A synthesis of feasible control methods for floating wind turbines

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Abstract

Wind energy has become a viable renewable energy source, and it has abundant potential in both onshore and offshore regions. The wind turbine is encouraged to implement in the deep waters with the support of floating platforms for better wind profile and larger potential than onshore wind. However, the wave load acting on the platform, coupled with varying wind load, introduces a dominant disturbance to its stability. During the operation, the motion uncertainty of the platform tends to compromise the system's performance in terms of power maximization, power regulation, and load mitigation. Various controllers are reported in the literature to deal with the platform instability of floating wind turbines. However, it is a great challenge to achieve optimal power, power regulation, and acceptable load mitigation in the presence of incident wind and waves. This paper presents a review of the published control algorithms used to suppress the platform's motion and evaluates their performance with respect to platform motion minimization, load mitigation, power optimization, and regulation. Potential controller performance improvement based on predicted incident wind and wave is discussed. Recommendations and suggestions for further research are also provided at the end.

Keywords: Floating Offshore Wind Turbines, Floating Platforms, Wind turbine control, Wind energy

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Nomenclature

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AR	Auto-Regressive
ARIMA	Auto-Regressive Integral Moving Average
ARMA	Auto-Regressive Moving Average
BEM	Blade Element Momentum
CBP	Collective Blade Pitch
CBPC	Collective Blade Pitch Control
DOF	Degree of freedom
DAC	Disturbance Accommodating Control
DMD	Dynamic Mode Decomposition
EMD	Ensemble Mode Decomposition
ESPRIT	Estimation of Signal Parameters via Rotational Invariance Techniques
ELM	Extreme Learning Machine
FAST	Fatigue Aerodynamics Structures and Turbulence
FOWT	Floating Offshore Wind Turbine
GSPI	Gain-Scheduled Proportional-Integral
GP	Gaussian Process
HAR	Hammerstein Auto-Regressive
HAWC2	Horizontal Axis Wind Turbine Code-Second generation
HAWT	Horizontal Axis Wind Turbine

HMD	Hybrid Mass Damper
IBP	Individual Blade Pitch
IBPC	Individual Blade Pitch Control
IEA	International Energy Agency
LSSVM	Least Square Vector Support Machine
LCOE	Levelized Cost of Energy
LIDAR	Light detection and ranging
LPV	Linear Parameter Varying
LQR	Linear Quadratic Regulator
MLC	Machine learning control
MPC	Model Predictive Control
MBS	Multi-Body System
MIMO	Multi-Input Multi-Output
NREL	National Renewable Energy Lab
P_{rated}	Rated Power
PI	Proportional Integral
V_{rated}	Rated Wind Speed
RNN	Recurrent Neural Network
SISO	Single-Input Single-Output
SINDy	Sparse Identification of Nonlinear Dynamics
SMC	Sliding Mode Control
SC	Structural Control

SVM	Support Vector Machine
TRL	Technology Readiness Level
TLP	Tension leg platform
TMD	Tune Mass Damper
TLD	Tuned Liquid Damper
V_{cut-in}	Cut-in wind speed
$V_{cut-off}$	Cut-off wind speed
V_{rated}	Rated wind speed
V_{wind}	Wind speed

1. Introduction

Wind energy is one of the leading commercial renewable energy resources, and it has significant potential in both onshore and offshore areas [1, 2]. There is a rapid increase in global wind power (onshore and offshore) production in the last decade to utilize this potential, as shown in Figure 1. The total installed capacity for onshore wind turbines has increased from 159GW to 651GW in the last decade. Moreover, an increase in the annual installed offshore wind energy capacity is reported, with a record capacity addition of 6.1GW annual offshore wind energy in 2019. An estimate of new annual offshore installed capacity may exceed 30 GW in 2030, with a compound annual growth rate of 18.6% for the first half and 8.2% during the latter part of the decade, as shown in Figure 2.

1.1. Outlook of Offshore wind

Wind characteristics in the deep sea are more steady, streamlined, and it has a higher annual mean speed than onshore wind [3, 4].Superior wind quality improves wind energy generation of wind turbines operating in the deep sea. 80% offshore wind energy potential of Europe lies in a water field deeper than 60 meters [5], and therefore, arises a need to install the wind turbine in the deep sea. Additionally, it is encouraged to utilize the offshore wind potential to ease the transition towards renewable energy resources and keep the global temperature at 1.5 degrees Celsius, according to the Intergovernmental Panel's recommendation on Climate Change (IPCC) [6]. The onshore wind farms pose environmental harm to human beings and wildlife (i.e., visual and noise impacts) [7–9]. The hazards caused by the land-based wind farms and the low characteristics of onshore wind may be avoided by installing the wind turbines in the deep offshore regions

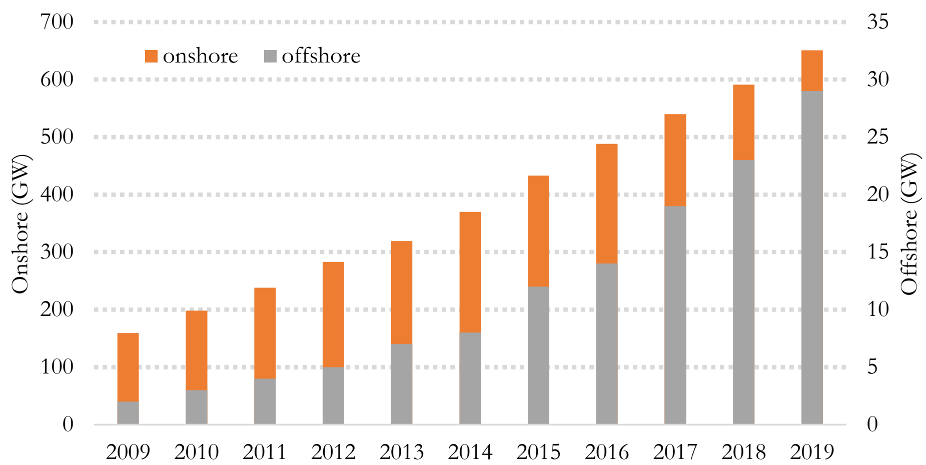

Figure 1: Cumulative installed (onshore and offshore) wind energy capacity of the world (data obtained from [10])

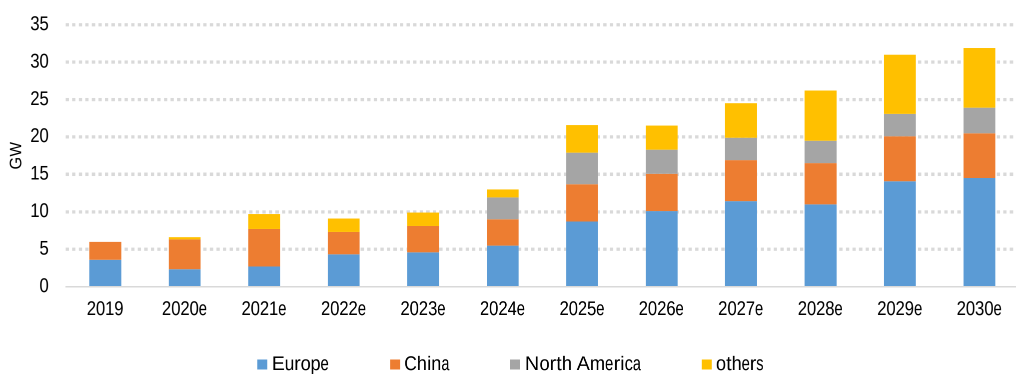

Figure 2: New annual installation prediction until 2030 (data obtained from [11])

1.2. Floating platform and associated problems

Wind turbine placed on top of a floating platform is a feasible solution to operate in deep-sea as the economic constraint hinders the development of a fixed bottom support structure for wind turbines operating beyond 60m water depth. Building a fixed bottom platform for a wind turbine in the deep sea would likely increase the overall cost. Offshore oil and gas exploration in the deep sea greatly relies on floating platforms [12]. Similarly, wind turbines may be operated in the deep ocean using a floating platform attached to the sea bottom. Several concepts exist in the literature to achieve platform stability for FOWT such as Barge, Tension leg platform (TLP), Spar-buoy and Semi-submersible, as shown in Figure 3. These concepts include buoyancy stabilized platforms, mooring lines stabilized platforms, and ballast stabilized platforms . Buoyancy stabilized platforms use submerged body volume to achieve stability, e.g., Barge and Semi-submersible platforms. The tension leg platform (TLP) is a typical example of mooring lines stabilized platform, where the platform is stabilized using mooing lines. In comparison, the spar-buoy is an example of ballast stabilized platform that benefits from the heavy ballasting of the platform's bottom to stabilize the structure. There are two type of wind turbines that are used to generate wind energy i.e., Horizontal axis wind turbines (HAWTs) and Vertical axis wind turbines (VAWTs), however the scope of this paper is limited to the HAWTs operating in deep-sea.

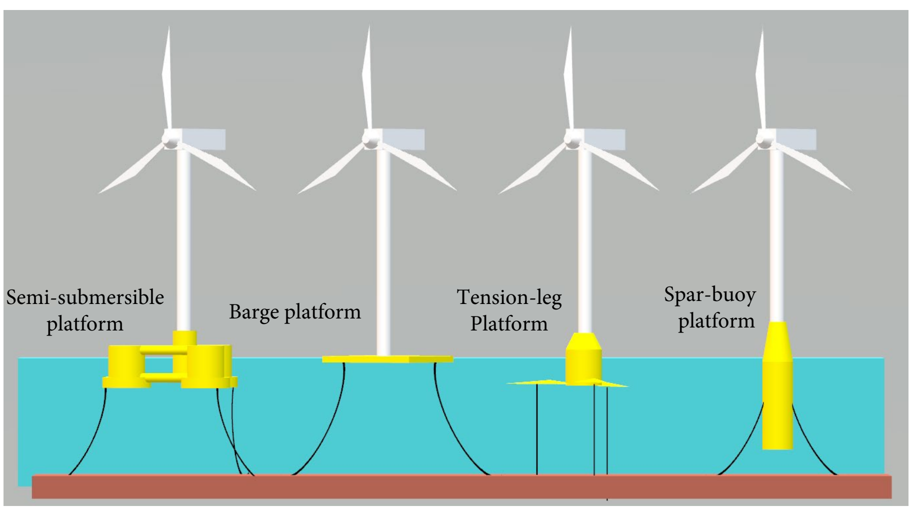

Figure 3: FOWT platforms (Semi-submersible platform, Barge, Tension-leg, and Spar-buoy)

Using these floating platforms, wind turbine extract energy from the superior offshore wind operating in the deep ocean. However, floating platforms introduce additional loadings (hydrodynamic loading, mooring loading) due to incident wave along with the aerodynamic loading on wind turbine. Incident wave associated loadings of floating offshore wind turbine (FOWT) leads to additional 6 degree-of-freedom (DOF) motion compared to the fixed bottom WTs, as shown in Figure 4 where a FOWT is stabilized using a TLP base. The stability of the floating platform is one of the dominant concerns of FOWT technology which may directly impact the performance and safety of FOWTs, leading to increased cost [13].

The performance of a FOWT system can be significantly compromised due to the motion of a floating platform. An unstable platform may decrease the nominal wind turbine area and affect energy generation. Platform motions may also increase tower loads compared to fixed bottom wind turbines and negatively impact the system's structural life. Furthermore, it also increases the cost and weakens the economic advantage as compared to onshore wind turbines. Various control algorithms attempt to achieve efficiency and platform motion suppressions by controlling the blade pitch actuator and generator torque of wind turbine. There have been numerous controllers designed to address the shortcomings of floating platform using a range of controllers, such as Proportional Integral (PI), Linear Quadratic Regulator (LQR), Linear Parameter Varying (LPV), and Model Predictive Control (MPC) [14–29]. Some advanced control algorithms utilize the blade pitch mechanism by actuating blades identically (Collective blade pitch) or separately (Individual blade pitch) to provide the wind turbine required aerodynamic thrust to suppress platform motions, maximize power generation and load mitigation. In comparison, Tuned Mass Damper (TMD) based structural control systems [30–33] introduce an extra degree of freedom and decouple the pitching mechanism from providing the required thrust to reduce the pitching phenomena. Advance controllers like MPC based on Light Detection and Ranging (LIDAR) information [25] incorporate the incident wind disturbance before reaching the wind turbine, thus enhancing the performance compared to traditional feedback controllers that function after experiencing incident disturbance. However, the levelized cost of energy cost of energy (LCOE) of FOWT is still higher than the fixed bottom wind turbines. Improved control mechanism may elevate the performance of a FOWT that would lead to reduction in LCOE.

The performance of advanced controllers can be improved by incorporating wind and wave forecast techniques. Predicted wind and wave information ahead of its encounter with the wind turbine can provide preview based advanced controllers enough time to respond to incoming disturbances

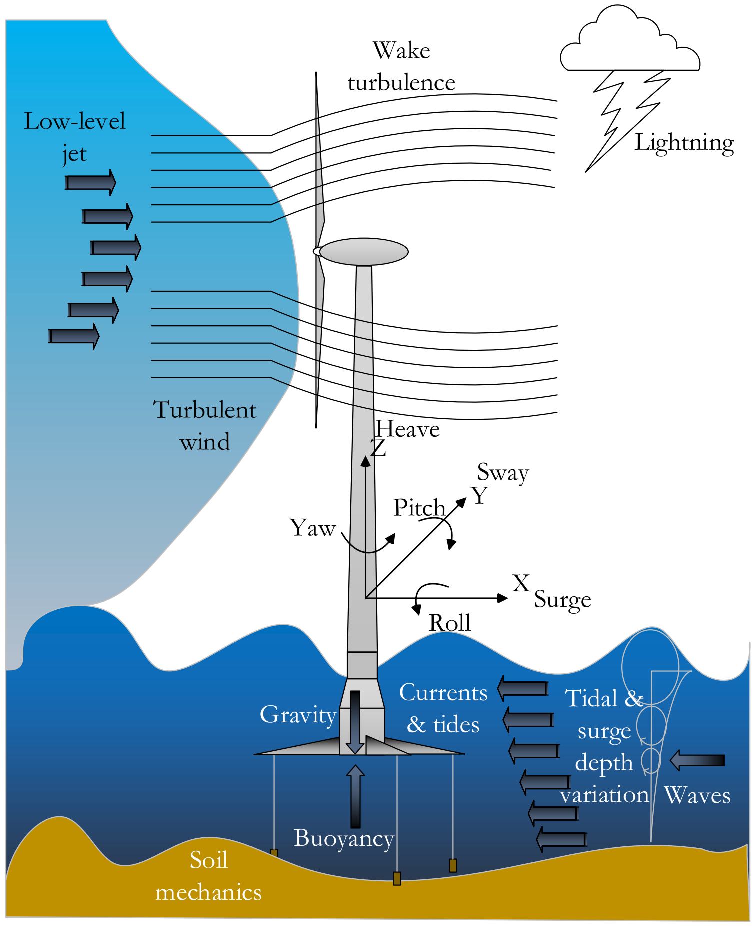

Figure 4: Floating offshore wind turbine in its surroundings

and orient wind turbine for optimal and efficient performance. The wind turbine industry is already benefiting from the wind forecast for wind farm planning, operation, and grid integration [34]. Numerous forecasting techniques for wind and wave are present in the literature, ranging from long-term (3 days - 1 week or more) to short-term(few seconds – 30 minutes) prediction horizons [35–50]. However, the controller response time for FOWT falls in the short-term prediction horizon category [51, 52]. An accurate short-term disturbance prediction incorporated in modern control systems, e.g., feed-forward control or MPC, can enhance the performance in terms of platform stability and loadings and deal with the incident disturbance better than the counterpart feedback controllers, resulting in further lowering the LCOE.

1.3. Objective

This paper reviews the controllers designed for FOTWs aiming at the platform stability enhancement, maximum power generation and structural life extension. A detailed discussion is presented, and potential improvements based on the reviewed controllers are provided. The paper outline is as followed: Section 2 presents the system overview. Control structure and methodologies used for FOWTs are discussed in Section 3. In Section 4, the wind and wave prediction for the control design is introduced. The discussion and the summary is presented in Section 5 and Section 6, respectively.

2. System description

FOWT operates in the deep sea with an extension of a floating platform attached to the sea bottom with mooring lines. However, the foundation of a FOWT exhibits 6 degrees of motion due to incident wave, as shown in Figure 4. The performance and operation of the wind turbine is coupled with the platform motion. Therefore, it is essential to minimize the platform motions during the operation of FOWT. A description of the operation of the FOWT is provided below.

2.1. Wind turbine

Wind turbines deployed in the deep sea operate similarly to land-based wind turbines to extract kinetic energy from the wind. Air passes through the blades and causes the rotor to rotate. The rotor is connected to a generator which produces energy. The maximum possible energy extracted from wind is 59.3%, known as the Betz limit [53]. Maximum power (P_{max}) generated by a wind turbine in a given scenario can be calculated by the following formula, as shown in Figure 5.

$$P_{\max} = \frac{1}{2}\rho A v^3 C_p(\lambda, \beta) \tag{1}$$

$$\lambda = \frac{\Omega R}{v} \tag{2}$$

where

- ρ= Air density

- A= Swept Area
- C_p = Power coefficient (based on tip-speed ratio (λ) and blade pitch angle β)
- R= Rotor radius
- Ω= Angular speed
- v= Wind speed

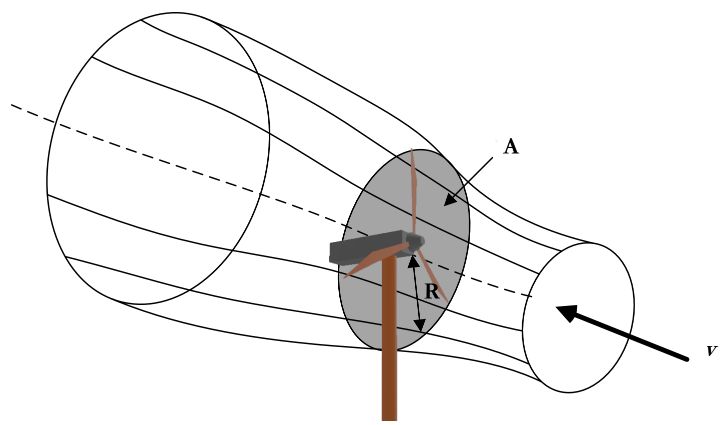

Figure 5: Wind energy extraction using wind turbine

The incoming wind speed is an essential factor in the control system design, control objectives and operation of wind turbines. The operating spectrum of a wind turbine is divided into three significant regions, as shown in Figure 6. In region I, the wind speed is less than the cut-in wind speed ($\mathrm{V_{cut\text{-}in}}$), and the wind turbine is in parked condition. In region II, the wind speed value is less than the rated value ($\mathrm{V_{Rated}}$). The control objective focuses on the maximum energy extraction from the wind by keeping the blade pitch at an optimal angle. In region III, where the wind speed value surpasses the ($\mathrm{V_{Rated}}$), the objective shifts towards regulating generated power with pitch angle activity. When the wind speed reaches cut-off wind speed ($\mathrm{V_{cut\text{-}off}}$) the mechanical brakes are applied for the safety of wind turbine. In the case of FOWTs, the number of control objectives are increased with the consideration of platform motion. For a FOWT, the floating platform, regardless of being tied to the seabed, may generate significant problems due to incident waves and wind loads.

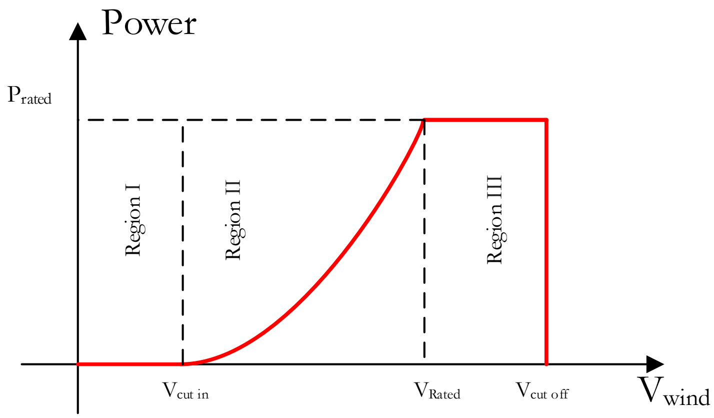

Figure 6: Operating regions of a wind turbine

2.2. Framework of FOWT control systems

FOWTs are prone to platform motions due to floating base which leads to performance deterioration. However, an effective control system may deal with the platform motions and achieve optimal wind energy generation. Existing control mechanisms for fixed bottom wind turbine are rendered infeasible for FOWTs due to the additional platform motion of FOWT. However, fixed-bottom wind turbine controllers maybe modified to include the platform motion suppression objective.

Majority of the FOWT controllers are based on feedback control mechanism. In addition, there are advanced feed-forward controllers available in the literature as well. A detail discussion on these controllers is given in the Section 3. The benefit of feedforward mechanism may be further extrapolated by using incident wind and wave forecast to improve the controller performance. An account of incident wind and wave forecast is given in Section 4.

3. FOWT Control structure

Control system of a wind turbine is responsible for handling the aerodynamic wind load and converts the wind energy into electric power. In general, there are multiple control levels to deal with the wind turbine operation. The primary-level supervisory control level deals with the startup and shutdown of the wind turbine. The wind turbine is only started up when there is enough wind, and shutdown is triggered in the presence of excessive wind, as it may harm the wind turbine structure. The second-level operational control is dedicated to achieving control objectives based

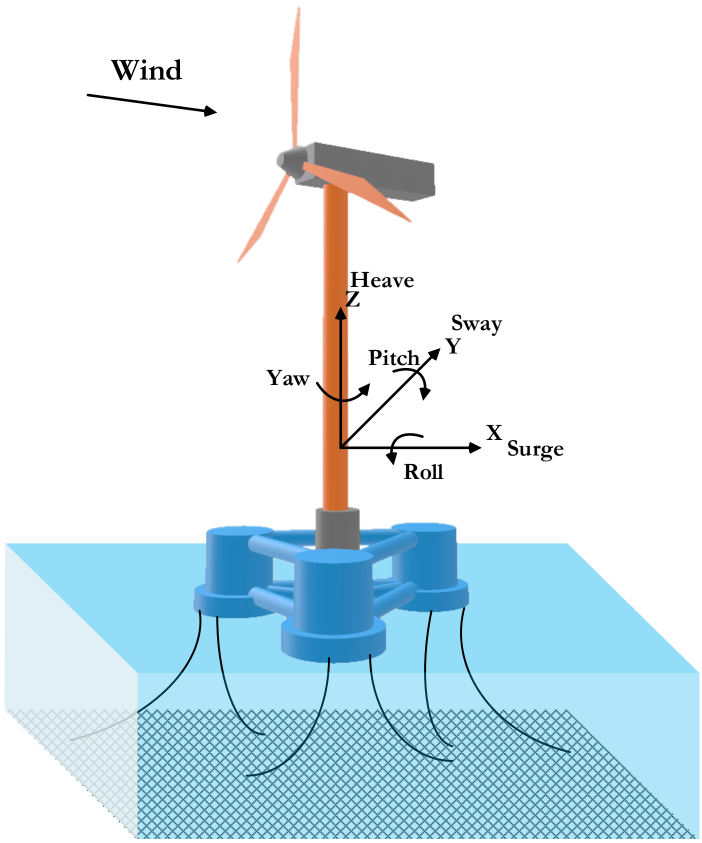

Figure 7: Associated platform motions of FOWT

on the wind turbine operating region, as shown in Figure 6. In comparison, the third-level control is concerned with the yaw and pitch actuation system and related electronic units. The scope of this paper is limited to the second-level operational control of a wind turbine. Later in this section, the control objectives and control methodologies used to achieve these objectives for FOWTs are discussed in detail.

3.1. Control objectives

Control objectives of a wind turbine vary based on the operating regions, namely maximum power generation operating in region II and power regulation in III, as shown in Figure 6. There are generally two control loops to achieve these control objectives, as shown in Figure 8. Operating in region II, the torque control loop of the wind turbine is used to maximize the generated power by operating near the optimal C_p by using fixed blade-pitch angle to an optimal value, based on equation 3. In region III, the objective shifts towards regulating the generated power at the rated value. The blade-pitch control loop regulates the aerodynamic loads and generated power by manipulating the blade pitch value. There are two standard pitching strategies for the region III pitch control loop, pitch-to-stall and pitch-to-feather [54]. The generator torque control while operating in region III, is calculated based on the relationship in equation 3.

However, the major problem associated with FOWT occurs due to platform motion while operating in region III. The wind turbine structure undergoes undesired pitching phenomena, often called negative pitching [55]. The frequency of the platform is coupled with the blade pitch mechanism while operating in region III, causing a surge in the pitching motions of the platform leading to issues like poor power quality and increased loads. Therefore, an adequate control mechanism to achieve the standard wind turbine control objectives and deal with the platform pitching phenomena associated with floating platform of FOWT is needed.

$$T_{gen} = \frac{\pi \rho R_{rotor}^5 C_{p,\max}}{2\lambda_o^2 N^3}\omega_{gen}^2 = K\omega_{gen}^2 \tag{3}$$

$$T_{gen} = \frac{P_{rated}}{\eta_{gen}\omega_{gen}} \tag{4}$$

where

- T_{gen}=Generator torque
- ρ= Air density
- R_{rotor}= Rotor radius
- N= Gear box ratio
- $C_{p,\max}$ = Maximum power coefficient

- λ_o = tip speed ratio related to $C_{p,\max}$
- ω_{gen}= Generator rotational speed
- η_{gen}= Generator efficiency
- P_{rated}= Rated generated power

A range of system models are available in the literature, that are used to develop control schemes for FOWT and preview the outcome without running the actual wind turbines. Appendix A contains the details of these simulation codes for the readers further interested in FOWT system models.

3.2. Control methodologies

Control methodologies for FOWT to deal with the undesired platform associated motions while operating the wind turbine at optimal level are based on traditional single-input single-output (SISO) and advanced multi-variable multiple-input-multiple-output (MIMO) mechanisms. This section provides a discussion on the range of these controllers reported in the literature.

3.2.1. Traditional FOWT controllers

The traditional FOWT controllers are simple and easy to design control mechanisms that are based on the single-input single-output (SISO) principle. Independent control loops are applied in parallel to achieve multiple control objectives, as shown in Figure 8.

Platform pitching motion of FOWT was minimized by keeping the frequency of the blade pitch mechanism lower than the resonance frequency of the platform by Larsen et. al [14]. For region 2, a variable speed control loop was used to maximize the generated power. A region of constant speed was introduced between regions 2 and 3, followed by a constant torque loop in region 3. Pitching action is determined by a gain-scheduled proportional-integral (GSPI) controller for region 3. Improved platform pitching was achieved using less aggressive control methodology at the cost of lowered power quality and poor rotor speed regulation.

Another GSPI controller based solution for negative platform damping problem of barge based FOWT was provided by Jonkman [15]. Two independent SISO controls were designed; A generator-torque controller to generate maximum power in region 2 and keep the power captured at the rated value in region 3. A GSPI controller was considered to adjust rotor speed as a function of blade pitch

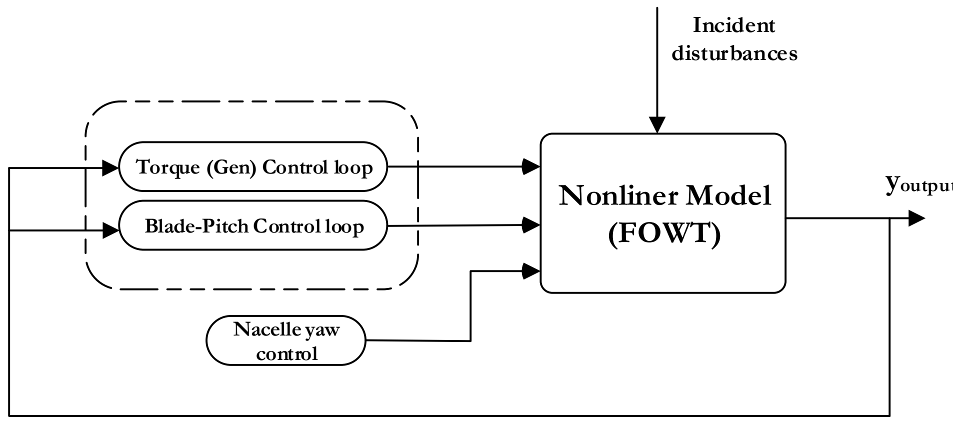

Figure 8: Wind turbine standard control loops

activity based on the collective blade pitch (CBP). Jonkman et al. [15] designed additional control loops upon facing complications regarding platform oscillations and power fluctuation during the early design synthesis. Tower-top feedback control, active pitch-to-stall control and a controller based on detuned gains were the additional loops included in the original design mechanism. These additional loops were proposed to minimize the fore-aft motion of the tower, instability of platform yaw, and excessive barge motions, respectively. Tower top feedback control failed to improve the pitching motions of the platform.

Furthermore, active pitch-to-stall control was found good at power regulation for the barge platform at the expense of increased platform pitching motion. Whereas, detuned gains proved to be the most suited controller among others, as it reduced the blade activity and addressed the platform pitching issue. This configuration is used for testing newly designed controllers and labeled as baseline FOWT control [56]. The use of individual blade pitch (IBP) and multiple-input-multiple-output (MIMO) state-space controllers were suggested to enhance performance further.

Baseline controller designed by Jonkman et al. [15] was analyzed for different platforms by Matha et al. [57]. The TLP, Barge, and Spar-buoy floating concepts were compared concerning fatigue loads and platform stability. Matha et al [57] modified the baseline controller for the spar-buoy platform. Constant torque control was designed to improve the platform pitching motion while operating in region 3, contrary to a constant power controller originally designed by Jonkman et al.

[15]. Meanwhile, the controller's bandwidth was kept low to avoid coupling with the frequency of the platform. It was noticed that the barge platform is cost-effective, but its inability to withstand incident loads may cause stability issues. The spar-buoy platform showed resistance towards tower loading as compared to the barge platform. However, the deployment of the spar-buoy platform is costly due to its intricate design and assembly. In comparison, TLP was found to have better performance among the compared concepts. However, it was found that the anchoring system of TLP may increase the cost.

Platform instability was addressed by using the pitching velocity as an input to regulate the generator rated speed in region 3 [16]. The generator speed was used to provide the counter thrust to suppress the platform pitch motion and achieve platform stability. This unique control methodology reduced negative damping and blade pitch activity at the cost of acceptable rotor speed fluctuations and power variation. In a subset simulation, Individual blade pitch control (IBPC) was implemented using the Coleman transformation [58] to reduce blade loads. However, the IBPC increased the blade pitch activity resulting in inadequate blade load reduction.

A control strategy based on the estimation of wind speed to suppress the negative damping for the Hywind concept platform [55] was proposed by Skaare et al. [17]. The control mechanism designed by Skaare et al. [17] improved the tower loading and the nacelle oscillations. Simultaneously, the poor rotor speed regulation and the reduced power generated were observed compared to the conventional blade pitch mechanism. Moreover, since the strategy was based on the estimated form of wind in region 3, this control scheme's effectiveness was mainly governed by the wind estimation quality.

3.2.2. Advanced control methods

The classical SISO controllers are easy to realize controllers, however may not be a suitable option for highly coupled multi-objective systems like FOWTs. The design process of SISO controllers requires a thorough understanding of the system and careful tuning of control loops separately. Otherwise, multiple control loops may couple with each other and affect the overall system operation. As suggested by Jonkman et al. in [15], advanced controllers based on multi-input multi-output (MIMO) may further improve the performance of FOWT due to its inherent ability to deal with short comings of SISO control. Multi-variable MIMO control schemes such as Linear Quadratic Regulator Control (LQR), Linear Parameter Varying control (LPV), Model Predictive Control

(MPC), used for FOTWs reported in the literature are described below.

Most of the advanced controller designed for FOWT are based on State-space control. State-space control design involves linearizing the non-linear system model at an operating point x_{op} such that state x transforms into the deviation Δx around the x_{op}. Later, linear control theory is applied to design a controller to achieve the given objectives. State-space equation is shown below,

$$\begin{aligned} \Delta\dot{x} &= A\Delta x + B\Delta u + B_d\Delta u_d \\ \Delta y &= C\Delta x + D\Delta u + D_d\Delta u_d \end{aligned} \tag{5}$$

where

- x= x_{op}+Δx
- y= Measurement matrix
- u= Actuator matrix
- Δu_d= Disturbance matrix
- A = State matrix
- B = Actuator Gain matrix
- B_d= Disturbance gain matrix
- C= Output matrix
- D= Feed-through inputs
- D_d= feed-through disturbance

Several advanced controllers were designed using MIMO state-space methodology on Barge, TLP, and Spar-Buoy platform based FOWT [20–22]. The collective blade pitch controller (CBPC) and IBPC were designed for a barge platform [20]. The IBPC and wind disturbance-based Disturbance Accommodating Control (DAC) were designed for FOWTs on a barge, and TLP [22]. The controllers designed for Barge and TLP were later used to investigate the performance of the Spar-buoy platform [21]. In region 3, the CBPC scheme for FOWT showed improvements in better speed regulation, mainly due to constant power control instead of constant torque control and the platform pitch motion reduction.

IBPC was utilized to deal with the overlapping blade pitch commands issued for the rotor speed control and the platform pitch minimization [21]. IBPC mechanism improved tower loading for the barge platform. In comparison, the performance of IBPC was found limited due to the relatively lower platform frequency spar-buoy platform. On the other hand, DAC has an advantage due to improved rotor and power regulation based on increased blade pitch actuation for the spar-buoy platform.

Controller-based on IBP achieved improvements when applied to the Barge platform compared to the CBP control [20]. DAC was rendered not useful for barge platform because the barge platform is mainly influenced by waves; however, DAC is used to influence wind disturbances. [22]. IBPC was shown to have improvements regarding rotor speed and power regulations for Barge and TLP, but for Spar-buoy, when dealing with the platform pitching, this scheme was not as effective due to the low natural frequency of the platform. Further improvements related to power and speed regulations were achieved using DAC for the TLP platform.

A study was conducted on the input-output relation of the 10MW FOWT to find out the frequencies with a substantial impact on the output with the least control variable impact by F. Lemmer et al. [23]. The wave information was added to produce a realistic environment and representation of the coupled frequencies with the parametric wave excitation model from [59]. Wind and wave disturbances with significant impact on the output due to the minimum control actuation were chosen. This information was used to design an LQR controller based on input blade pitch angle and generator torque, and a comparison to a conventional PI controller was made. The designed controller was noticed to have improvements concerning system response reduction and damping various resonances. However, the control mechanism could not completely overcome the effect of incoming wave disturbance.

Gain scheduled output feedback H-infinity control based on collective blade pitch approach for FOWT operating in region 3 was designed by T. Bakka et al. [18]. A simplified model is generated based on significant FAST model dynamics for control synthesis, namely, the rotor generator and tower. Linear models are generated at multiple operating points based on output feedback H-infinity control, and a scheduling mechanism is developed. Substantial improvements were found in terms of the tower loadings and rotor speed regulation.

Linear Parameter Varying (LPV) and Linear Quadratic Regulator (LQR) developed by using gain-scheduled (GS) blade pitch controller for a barge platform-based FOWT [19]. The objective was to regulate the generated power and minimize structural loadings while operating in region 3. The LPV was further modified with the state feedback and output feedback control mechanisms and compared with the baseline wind turbine [15, 60]. It was found that the GS-LPV and GS-LQR controllers performed better in terms of power regulation and platform pitch minimization. Whereas, LPV-GS controller with state-feedback has shown superior improvements in platform pitch motion damping than the rest of the controllers.

Input/output feedback linearization (IOFL) and Sliding Mode Control (SMC) methods were used to analyze the effects of incident disturbance on platform motions and regulate generator speed and of FOWTs operating in region 3 [24]. A simplified model based on the DOFs of blade pitch and generator speed, and platform pitch was obtained. Later, a simplified non-linear model based on series of linearized simplified models is designed. The switching mechanism between these linear models is obtained based on the LPV model as a blade pitch angle function. Compared with the baseline model, SMC showed improvements regarding generator speed regulation, while the platform pitch motions were on a similar level as for the baseline wind turbine. The reason for speed regulation was, the wind speed was considered for control design. However, the platform motions were observed without adding to the control design. Contrary to SMC, IOFL control causes increased platform pitching motion when compared with the baseline controller. Another important finding was observed that the performance of the developed controller was degraded when implemented on complex models.

Model predictive control (MPC) is an advanced control method that predicts future action based on the internal system model's available information fulfilling a set of constraints. Numerous examples are available in the literature regarding the use of MPC for fixed bottom wind turbines. [61–64]. D. Schlipf et al. [25] designed a non-linear-MPC (NMPC) for FOWTs operating in region 3 based on the simplified Sander model [65]. The incident wind and the wave preview was used for the controller design based on CBP and generated torque. The control objective was to keep the generated power and rotor speed steady based on an ideal estimation of the wind and the wave preview [61]. The designed controller was later used on the baseline FOWT [15] placed on a spar-buoy platform under an intense wave and wind profiles. The controller showed satisfactory results regarding the generated power and speed regulation error, including the blade load reduction; However, the NMPC controller requires higher computational resources.

Following the CBP-based non-linear MPC design for FOWT in [25], S. Raach et al. [26] came up with an extended version of NMPC based on the IBP mechanism. The IBPC-NMPC included the rotor and the blade load reductions alongside the existing benefits of the original CBP-NMPC, platform pitch reduction and rotor speed regulation. After the controller design, its successful implementation on the baseline wind turbine exposed to the turbulent loads was achieved. The rotor's fatigue loads were reduced significantly by using the extended NMPC based on the IBP mechanism.

An optimal linear MPC implemented on a 10 MW FOWT by F. Lemmer et al. [27]. A tunable controller was designed to provide early-stage design assistance during the fabrication of FOWT. The linear-MPC based on the MIMO system was designed to operate in region 3 to regulate the power to a constant value and minimize the structural loads. In comparison, maximum power generation was the primary objective for region 2. Linear-MPC showed adequate improvement than a PI controller for the rotor speed and generator power regulation. Moreover, the tower top movement and negative platform pitch were also minimized.

3.2.3. LIDAR based advanced control

Reduction in LCOE of FOWT may be achieved through enhanced structural performance against incident loads . For this purpose, we have discussed several feedback controllers. One major drawback is that these control mechanisms are designed to respond to the incident impact after its interaction with the system structure. For FOWT, wind turbine structure experiences the incoming wind and wave and feedback control system is activated after the interaction of incoming wind and waves with the system. Such interaction may degrade the structural life over a period of time. Thus traditional controllers may not achieve extended structural life and would increase LCOE subsequently.

To circumvent the shortcomings of feedback controllers, the researchers may use feedforward control loops to deal with the incident disturbances before contacting the wind turbine. LIDAR is used to measure the incoming wind disturbance. There have been numerous attempts made to use LIDAR for fixed-bottom wind turbines. [66–68], LIDAR is based on Doppler's principle, where a laser beam is spread out which upon reflection is received [69]. The wavelength of the transmitted and received beam is used to estimate the incoming wind speed. Two types of LIDARs are available based on the wind speed calculation methods, i.e., continuous and pulsed wave. The continuous wave LIDAR uses a laser beam focused at the focal point while the pulsed wave LIDAR calculates wind speed at multiple distances [66].

Unlike fixed-bottom wind turbines, preview-based LIDAR assisted control for FOWT is still under development. An extended version of feedforward collective blade pitch control, initially used for fixed-bottom wind turbines in [70], was designed for FOWT using H-infinity control synthesis by S.T. Navalkar et al. [28]. Based on the combination feedforward-feedback newly formulated CBPC was found useful at minimizing the loads and generator speed oscillations. D. Schlipf et al. [29] designed a CBP-feedforward controller for FOWTs based on LIDAR data. The feedforward control was designed using a simplified non-linear model for ideal wind preview and used along with the traditional feedback controller designed by Jonkman et al. [56]. Later, the design procedure was followed by using nacelle-based LIDAR information instead of ideal preview wind. With the addition of wind uncertainty, a realistic feedforward controller proved useful compared with the standalone baseline controller to minimize rotor speed and power fluctuation and reduce blade, rotor shaft, and tower loads, respectively.

3.2.4. Structural control

There is another approach reported in the literature to minimize the structure loadings, and external influences called structural control (SC). In this methodology, extra DOFs are introduced to influence the structural behavior of the system. This methodology has been vastly used to minimize the oscillations and vibrations of mechanical structure efficiently, and systems [71–74]. For FOWTs, the aim of using the SC is to damp the platform oscillations and tower loading. The critical advantage of the SC for the FOWT is observed while operating in region 3. Blade pitch mechanism is not required to regulate the platform stability, a significant issue observed in region 3, and SC addresses the platform's pitching phenomenon. The SC is based on passive, semi-active, and active control approaches [75]. Passive structural control systems use a set of constant parameters to damp the oscillations. Whereas, the semi-active controllers are mainly tunable over a period of time. Contrary to the passive control approach, active structural control differs based on generating the restoring force with dedicated actuators to address the structure loading and oscillation.

Passive and active structural control schemes based on two independent Tuned Mass Dampers (TMDs) to deal with the loading and damp the platform oscillation were designed by M. Lackner et al. [30]. These TMDs were placed in the nacelle of a floating barge, operating in region 2 and 3. M. Lackner et al. [30] modified the baseline wind turbine [15] by integrating TMD systems and incorporating passive, semi-active active structural control synthesis. Based on input-output data, a high order design model is created using system identification. The control synthesis is achieved based on the loop shaping mechanism. It was observed that both techniques reduced wind turbine loadings when compared with the baseline wind turbine. On the other hand, the complexity and overall cost were increased due to the addition of TMDs. Moreover, active structural control outperformed in reducing the tower's fore-aft fatigue load at the expense of energy consumption, which may be obtained from the high wind while operating in region 3. However, in region 2, active structural control proved costly, and for this purpose, a hybrid mass damper (HMD) was incorporated to work as passive TMD while operating in region 2.

Nacelle-based TMD system used Lackner et al. [30] is redesigned by Namik et al. [31]to examine the impact of actuator dynamics on TMDs. Load reduction and power consumption were also investigated for the passive and active control strategies on a barge platform-based FOWT. Although the newly designed controllers followed the simulation trends as shown by Lackner et al. [30] concerning load reduction, the redesigned TMD system achieved platform pitch minimization by consuming relatively less average power.

Simplified models of the Mono-pile, Barge, Hywind Spar-buoy, and TLP were used to design an optimal passive TMD based on genetic algorithm by Stewart et al. [32]. This TMD was found to reduce the side-to-side tower fatigue load, which is one of the main components of fatigue loads of FOWTs, better for barge and mono-pile than the TLP and Spar buoy platforms.

A Semi-active TMD placed in the nacelle of a wind turbine was used to minimize the incident loads for two platforms: a fixed bottom mono-pile and a TLP, while operating in region 2 and 3 [33]. The designed semi-active TMD has a low power energy source, and it swiftly switches between active and passive modes. This mechanism minimizes the side-to-side tower loading of mono-pile and slackline incidents regarding TLP. A platform-based TMD for barge platform FOWT is used to minimize the platform motions and tower loading while operating in region 2, and 3 [76]. A simple static output-feedback mechanism was proposed to generate the stroke, using generalized $H\infty$ control. Input-output linear model was obtained using system identification. Improved results were obtained in terms of fatigue load and generator power error reduction, while upon comparison, the generalized $H\infty$ control overperforms $H\infty$ structural control. Similarly, a Multi-layered Tuned liquid damper (TLD) was developed in [77] for a spar-buoy floating platform and was found useful to minimize platform motions.

The traditional passive TMD system's performance was improved by introducing an inerter in the system [78]. The proposed TMD system was placed in the nacelle of the FOWT attached to a barge. The improvement was evaluated in the presence of real incident disturbances, waves and wind. This novel extension of the TMD was found helpful in reducing tower loading. In a relatively similar approach, a STAM (sewing thread artificial muscle) based on thermal actuation attached to mooring lines of the TLP platform was proposed to minimize platform pitching and tower loading for regions 2 and 3 [79]. The active mooring method showed improved results regarding tower loading and pitching motions.

4. Wind and wave forecast algorithms for FOWT control

Incident disturbance forecast is an essential feature of advanced control algorithms like predictive model control and feedforward control. Unlike feedback control, where the controller responds to the disturbance after the system interacts with it, feedforward controllers react to the preview of incoming disturbance ahead of its contact with the system. This approach elevates the performance because the incident disturbance preview provides the controller enough time to respond to the incoming disturbance and adjust parameters to achieve control objectives. Preview-enabled control also enhances the system's structural life as it responds to the incident disturbances ahead of its contact with the system structure.

FOWTs are exposed to incident wind and wave disturbance operating in the deep sea. A lot of controllers are designed to stabilize the platform and achieve the control objectives by minimizing the effects of wind and wave disturbances. However, the performance and structural life of FOWTs is still lagging behind when compared with the fixed bottom offshore wind turbines, as most of these control systems are feedback control systems. The incident wind and wave prediction may effectively improve the performance, loading, and structural life of FOWTs with the help of advanced control algorithms like MPC or feedforward control, as proven by the LIDAR based incident wind preview enabled feedforward controllers [29].

There are several forecast techniques for wind and wave are reported in the literature, which could be used for preview-based advanced controllers. However, there are issues concerning the prediction horizon length and the forecast quality are to be considered when using these prediction mechanisms. In this section, wind and wave forecast algorithms are discussed.

4.1. Wind forecast

The wind turbine industry extensively employs the wind forecast to examine a region's seasonal power production, grid integration, and wind farm design [80]. Based on its application, the length of the prediction horizon of wind forecast ranges from few hours to months, namely; short, medium, and long-term. However, the prediction horizon length for individual wind turbine control systems based on preview information is few seconds. Advanced controllers such as feedforward control require a preview time of a few seconds [51]. Similarly, MPC uses a 5-10s long horizon to compute the input values for system response [52]. Therefore the scope of this paper is limited to the wind forecast for wind turbine control, referred to as ultrashort wind forecast in this paper. An overview of models and devices used for ultra-short wind forecasts is provided below.

Statistical time-series models used for wind forecasts are based on the historical site data. Based on the historical wind data, these models tend to learn the underlying patterns in the available data and calculate the future values ahead of time. Widely used conventional statistical models for wind forecast includes autoregressive model (AR) [42, 43], autoregressive moving average model (ARMA) [44], autoregressive integral moving average (ARIMA) [45], fractional-ARIMA [46], and Hammerstein auto-regressive (HAR) [47] etc. Statistical methods heavily rely on historical wind data thus may provide faulty wind forecasts in the absence of enough historical site data.

Machine learning (ML) techniques rely on historical data and consider the atmospheric variables that affect the wind speed, such as humidity, elevation, and atmospheric pressure for wind forecast. Therefore, ML methods deal with the nonlinearity of wind better than the statistical methods. ML non-linear prediction methods include artificial neural networks (ANNs) [81, 82], recurrent neural networks (RNN) [83], support vector machine (SVM) [84, 85], least-square support vector machine (LSSVM) [86, 87], Gaussian process (GP) [88], Bayesian networks [89], and extreme learning machine (ELM) [90]. Overfitting and minimum local existence are major drawbacks of ANNs [91]. Whereas ELM is proven to have better performance than conventional ANNs and is used for both speed estimation and power forecasting [90, 92, 93]. Hybrid models, a combination of existing model techniques, are also reported in the literature for improved performance. For example, A linear ARIMA and a non-linear ANN are used in a combination for improved wind forecast [94]. Similarly, a combination of ELM and ARIMA is shown to have enhanced performance for wind forecast [95].

LIDAR is used in the wind turbine industry for several applications such as wind power estimation and site analysis [96]. They are also used to provide the preview of incident wind for an ultrashort scale horizon upstream of the wind turbine. Wind speed is calculated based on the reflected lasers from the incoming wind particles emitted from LIDAR. Preview measurement of incoming wind speed for FOWT control is discussed in Section 3]. LIDAR-based forecasting techniques are reported to outperform forecasting techniques like ARIMA and persistent methods [97, 98]. However, the higher cost and weather-dependent performance are challenges yet to be further researched.

4.2. Wave forecast

Incident wave accounts for a significant part of FOWT loads when minimizing the platform motions. Therefore, it is also an essential feature to be considered alongside the incident wind in the preview-based FOWT control. Feedforward controllers based on the wind and wave preview may improve the FOWTs loading and platform stability compared to feedback controllers by providing the system enough time to deal with the incoming disturbances. Many wave forecast methods are reported in the literature, such as physics-based models, statistical models, and machine learning models. A discussion on these models is given below.

Physics-based models are numerically designed models that solve the complexity of waves based on the physics behind wave mechanics. Physics-based wave forecast models include WAVEWATCH III (WW3) [99], European Center for Medium-range Weather Forecasts (ECMWF) [100], and SWAN (Simulating Waves Nearshore) [101]. These models are generally used for long-term prediction horizons over an extensive area. In contrast to the physics-based theory-driven models, data-driven statistical and machine learning provide accurate predictions based on the historical site data. These time-series algorithms extrapolate the past values to provide future wave predictions. Statical wave prediction models for wave prediction reported in the literature includes AR, ARMA, ARIMA [48–50]. As compared to statistical models, machine learning prediction models provide improved nonlinear trends identifications in time series wave data. ANN, RNN, CNN, and ANFIS based prediction models [102–106] are some of the examples of machine learning models used for wave prediction in the literature. A comparison of time series-based models and physics-based model (ECMWF) at multiple sites highlights the weakness and strengths of these models [107]. Physics based model performs better for longer prediction horizons, whereas the time series models are better for a shorter prediction horizon. Combinations of physics-based and data-driven statistical models are also reported in the literature [108, 109].

5. Discussion

FOWT technology is still in the pre-commercial phase as compared to the fixed-bottom offshore wind turbines. The primary concern of FOWT development is the associated cost of energy production and the potential to achieve a cost-effective advantage compared to the fixed-bottom, which is deteriorated by the floating base of FOWT. However, an efficient control mechanism may deal with the shortcoming of the platform, making it economically feasible. These control methods aim to lower LCOE while operating the region below and above the rated wind speed, making it economically feasible. Several control schemes are recently developed for this purpose.

5.1. Comparison between traditional SISO and advanced controllers

The conventional SISO feedback controllers are a natural choice for FOWTs by manipulating the aerodynamic wind load using blade pitch angle and generator torque. Its simple design and easy realization make them a suitable option for fixed-bottom wind turbines. However, the floating platform's natural frequency is lower than the fixed-bottom wind turbines foundation, which causes negative platform damping operating in region III [14]. Controllers designed for fixed-bottom wind turbines may increase the negative platform damping when used for FOWT. Several SISO control strategies are reported in the literature to deal with this issue; refer to Table 1 for details. For example, negative platform damping is addressed by reducing control bandwidth; however, power and speed variations were observed [14]. B. Skaare et al. [17] came up with wind speed estimator-based blade pitch control to deal with the platform's floating motions. Improvement in terms of platform motion damping was achieved at the cost of rotor speed and power output deviation. Jonkman et al. [15] utilized Gain scheduled SISO controller with detuned gains to deal with negative platform damping on a barge platform. However, achieved performance is likely to increase using MIMO controllers, suggested by Jonkman et al. [15]. The coupling between the unmodelled DOF and SISO control loops of FOWT causes inadequate platform motion minimization, power and rotor speed regulation.

On the other hand, advanced MIMO controllers can deal with cross-coupling between the unmodeled DOF and control loops better than SISO controllers. These controllers are based on the linearized system model and exhibit superior performance compared with the baseline SISO controller. The conflicting blade pitch commands for the platform and rotor regulation are dealt with Individual blade pitch control (IBPC) by creating asymmetric rotor load. However, the platform properties affect the performance of MIMO controllers, as shown in the Table 4. For example, the Barge platform is prone to increased loads due to the inherent platform motion inducing incident waves. MIMO control based on Individual blade pitch control (IBPC) used for barge results in lowered tower loads and platform motion. However, the rotor and power regulation are at a similar level compared to the baseline controller. The reduction in loads is due to increased blade pitch activity. DAC is seen to have no further improvement as it is mainly responsible for lowering the wind disturbances, and the barge platform is mainly affected by incident wave load [22]. Due to its lowered pitch frequency, the Spar-buoy platform is observed to have a slight improvement in the use of IBP based MIMO control compared to other platforms. DAC control effectively reduced the wind disturbance for Spar-buoy, thus leading to better rotor regulation. However, DAC negatively affects the platform motions based on the increased blade pitch activity [21] For the case of TLP, the platform is less affected by the incident waves. IBPC improves the tower loads and platform motions. A significant improvement is observed in the rotor and power regulation which may be attributed to the platform's inherent stability due to tensioned mooring lines. Subsequently, the DAC controller incurs additional improvement by reducing incoming wind disturbance [22].

Most of the MIMO controllers for FOWTs are designed around a single operating point. The controller performs well around the operating point; however, moving away from the operating point may lead to performance degradation. To overcome this obstacle, a gain-scheduled controller based on a series of linearized models on a range of operating points improves power regulation and platform motions. LPV controllers offer another switching mechanism to incorporate multiple linear models for a range of operations and deal with the limitation of linearized MIMO models that are only valid around linearization points.

Advanced controllers like MPC controllers improve performance while dealing with uncertainties and unmodeled system dynamics. Based on preview wind and wind measurements, MPC corrects the control trajectory based on the plant model at every step. It also allows designers to include the constraints on inputs and states in control design, thus effectively avoiding physical saturations. However, MPC is a computationally demanding control mechanism for complex systems like FOWTs. Advanced controllers based on preview information of incident disturbance are superior alternatives to feedback controllers. LIDAR is a valuable addition to improving fixed-bottom wind turbines; however, LIDAR performance is yet to be evaluated for FOWTs are exposed to wave disturbances. Details of advanced MIMO controllers is provided in Table 2.

Structural controllers based on TMDs adequately reduce the pitching phenomena and reduce the wind turbine loads, mainly operating in region 3. Controllers we have discussed until now are mainly based on blade pitch mechanism control. However, structural controllers include additional DOF that deals with platform motions and tower loading. This way, controller mechanisms ease the high blade pitch activity and provide a further performance improvement. However, the addition of TMDs causes an increase in the complexity of the FOWTs. Moreover, the power required to generate a heavy stroke in active dampers requires further investigation regarding cost-effectiveness on an industrial scale. List of existing structural controllers is provided in Table 3.

Table 1: Traditional control methods

Method	Model	Platform	Description	Economic viability	OR
CBP- GSPI [14]	HAWC2/ SIMO - RIFLEX	Spar-buoy (Hywind)	Region-dependent control based on simple switching process, pitching controller of frequency lower than the platform pitching frequency is employed for region 3.	Improved tower stability. however, degraded power quality and poor rotor speed regulation.	2,3
CBP-GSPI [15, 57]	FAST	Barge, TLP, Spar - buoy	Feedback loop based on Tower-top movement,pitch-to-stall regulation and detuned gains.	Only detuned gains control improves the negative damping issue. Further use of MIMO control is suggested including IBPC.	2,3
Simple Platform Pitch Control [16]	FAST	Barge	Platform pitch velocity based generator speed control in region 3. Also used IBPC.	Reduced negative damping and blade pitch activity at the cost of the rotor speed fluctuations and power variation. IBPC showed inadequate load reduction.	3
Control based on estimated wind speed [17]	HAWC2/ SIMO - RIFLEX	Spar-buoy (Hywind)	Estimator based control mechanism.	Tower Loading, nacelle oscillation and rotor loads are found reduced. However, poor rotor speed regulation and reduced power generated are observed.	3

5.2. Impact of the platform on the controllers performance

So far, we have discussed a range of controllers designed for FOWTs for their pros and cons. SISO and advanced MIMO controllers are incorporated to deal with shortcomings associated with the platform motions. However controller performance may vary based on the type of platform used for the operation. We have compared several advanced controllers based on the utilized platform type and their performance in Table 4. Comparison is made in terms of improvement in tower loading, power regulation and platform motions damping to give readers an overview of how control performance may vary based on different platform types. Controllers for the barge platform improved tower loadings and platform motions; however, they perform poorly in terms of power regulations. The TLP platform has inherent stability over its counterpart platforms thus we see improvement compared to the barge platform. MIMO controller based on the IBPC with an extension of DAC ranks higher because it manages to minimize the incident wind disturbance better for the TLP than the barge. Due to lower platform frequency, the spar-buoy platform may not perform well enough, although it has better power regulation, which is mainly due to increased blade pitch activity. However, advanced controllers like MPC and preview-enabled feed-forward controllers exhibit superior performance, especially for the case of power regulations. MPC has a higher ranking also due to the ability to deal with the input and system state constraints.

6. Summary

The control mechanisms we have discussed are all based on model-based design. In complex systems like FOWTs, accurate system modeling is essential for dealing with model uncertainties and complex incident disturbances – wind and wave. In an ideal situation, the plant represents the actual systems and actuators, whereas, in reality, it is a fair approximation of the system. There are expected errors that may result from a poor understanding of the system and un-modeled dynamics, leading to a compromise of system performance. In this case, the model-free control approach may be utilized to represent the plant model and deal with the shortcomings not addressed by first-principle mathematical modeling. Input-output data may be used to deduce a plant representation for the respective controller design after careful assessment and performance evolution. Unlike the model-based design, the data-driven model-free controllers don't rely on the system characteristics, eliminating the need for controller dependency on the plant model. Furthermore, unlike the model-based control approach, in the model-free methodology, the system stability is not relying on the model accuracy [110]. Machine learning techniques may address this issue by finding the optimal control laws by mapping the sensor's output to control actuators. These techniques are based on bio-inspired computational methods, including Genetic Algorithm and Reinforcement and Iterative learning [111]. These algorithms may be used to minimized constraint-based cost functions designed according to the control objectives. One such example of MLC usage for complex structures like FOWTs is reported in the literature [112]. Input-output data is correlated to for a control law

$u = k(y)$ and evaluated using a cost function J, as shown in schematic Figure 9. It shows improved performance compared to the baseline controller and demonstrates a viable solution for further research for complex control synthesis for FOWTs.

Table 2: Advanced control methods

Control methods	Model	Platform	Description	Economic viability	OR
MIMO-CBP [20]	FAST	Barge	CBP based Rotor thrust is used to regulate platform pitch and rotor speed.	Poor power and rotor regulation compared with baseline controller. Improved tower loading, platform motions.	3
MIMO-IBPC [20–22]	FAST	Barge, TLP, Spar-Buoy	Asymmetric rotor aerodynamic load is used to regulate the platform pitch and rotor speed.	Tower loads are decreased for the barge, however poor rotor and power regulation. TLP, compared to the Barge and spar-buoy, exhibits less platform movement when IBPC. Due to the lower natural platform frequency, IBPC on Spar-buoy is not useful regardless of the improved rotor regulation.	3
IBPC-DAC [21, 22]	FAST	Barge, TLP, Spar-Buoy	DAC is used as an extension of IBPC with an additional wind disturbance rejection.	DAC has no further improvement on the barge compared to the IBPC applied on a barge. Whereas, when it is utilized on TLP, power and speed regulation are improved with a reduction in side-to-side loads. DAC used on spar-buoy improves rotor speed but increases the blade pitch activity and loads.	3
MIMO (LQR) [23]	DTU-10MW	Spar-Buoy Triple Spar	Effects of the control inputs are analyzed based on how they affects the output for a floating wind turbine in an open loop scenario and an LQR based on observations is synthesized.	Damped various resonances, but observed not being able to suppress the wave excitations entirely.	3
GS-Output feedback H∞ [18]	FAST	Barge	Generator speed is regulated at the rated value using a gain scheduled controller to keep drive train and tower oscillations low.	Improvements in platform stability and reduced fatigue loads, LPV based GS controller is suggested for further improvements.	3
LPV and LQR based GS [19]	FAST	Barge	GS-LPV and GS-LQR based on output feedback and state feedback are employed.	Improved power regulation and platform pitch minimization is achieved.	3

SMC and IOFL [24]	FAST	Barge	Methods based on LPV control are implemented; to regulate generator speed, and to analyze the effects of incident disturbance on platform motions.	SMC is found to have achieved generator speed regulation better than IOFL for simplified wind turbine models and performance degraded when complex wind turbine models are utilized.	3
NMPC (CBP) [25]	Sandner Model	Spar-buoy	NMPC based on CBP mechanism and generator torque is employed.	Enhanced performance in terms of rotor regulation, platform motion minimization and improved loads. However, the computational cost is significantly higher.	3
N-MPC (IBP) [26]	Sandner Model	Spar-buoy	IBP mechanism is extended based on the collective blade pitch approach.	Lowered pitch and yaw motion, improved speed regulation and reduction of the loads on blades.	3
Linear - MPC (CBP) [27]	Sandner Model	Modified Spar	Linear-MPC based MIMO system is deigned using CBC approach.	Speed and generated power regulation. Improved negative platform pitch motions.	2,3
LIDAR (FF-CBPC) [28]	FAST	TLP	Feed-forward controller based on CBP mechanism is introduced for wind speed regulation.	Improved speed regulation and minimized the loads.	3
LIDAR (FF-CBPC) [29]	FAST	Spar-buoy	CBP FF controller is formulated based on ideal wind speed estimation.	Improved rotor speed and power regulation, along with blades, rotor, and tower load reductions.	3

The complex nature of incoming wind and wave limits the control design for FOWTs. Instantaneous changes in these disturbances, such as wind and wave gusts, may affect the control systems' design for FOWTs. Moreover, if not considered, these flows' stochastic nature may also degrade the structural life and performance of wind turbines. Incoming disturbances may be modeled to circumvent these issues. However, it is challenging to design perfect mathematical models of incident wind and wave due to the inherent complicated properties and high dimensions. Data-driven machine learning plays a promising role in solving complex real-life problems. Dynamic Mode Decomposition (DMD) [113], Sparse Identification of Non-linear Dynamics (SINDy) [114], and Koopman Operator Theory [115] are some of the data-driven methods that may be used to understand complex turbulent flows and interpret the underlying behaviors. Simplified models of the incident disturbance - wind and wave - may improve the incoming disturbance prediction and estimation process based on these techniques. The LCOE of large FOWT can be reduced by better understanding the effect of incident disturbances on FOWT and subsequent efficient control design.

In this review paper, we have reviewed a range of control mechanisms listed in the literature to deal with the shortcomings of FOWT associated with floating platform. SISO and MIMO controllers are discussed based on their improvements in the control objectives of FOWT. structural controllers are analyzed for their unique way of dealing with FOWT loadings. The possibility of utilizing forecasting techniques and model-free control is drawn as well.

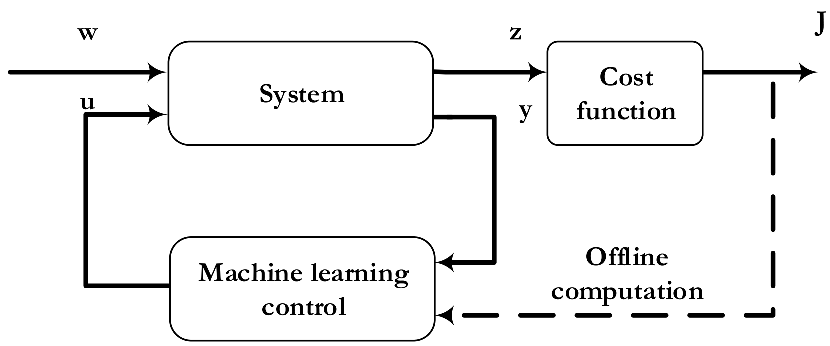

Figure 9: Machine learning control

Table 3: Structural control methods

Control methods	Model	Platform	Description	Economic viability	OR
Active and passive TMD [30]	FAST-SC	Barge/ Fixed bottom monopole	TMD placed in the nacelle, H∞ based loop shaping controllers.	Reduced tower loading, Increased complexity and power consumption due to active-TMDs.	2,3
Improved Active and passive TMD [31]	FAST-SC	Barge	Nacelle based redesigned TMDs taking actuator model into consideration.	Fore-aft loads reduction and tower base bending minimization.	2,3
Optimal Passive TMD [32]	FAST-SC	Mono-pile, barge , Hywind spar-buoy and TLP	Optimal passive TMD is developed based on available platforms using genetic algorithm.	Fatigue loads are found reduced for barge and mono-pile better than the TLP and Spar buoy.	2,3
Semi active TMD [33]	FAST-Orcaflex	Mono-pile and TLP (Pelastar)	Nacelle based semi-active TMD.	Minimized side-to-side tower loading of mono-pile and slackline incidents of TLP.	2,3
Active TMD [76]	FAST-SC	Barge	Platform-based TMD, A static output-feedback mechanism is proposed using a generalized H∞ control	Fatigue load and generator power error is reduced while reliability and robustness issues of controller designed are found.	2,3
TLD [77]	Numerical methods	Spar-buoy	Nacelle based single and multilayer TLDs are examined and validated.	Enhanced platform pitching motion based on Multilayer TLD than single layer TLD.	-
Passive TMD [78]	FAST-SC	Barge	TMD placed in nacelle, Inerter based damping mechanism.	Effectively reduced wind and wave induced loads in comparison with similar traditional TMD control.	2
Active Mooring line control based on STAM [79]	FAST	TLP	STAM-integrated mooring lines.	Platform motions (pitch and roll) and tower bending moment, are minimized.	2,3

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The different aspects of FOWTs reviewed for controller design lay a foundation for future work with the following recommendations:

- Most of the research on the control design concerns the wind disturbance and neglects the wave disturbance. It may be advantageous to include the wave information in the control design and the wind disturbance to improve performance further.

- Structural controllers may be further investigated as a viable solution for pitching phenomena and wind turbine loading. Its ability to minimize the platform pitching phenomena without using blade pitch can give designers more freedom to design controllers. However, a cost-effective approach and subsequent validation studies are needed.

Table 4: Performance comparison of MIMO control schemes compared to baseline controller

		Tower Loads	Power regulation	Platform motions	Cost
Barge	IBPC	3	1	3	2
	IBPC- DAC	3	1	3	2
TLP	IBPC	2	3	3	3
	IBPC- DAC	2	4	4	5
Spar-buoy	IBPC	2	3	3	3
	IBPC- DAC	2	4	2	3
	FF-CB	2	5	2	4
	NMPC-CBP	2	5	3	5
	NMPC-IBPC	2	5	3	5

5= Massive improvement

4= Major improvement

3= Minor improvement

2= Slight improvement

1= Decrease in performance

- The effectiveness of the LIDAR for FOWTs needs to be experimentally validated. Moreover, a device capable of sensing waves similar to LIDAR may help designers include wave preview information alongside wind preview in advanced control mechanisms like MPC.

- Further development is suggested in the use of prediction algorithms together with advanced controllers. Developing models based on machine learning tools would be of significant advantage, especially in understanding the underlying behaviors and designing optimal control laws.

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Appendix A. Simulation codes and models for FOWTs

The existing system models designed for the fixed-bottom WTs may not be able to reflect the performance of FOWTs. It is mainly due to the moving base of FOWTs and associated motions. Therefore, a system model is required to analyze the FOWTs that incorporates all the significant DOFs, including the floating base. A brief description of some of the major simulation codes used is given below.

Fatigue, Aerodynamics, Structures, and Turbulence (FAST)

The National Renewable Energy Lab (NREL) has designed a modular computer-aided engineering (CAE) open-source software testFatigue, Aerodynamics, Structures, and Turbulence (FAST) to simulate WTs at the desired operating conditions [116]. The FAST code may be used to model WTs by inflow wind, structural dynamics, aerodynamics, and for the case of offshore scenario, mooring line dynamics, hydrodynamics, etc.[117]. FAST uses a Multi-body/modal system (MB/Mod) representation. The aerodynamics module is based on the Blade element momentum (BEM) theory (quasi-static). At the same time, the hydrodyn modules offer modeling based on Potential flow (PF) and Morison's equation (ME). Furthermore, models based on FAST can generate linearized models useful for the linear control design.

A standard multi-megawatt fictitious model of a FOWT is designed based on FAST to assist the development of FOWTs, named NREL 5MW baseline WT [56]. This utility-scale WT is developed based on the publicly available data of existing WTs and simulation models such as WindPACT [118], RECOFF [119], and DOWEC [120].

Horizontal Axis Wind Turbine Code-Second generation (HAWC2)

Horizontal Axis Wind Turbine Code-Second generation (HAWC2) is a time-domain commercially available code that is mainly used to study the dynamics of fixed bottom WTs operating under externals loads [121]. The structural dynamics is based on MBS, whereas the aerodynamic module relies on BEM theory. The WT with a floating base is simulated using the SIMO/RIFLEX code coupled with HAWC2 [55], where SIMO/RIFLEX is used to model the floating foundation and mooring lines, whereas the rotor, blades, and nacelle are designed in HAWC2.

A next-generation 10 MW reference WT based on HAWC2 [122] similar to 5 MW baseline WT [56] is also available for the research and development. It was originally designed for the project INNWIND.EU [123].

Bladed

Bladed is a commercial software to simulate WTs for both onshore and offshore sites [124]. The FOWTs may be modeled using Bladed by considering the dynamics and the complexity of the system parameters. Bladed code also considers incident wave and wind loads, structural dynamics, aerodynamics, and suitable controller response.

The structural dynamics of the Bladed code are based on the multi-body modal (ModMB) system representation. The aerodynamic module uses both the momentum and blade element model. Simultaneously, an extended version of this model is used to consider models such as Prandtl's tip and root losses, dynamic wake models, and Glauert skew wake model. The hydrodynamic module utilizes the penal method and Morison equation. With a built-in Light detection and ranging (LIDAR) module, Bladed code may be used to develop advanced control designs based on the LIDAR preview information. The Bladed code can generate the linearized model and state-space matrices, an essential part of linear control theory.

As a part of LEANWIND project [125] an 8 MW reference WT [126] is designed based on data available online of WTs and validated using Bladed.

SIMPACK

SIMPACK code is designed to simulate a range of industrial applications such as robotics, automotive aerospace, and railway [127].It a general-purpose software based on MBS and is applicable for the WTs as well. An extension to the existing code is used for FOWT, connecting HydroDyn and SIMPACK with the help of SIMHydroDyn [128] . These additional modules are to deal with the hydrodynamics and the mooring lines of FOWTs.

A comparison of the parameters and properties of the 5 MW, 8 MW and 10 MW reference wind turbines is given in Table Appendix A1.

Table Appendix A1: Summary of 5, 8 and 10 MW reference wind turbines

Turbine Name	NREL (5MW)	LEANWIND (8MW)	DTU (10MW)
Number of blades and rotor orientation	3 blades, Upwind	3 blades, Upwind	3 blades, Upwind
Rotor Diameter (meters)	126	164	178.3
Tower and Hub height (meters)	90, 87.6	110, 106.3	119, 115.6
Cut in, cut out and rated wind speed (m/s)	3, 25, 11.4	4, 25, 12.5	4, 25, 11.4
Rotor speed range (rpm)	6.9, 12.1	6.3, 10.5	6, 9.6
Hub Nacelle and blade mass (tons)	56.8, 240, 17.7	90, 285, 35	105.5, 446, 41.7

Simplified models

To minimize external disturbances, achieve platform stability, and improved power quality, complex simulation codes like FAST are considered an appropriate choice. However, the complex nature of these models may cause problems in the control design process. To circumvent shortcomings associated with the complex models, a simple yet accurate model can be developed to model the essential dynamics and behavior of a FOWT with high accuracy. The effectiveness of simplified models for FOWTs in designing useful controllers has been proven [129]. To facilitate the simple control design process, researchers have produced simplified FOWT models. Below are a few noticeable models available in the literature.

Betti model

To address the complexity of the existing simulation models for the FOWTs, a simplistic control-oriented 2-D rigid model is proposed by Betti et al. [130]. Betti model is designed with 7 states, whereas incident wind and wave disturbances are considered acting in 2-D plane. The schematic of this model is given in Figure Appendix A1. This model may also generate linearized models at various locations within the operating range. Unlike FAST, this model may also be used to calculate the wave disturbance matrix, which provides the incident wave information into the advanced control design process. The Betti model is used for the controller synthesis on a TLP based 5 MW FOWT considering 2-D incident disturbances. However, it was found that the model had a small effect on the platform motions and generated power despite the accurate 2-D motion representation [129, 130].

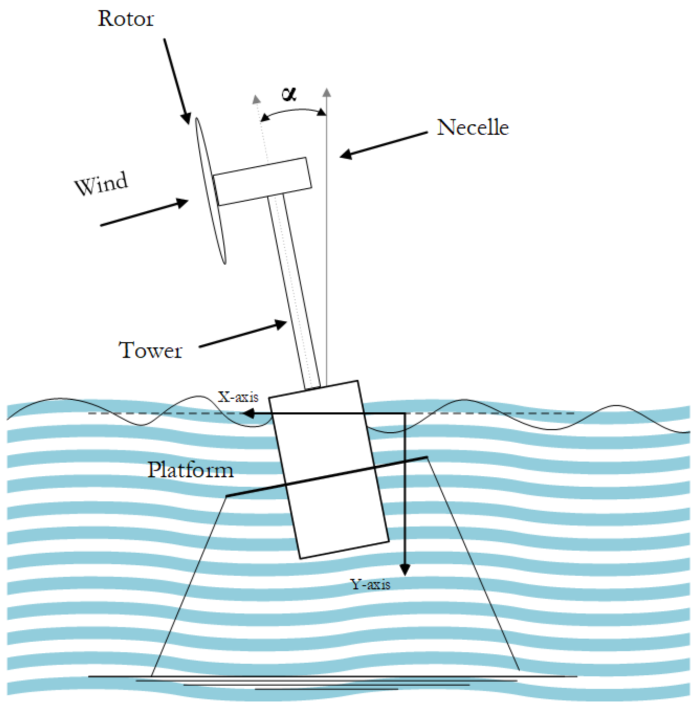

Figure Appendix A1: Adapted layout of Betti model [129]

Sander Model

Sandner et al. [65] designed a less-complex FOWT model for a spar buoy platform as shown in Figure Appendix A2. The DOFs of this model includes platform motion, rotor speed, nacelle movement, and pitching angle of the blades. The Sander model has a 2-D structure similar to Betti model [130] and it's performance is found accurate when compared with the complex FAST model. However, Sander model may not be used to study FOWT based on other platforms because it is designed for a spar boy platform, where there is less hydrodynamics involved due to its unique geometry. Moreover, Sandner model is only used for the 2-D disturbances, and its effectiveness in a 3-D scenario is yet to be assessed.

Homer model

Homer et al. [131] proposed a simplified and effective control-oriented 3-D design for advanced control synthesis of a FOWT, as shown in Figure Appendix A3. Like other similar models, the Homer model also has fewer DOFs (15/16), and it may also be used to generate linearized models

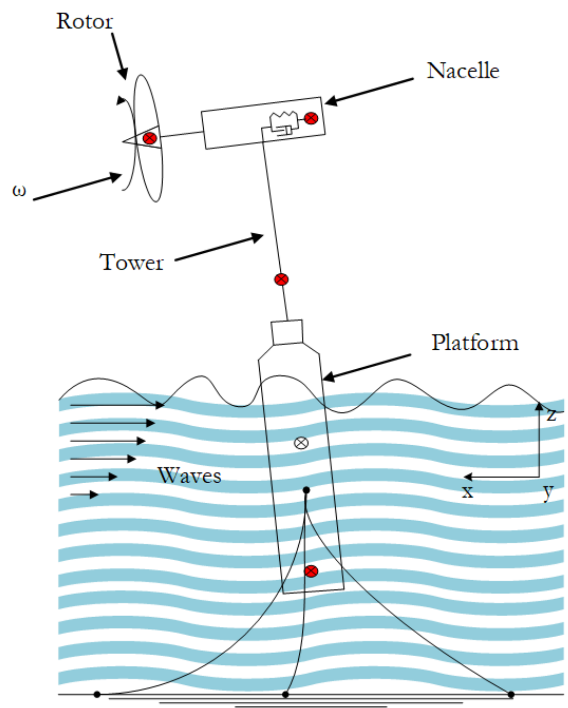

Figure Appendix A2: Adapted layout of Sander model [65]

at a given operating point. The model is capable of reflecting 3-D motion, and assist controller synthesis to eliminate or reduce the effect of wind and wave disturbances. Furthermore, the Homer model also comes with an ability to generate wave disturbance matrix. The simplified models are compared with complex model FAST in terms of their particular characteristics in Table Appendix A2.

Table Appendix A2: Model comparison of existing FOWTs controllers

Model	Nature	DOFs	Incorporates incident wind/wave in controller synthesis
Jonkman [116]	Flexible 3-D	22/24	Wind only
Betti [130]	Rigid 2-D	7	Wind and Wave
Sandner [65]	Flexible 3-D	18	Wind and Wave
Homer [131]	Rigid 3-D	15/16	Wind and Wave

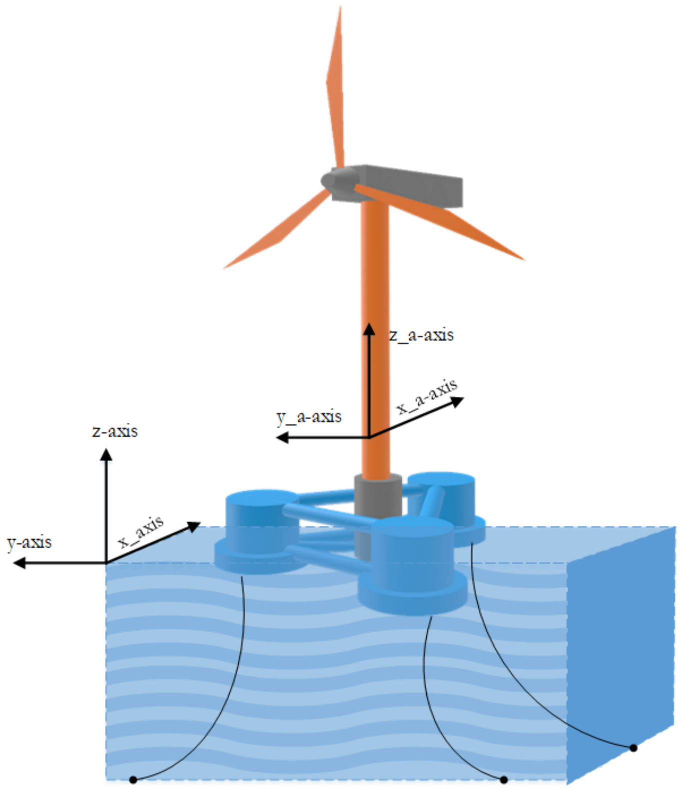

Figure Appendix A3: Adapted layout of Hommer model

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