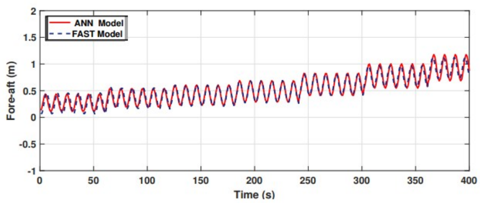


Figure 7: Fore-aft displacement from FAST and ANN

For sea depths, of more than 60 meters, FOWT-OWC is a viable option. As a result, they have an extra six degrees of freedom of motion. These additional motions, particularly the platform pitching motion and tower fore-aft can have a considerable impact on turbine loads and power production and this is the reason behind the interest in these factors. The platform pitch angle and fore-aft displacement are depicted in Figure 6 and Figure 7. They show that the model was adequately trained and that there is a high agreement between the values obtained from FAST and the proposed ANN model, with minor differences for non-representative low wind speeds.

The results reveal that the suggested control-oriented ANN model is remarkably precise at tower displacements, and platform pitch. In this sense, the forecasting and predicting characteristics of ANN model make them an efficient and promising option for modelling complex systems, such as FOWT-OWC hybrid systems, simplifying further research for platform stabilization closed-loop controller implementation.

V. CONCLUSIONS

The development and evaluation of artificial neural network models of a hybrid floating offshore wind turbine with embedded oscillating water columns have been presented in this article. Hydrodynamics and FAST aerodynamics properties for the entire hybrid system were used to collect the data. The proposed ANN model primarily designed to replicate the hybrid FOWT-OWC system behaviour and structural performance. To accomplish this objective, the model was trained with the appropriate parameters while keeping a low MSE target function in consideration. The model was then tested for a range of wind and wave scenarios to verify their computational efficiency, validity, and accuracy, as well as to compare the outputs of the ANN-based FOWT model to those of the complete non-linear computationally demanding FAST model.

The findings demonstrate the superior performance of the proposed control-oriented ANN model for predicting platform pitch and top tower displacements.

In the future, this work will use machine learning control algorithms with a feedback loop to mitigate unwanted platform motion. Last, but not the least, this work will also be expanded to include uncertainties and irregular waves for robust modeling and control of hybrid systems.

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