Enhancing Stability and Performance of Hybrid Offshore Wind Platforms: A Novel Fuzzy Logic Control Approach with Computational Machine Learning

Irfan Ahmad
Automatic Control Group - ACG
Department of Automatic Control and Systems Engineering,
Engineering School of Bilbao – EIB/BIE,
University of the Basque Country – UPV/EHU,
Rafael Moreno 3, 48013 Bilbao, Spain
ORCID: 0000-0001-6075-2464

Fares M'zoughi
Automatic Control Group - ACG
Department of Automatic Control and Systems Engineering,
Engineering School of Bilbao – EIB/BIE,
University of the Basque Country – UPV/EHU,
Rafael Moreno 3, 48013 Bilbao, Spain
ORCID: 0000-0003-2935-3830

Payam Aboutalebi
Department of Marine Technology,
Norwegian University of Science and Technology (NTNU),
Moholt, 7491 Trondheim, Norway
ORCID: 0000-0003-2716-1894

Izaskun Garrido, *Senior Member, IEEE*
Automatic Control Group - ACG
Department of Automatic Control and Systems Engineering,
Engineering School of Bilbao – EIB/BIE,
University of the Basque Country – UPV/EHU,
Rafael Moreno 3, 48013 Bilbao, Spain
ORCID: 0000-0002-9801-4130

Aitor J. Garrido, *Senior Member, IEEE*
Automatic Control Group - ACG
Department of Automatic Control and Systems Engineering,
Engineering School of Bilbao – EIB/BIE,
University of the Basque Country – UPV/EHU,
Rafael Moreno 3, 48013 Bilbao, Spain
ORCID: 0000-0002-3016-4976

***Abstract*—Harnessing the power of wind and waves for renewable energy production has become vital in the quest for sustainable electricity generation. The fusion of Floating Offshore Wind Turbines (FOWTs) and Oscillating Water Columns (OWCs) has introduced a groundbreaking concept of hybrid offshore platforms, offering immense potential for energy absorption, reduced dynamic response, load mitigation, and improved cost efficiency. This study focuses on two primary objectives: firstly, the development of a regression-based modeling method for a hybrid aero-hydro-elastic-servo-mooring coupled numerical system, and secondly, the implementation of a customized fuzzy-based control mechanism aimed at ensuring platform stability. To achieve these objectives, Artificial Neural Networks (ANNs) are employed as computational Machine Learning (ML) tools to accurately simulate the complex behavior of the hybrid system. The experimental results confirm the potential of ANN-based modeling as a simpler yet effective alternative to complicated nonlinear NREL-5MW FOWT dynamical models. Furthermore, the use of the FLC system enhances platform stability in a variety of wind and wave conditions.**

***Index Terms*—hybrid offshore platforms, energy absorption, dynamic response, load mitigation, cost efficiency, regression-based modeling, aero-hydro-elastic-servo-mooring system, Fuzzy Logic Control (FLC), wind and wave conditions, MultiSurf, WAMIT, FAST.**

I. Introduction

Renewable energy has emerged as a crucial component in addressing the challenges of climate change and achieving energy security. The deployment of renewable energy technologies, including wind, solar, hydro, and bioenergy, has gained momentum in recent years. Among these technologies, offshore wind power has emerged as a promising and rapidly growing sector, particularly in Europe [1]. Europe has witnessed significant progress in offshore wind energy projects, contributing to its transition to a low-carbon economy. The expansion of offshore wind farms has been fueled by technological advancements, favorable policies, and substantial investments, leading to increased energy generation and reduced greenhouse gas emissions [2].

Numerous research teams have been working to harness energy by combining wave energy converters (WECs) and

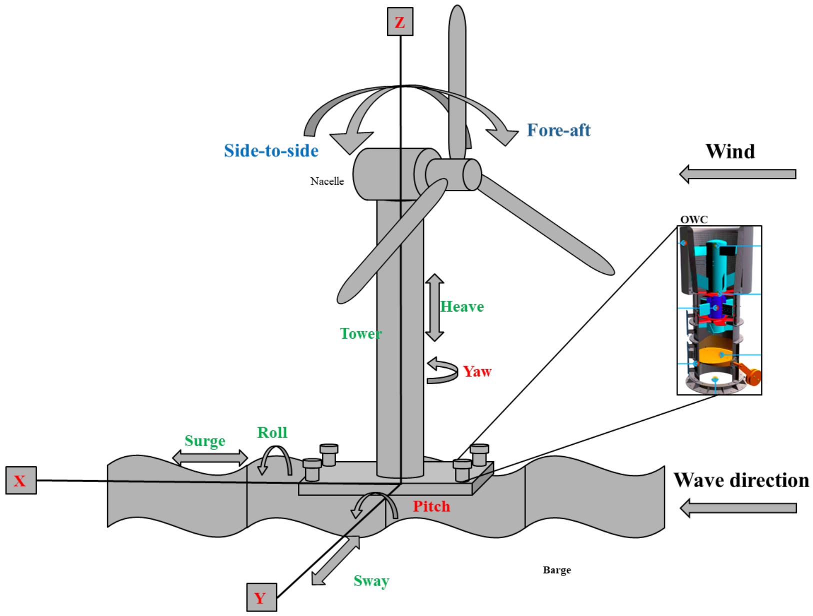

Fig. 1. FOWT hybrid barge platform integrated with four OWCs.

FOWTs during the past ten years [3]. Combining floating offshore wind turbines (FOWTs) with oscillating water columns (OWCs), a type of wave energy converter is a viable way to generate hybrid renewable energy. The platform can be successfully stabilized by including OWCs in FOWT designs, leading to a more effective capture and usage of renewable energy sources. This synergy not only improves the overall energy output in terms of quantity and quality, but it also offers a cutting-edge strategy for overcoming the difficulties associated with generating sustainable energy. By combining FOWTs with OWCs, researchers aim to maximize energy production and exploit the synergies between wind and wave resources [4]. This integrated approach holds promise for advancing the field of renewable energy and facilitating the transition toward sustainable and efficient hybrid energy systems. The hybrid design has been shown in Fig. 1.

It can be challenging to design a hybrid offshore structure because it contains aero-hydro-servo-elastic dynamics which must be taken into account [5]. While bottom-supported offshore wind turbines are more appropriate for shallow water areas, floating wind turbines are better suited for deep sea locations. Designs for floating wind turbines can be classified into three categories based on their stabilizing mechanisms: buoyancy-stabilized (barge platform), mooring-stabilized (tension leg platform), and ballast-stabilized (spar buoy) [6].

Significant advancements have been made in modeling and control techniques for FOWTs integrated with OWCs [7]. Researchers have been actively investigating innovative ideas to optimize the performance and reliability of these complex systems through machine learning approaches, with their ability to extract patterns and make predictions from large datasets [8]. By exploiting the power of artificial intelligence, machine learning techniques enable the development of accurate and efficient models for FOWTs integrated with OWCs [9].

Several types of Wave Energy Converters (WECs) have been deployed across Europe, with notable examples being the NEREIDA Wave Power Plant in Mutriku, Spain [10] and Limpet in Scotland [11].

D. Zhang et al. [12] conducted a study where they developed a time-domain coupled numerical framework to simulate the integration of FOWT with OWCs within a semisubmersible floating platform. The objective of their research was to validate the performance and feasibility of this integrated system. Another article [13] presented experimental work aimed at validating a novel floating semisubmersible structure that combines three oscillating water columns with a 5 MW wind turbine, enabling simultaneous harvesting of wind and wave energy. Furthermore, recent research by P. Aboutalebi et al. [14] successfully validated a hybrid platform capable of harnessing energy from both wind and waves. Their study demonstrated the feasibility of integrating two and four OWCs into barge platforms [15]. Figure 1 illustrates the integration of four OWCs into a platform, highlighting the potential for active structural control. In comparison to spar and tension leg platforms [16], the size and design of barge platforms facilitate easier integration of Wave Energy Converters (WECs).

This article presents a novel machine-learning approach for the development of a FOWT model integrated with four OWCs. By taking the power of artificial intelligence and advanced control techniques, the study aims to enhance the efficiency, stability, and control of this innovative renewable energy system. The results obtained from this research have the potential to contribute significantly to the advancement of offshore wind power generation and promote a sustainable future. The contributions of this study extend beyond the renewable energy sector, as the developed methodologies and

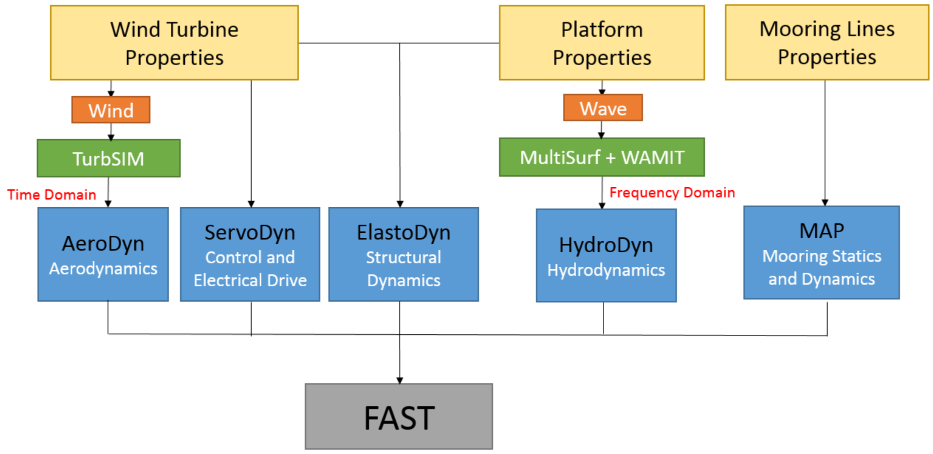

Fig. 2. Advanced Tools and Modules for Integrated Platform [17].

insights gained can also be applied to other complex systems, such as quadrotors [18] and robotic manipulators [19]. The robustness and adaptability of the proposed approaches make them promising candidates for a wide range of engineering applications.

II. Theoretical Background

From an engineering standpoint, offshore projects present distinct challenges that require careful consideration and innovative design approaches. Developing effective designs for offshore structures necessitates a comprehensive understanding of their analysis and fundamental principles. The incorporation of inventive platform geometries is believed to hold the potential for reducing the environmental stresses experienced by these structures. Therefore, a deep understanding of analysis techniques and core design principles is crucial in tackling the complexities of offshore projects.

Developing models for the aerodynamics, hydrodynamics, servos, and mooring lines of a floating turbine system heavily relies on simulation tools. This section examines the simulation tools and modules required for the combined platform, mooring, and turbine simulations. These resources are crucial for developing comprehensive models and assessing system responses. Analyzing and understanding the control performance of an aero-hydro-servo-elastic floating structure is a challenging and complex task. To enable active control of the structure, we integrated four OWCs moonpools into the J. Jonkman barge platform, placing four at each corner and a 40 x 40 x 10 m moonpool in the middle. Several numerical engineering programs, including MATLAB, WAMIT, FAST, and Multisurf, were employed to construct the hybrid platform. Advanced Tools and Modules for Integrated Platforms that are required have been shown in Fig. 2.

1) MultiSurf: MultiSurf is a 3D modeling tool used for intricate surface representation and direct import of geometry files into WAMIT. It scales up platform geometry by a factor of 1.8 using B-spline curves.

2) WAMIT: WAMIT is a hydrodynamic analysis program developed jointly by WAMIT Inc. and MIT, assessing unsteady hydrodynamic loads through a radiation and diffraction panel approach.

The platform's geometry was generated using MultiSurf, resulting in the creation of two distinct platforms, each possessing unique characteristics. Fig. 3 showcases the first platform, which exhibits a typical barge platform configuration. On the other hand, Fig. 4 illustrates the second platform, designed as a barge platform with four Oscillating Water Columns (OWCs) positioned at the corners.

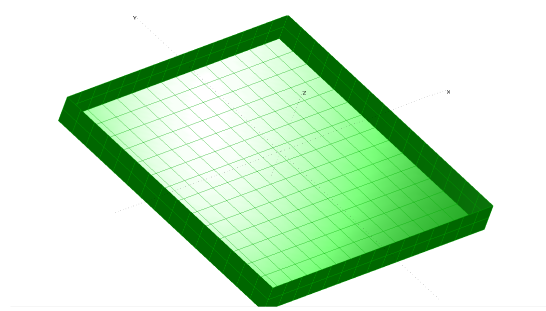

Fig. 3. The standard barge platforms' geometry

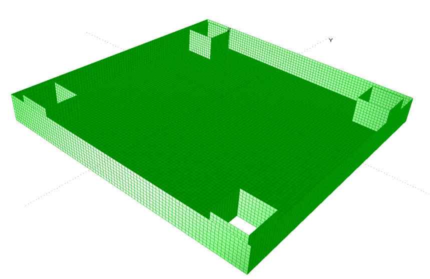

Fig. 4. The four OWC-based barge platforms' geometry

3) FAST: FAST, from NREL, is open-source software for simulating wind turbine systems, enabling coupled dynamic analyses for onshore and offshore turbines, with modules like AeroDyn, ServoDyn, ElastoDyn, HydroDyn, and MAP.

4) MATLAB/Simulink: Following the simulations conducted using FAST, the collected data is utilized to train models through deep neural networks. Additionally, control algorithms are implemented in Simulink to stabilize the hybrid system.

III. Methodology

The ANN-based Hybrid FOWT-OWCs Model employs Artificial Neural Networks (ANNs) to estimate corresponding outputs based on learned patterns from data. The feed-forward ANN used in this study consists of three input neurons representing wave elevation, wind speed, and throttle valve angle (ranging from 0 to 90 degrees). The output layer consists of a pair of neurons representing the estimated fore-and-aft displacement and platform pitch. Determining the optimal number of hidden layers and neurons is a challenging task, and the chosen methodology involves searching for the best network structure. Initially, a small number of hidden layers or neurons is used. Fig. 5 provides a visual representation of the intricate architecture of an ANN network. ANNs are characterized by weighted signals within the input y_j, output y_k, and hidden layers. Each neuron consists of an activation function σ_j , a bias function b_j, and a weighted sum function. These functions can be defined as follows:

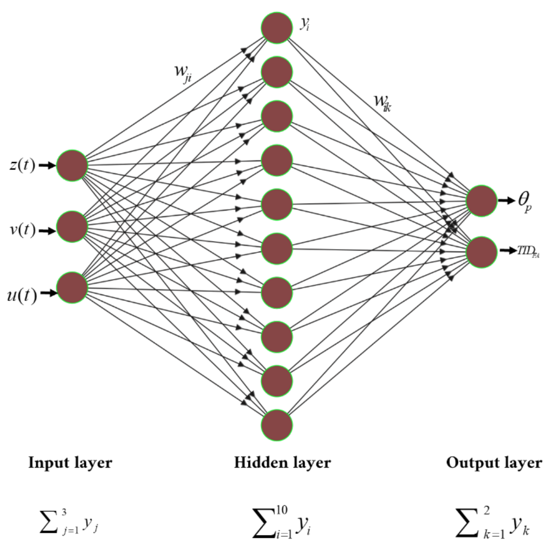

Fig. 5. A Visual Representation of the ANN Network

$$y_k = \sum_{k=1}^{N} a_{jk} z_k + b_j \tag{1}$$

The network structure is iteratively expanded to minimize the Mean Squared Error (MSE) during training.

$$MSE = \frac{1}{n}\sum_{k}^{n} o_k - {o_k}' (2)$$

$$y_k(t) = \varphi_o\left(\sum_{i=1}^{10} w_{ik} y_i(t) + b_k\right),\ k = \{1\,;\,2\} \tag{3}$$

$$\theta_p = y_1(t) = \varphi_o\left(\sum_{i=1}^{10} w_{i1}\varphi_h\left(\sum_{j=1}^{3} w_{ji} Z_j(t) + b_i\right) + b_1\right) \tag{4}$$

$$TTD_{FA} = y_2(t) = \varphi_o\left(\sum_{i=1}^{10} w_{i2}\varphi_h\left(\sum_{j=1}^{3} w_{ji} Z_j(t) + b_i\right) + b_2\right) \tag{5}$$

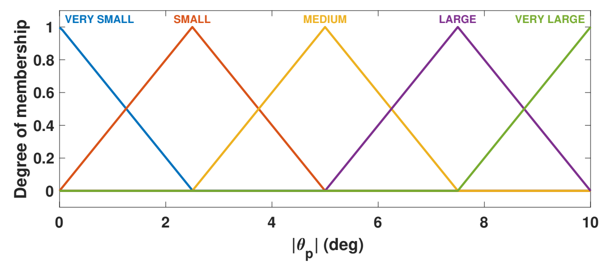

Fig. 6. Membership functions for input $|\theta\mathrm{P}|$

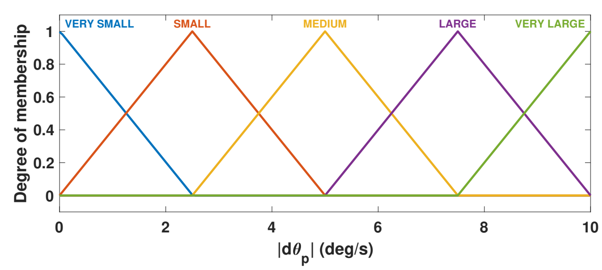

Fig. 7. Membership functions for input $|d\theta\mathrm{P}|$

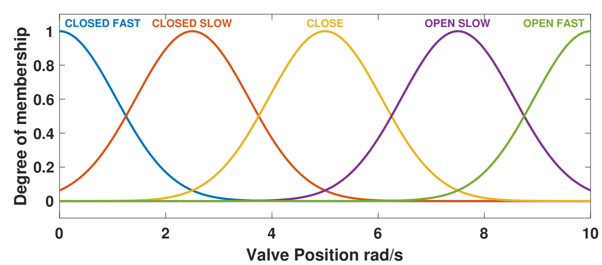

Fig. 8. Membership functions for output valve

IV. Model Validation and Control Results

This section describes the simulations that were carried out to evaluate the efficacy of the suggested methodology for modeling and controlling the hybrid FOWT-OWCs system.

The modeling and control framework for the hybrid system comprises five essential steps:

Geometry design: The structural geometry of the platform is defined using MultiSurf, a software tool.

Forces calculation: Hydrodynamic forces, added masses, damping coefficients and hydrostatic matrices are calculated using WAMIT.

Structure dynamics and dataset collection: The data obtained from MultiSurf and WAMIT is inputted into FAST, the NREL 5 MW tool, to conduct simulations and analyze the hybrid platform's dynamics and behavior. Datasets required for the proposed computational machine-learning algorithm are collected during these FAST simulations.

Model training and establishment: The collected data is processed, and an Artificial Neural Network (ANN) model is developed. The model is trained to minimize the Mean Squared Error (MSE) and establish accurate predictions.

Control development: A Fuzzy Logic Controller is adapted to synchronize the pitch and fore-aft movement of the platform. The primary objective of the controller is to stabilize the system and ensure optimal performance. Figures 6, 7, and 8. illustrate the membership functions corresponding to these linguistic sets.

By following this framework, the proposed methodology is evaluated and validated through simulations to demonstrate its efficacy in modeling and controlling the hybrid FOWT-OWCs system.

Different configurations with varying hidden layers and neurons were tested using a feed-forward approach to minimize the Mean Squared Error (MSE). Three inputs were analyzed: wind speed (ranging from 8 to 15 m/s), wave elevation (ranging from 0 to 90 degrees), and valve position. These inputs are illustrated in Figs. 9-11. To ensure stability, the initial 500 simulations were excluded from the analysis.

The results of the study are presented through line graphs, with the developed model represented by blue lines and the Artificial Neural Network (ANN) model depicted by red lines. Fig. 12 displays the platform's pitch angle. The model exhibits superior accuracy and computational efficiency in comparison to the widely adopted OpenFAST model.

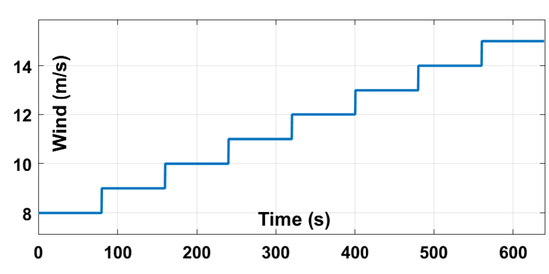

Fig. 9. Varies wind speed

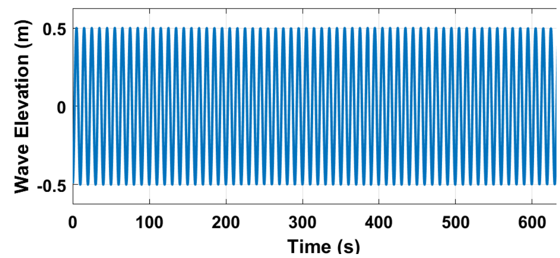

Fig. 10. Wave Elevations

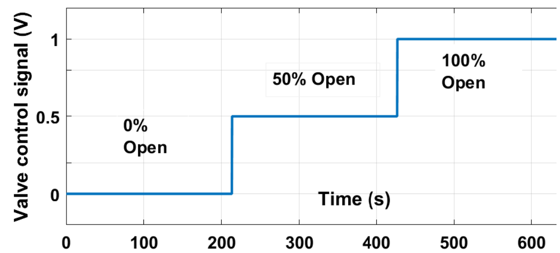

Fig. 11. Valve Position 0%, 50%, and 100% open

Fuzzy Logic Control (FLC) is advantageous for handling nonlinear dynamics without requiring knowledge of mathematical model parameters. In the studied Oscillating Water Column (OWC) system, the air valves are connected to the turbine duct at the top of the capture chamber. Extensive research has been conducted on modeling and control, utilizing experimental data from the Mutriko OWC plant. The valve controls pressure, air separation, and airflow between the capture chamber and the chamber air. An actuator is used to control the valve by turning the valve plate to the desired angle and applying an electromagnetic brake for stability. In this hybrid platform, the pitch is controlled by the valve plate's opening angle.

The proposed FLC aims to reduce the platform's pitch angle by appropriately closing the actuator valve as the angle increases. Based on observed data, the desired behavior for the hybrid platform is to resemble a barge platform based on open-OWCs, even with varying pitch angles.

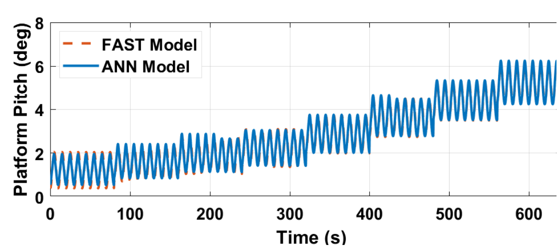

Fig. 12. Platforms Pitch with open and close valves

The utilization of Fuzzy Logic Control (FLC) for the opening and closing of the OWCs valves serves to stabilize the platform with the help of the counterforces generated from the accumulated pressure within the OWCs air chambers. This approach effectively mitigates undesired platform pitch motion

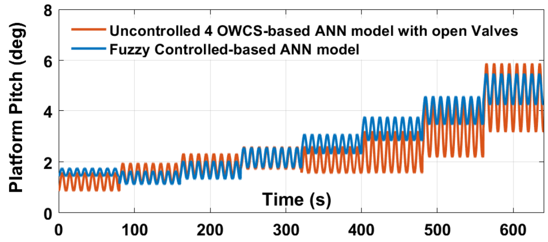

Fig. 13. Platform pitch angle with FLC versus uncontrolled open valves

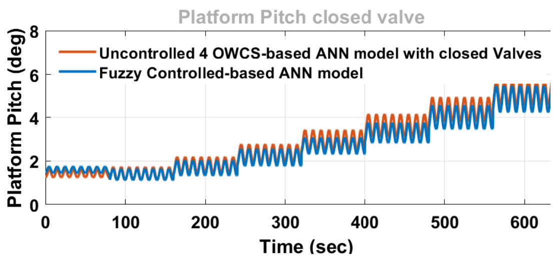

Fig. 14. Platform pitch angle with FLC versus uncontrolled closed valves

as shown in Fig.13 and Fig.14. It is worth emphasizing that the fuzzy control system designed for platform stabilization demonstrates reliable performance even in challenging conditions.

V. Conclusion

In conclusion, this study successfully integrates oscillating water columns (OWCs) into a floating offshore wind turbine (FOWT) platform and develops a control-oriented model using Artificial Neural Network (ANN) algorithms. The model demonstrates high accuracy and computational efficiency when compared to the widely accepted OpenFAST model. Additionally, the implementation of a Fuzzy Logic Control (FLC)-based controller effectively reduces undesired oscillations, improving platform stability by mitigating platform pitch and displacement of the top tower. The developed model and control scheme offers potential for the straightforward implementation of advanced controllers in the hybrid FOWT-OWCs system.

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