

Data-Based ISMC of FOWTs with Unknown Dynamics

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Outline

1 Introduction

- About Me
- Motivation

2 Background

- ISMC basics
- Neural Approximators

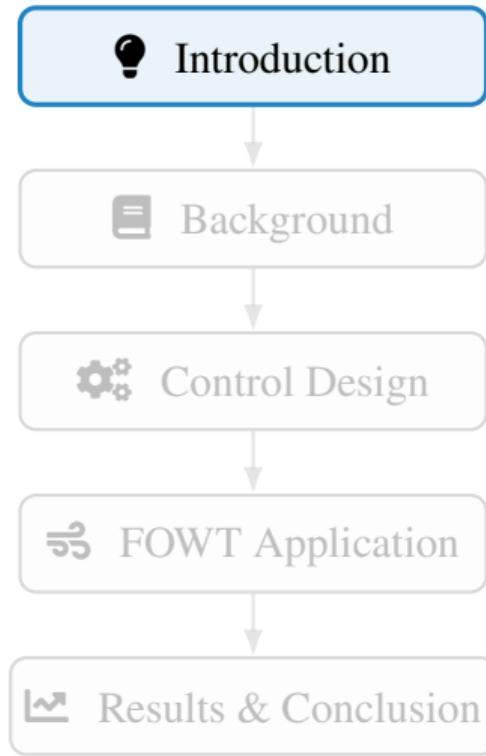
3 Control Design

- Problem Formulation
- Proposed Controller
- Sketch of Proof

4 Application: Floating Wind Turbines

- Control Objectives in FOWTs
- simulation software and conditions

5 Results & Conclusion



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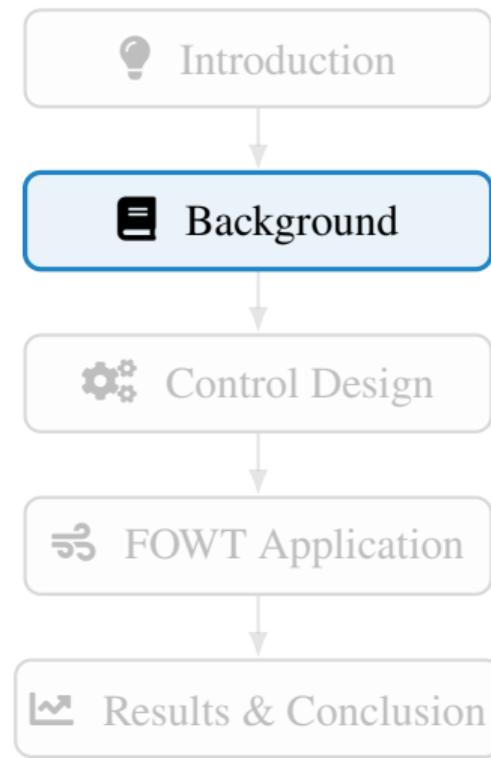
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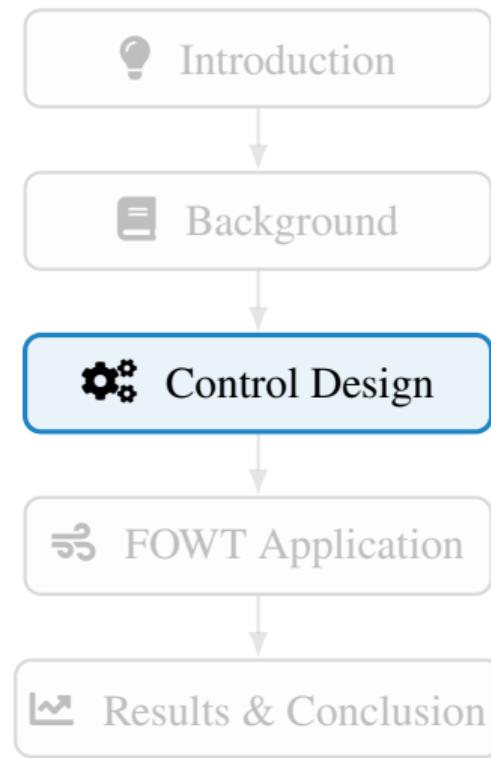
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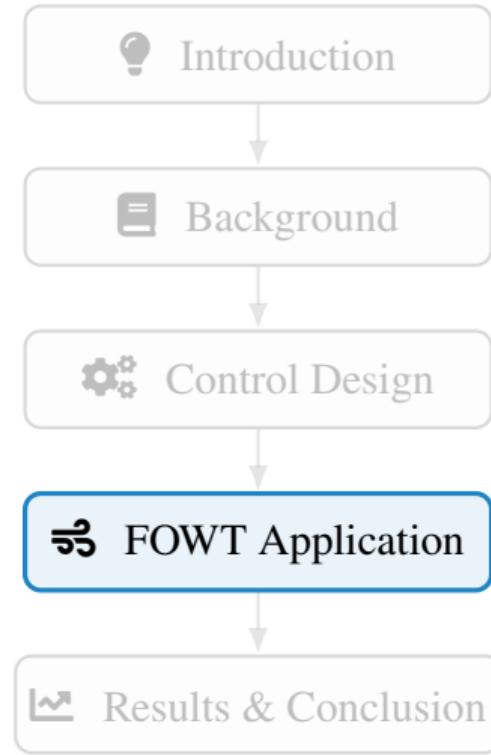
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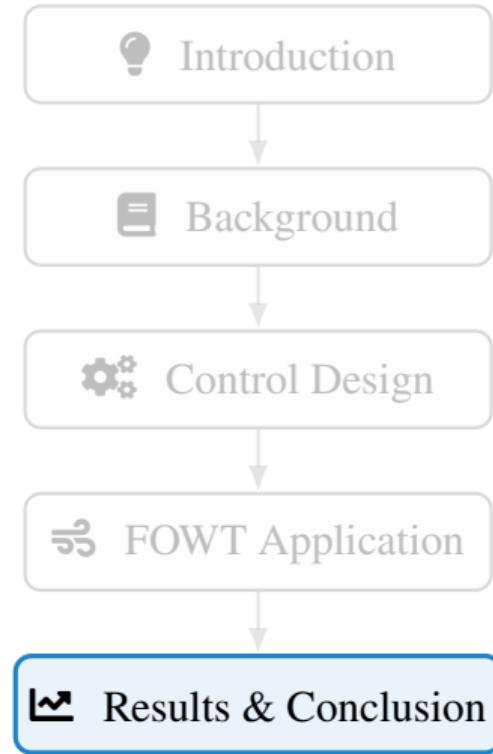
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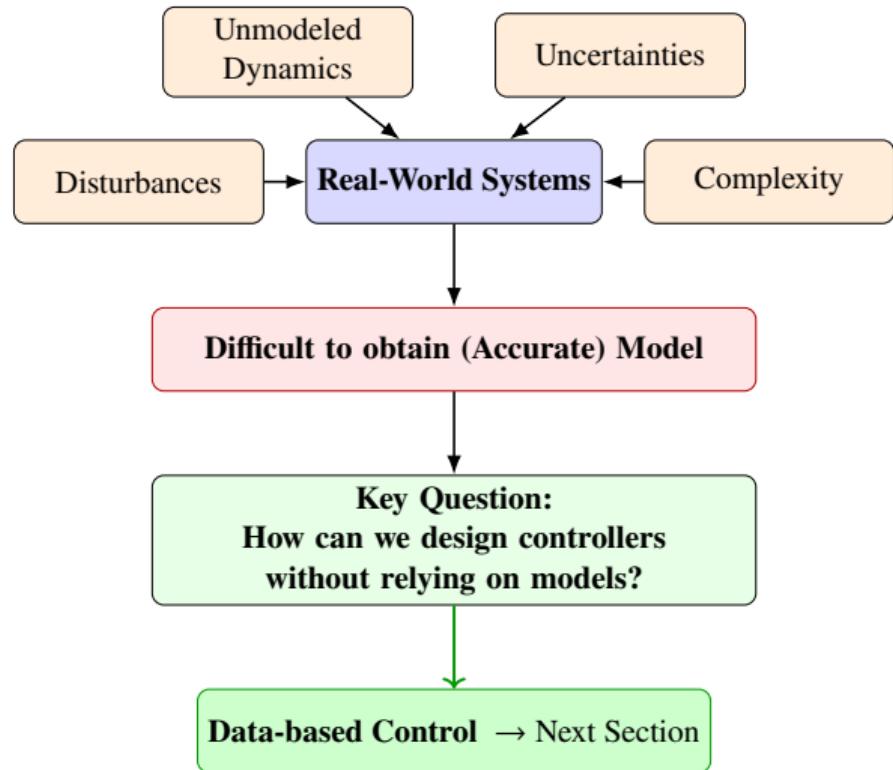
About Me

- **Affiliation:** LS2N, École Centrale Nantes
- **Position:** Ph.D. Candidate in Control Theory
- **Project:** Marie Curie DENSE Network
- **Research:**
 - Nonlinear adaptive and robust control
 - Data-based methods
 - Applications to FOWTs



Motivation – Why this project is important

- Many real systems are **nonlinear**, with **unknown/uncertain** dynamics and **disturbances**.
- Robust control exists (H_∞ , robust MPC, sliding mode control, etc.), but they require a model.

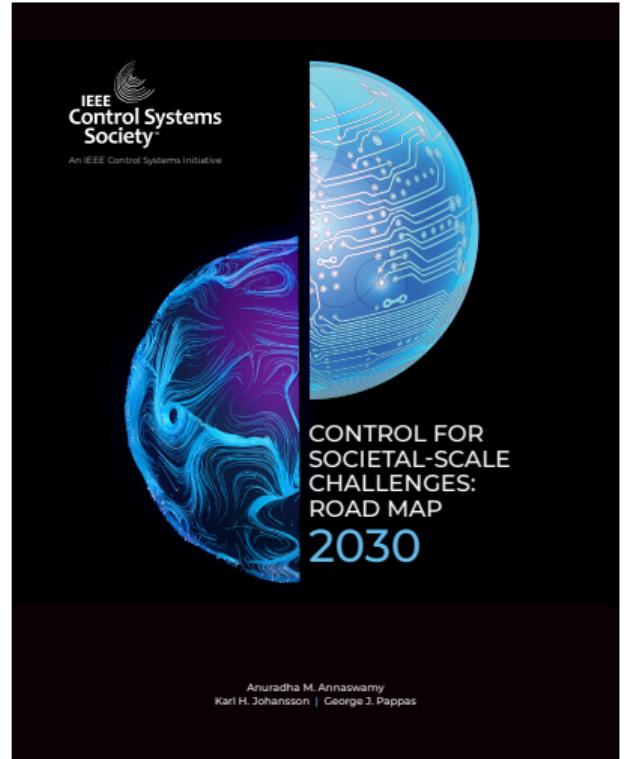


Motivation - IEEE Roadmap

- This aligns with the **IEEE Control Systems Roadmap**.
- Emphasizes the importance of **data-driven control strategies** for complex, uncertain, and large-scale systems.
- Highlights the **promising future** of such approaches in control applications.



digital futures



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Why ANNs in Control?

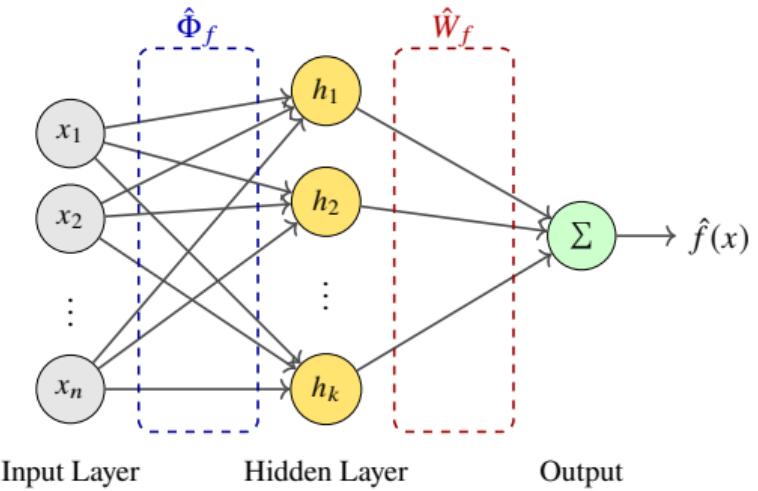
- Thanks to the *Universal Approximation Theorem*¹, the use of **Artificial Neural Networks (ANNs)** has grown across scientific fields, and control theory is no exception.
- System identification²
- State estimation and observers³
- Inverse dynamics / feedforward control³
- Learning optimal control laws⁴
- Model predictive / constrained control⁵

1. Scarselli *et al.*, *Universal approximation using feed-forward neural networks: A survey of some existing methods, and some new results*, Neural Networks, 11(1), 15–37, 1998.
2. Kuschewski *et al.*, *Application of feedforward neural networks to dynamical system identification and control*, IEEE Trans. Control Systems Technology, 1(1), 37–49, 1993.
3. Hunt *et al.*, & Gawthrop, P. J., *Neural networks for control systems—a survey*, Automatica, 28(6), 1083–1112, 1992.
4. Åkesson *et al.*, *A neural network model predictive controller*, Journal of Process Control, 16(9), 937–946, 2006.
5. Chen *et al.*, *Approximating explicit model predictive control using constrained neural networks*, Proc. ACC, pp. 1520–1527, 2018.

Why ANNs in Control?

Universal Approximation Theorem

The *Universal Approximation Theorem* states that **any continuous function** can be approximated arbitrarily well by a neural network with at least **one hidden layer** with a **finite number of weights**.



Objective & Approach

Challenge: NN is not enough for control ✗

- NNs approximate with *nonzero* error.
- Approximation quality changes based on the input and tuning.
- Difficult to guarantee stability.

Solution: Data-based ISMC ✓

- Use NNs to learn functions *online*.
- Adapt all NN weights with Lyapunov-based laws.

Key idea: NNs for modeling + ISMC for robustness

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Objective & Approach

✓ Summary of objective and contributions

- 1 A **robust data-based** ISMC approach is developed for nonlinear systems with unknown dynamics. This method employs online NN approximations for both the drift and input functions.
- 2 A **Lyapunov-based adaptation law** is proposed for updating all NN weights, including input-to-hidden and hidden-to-output connections.
- 3 **Closed-loop stability** formally established.
- 4 **Application to FOWT collective blade pitch.**

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Problem Formulation

Nonlinear System

$$\begin{aligned}\dot{x} &= \mathcal{F}(x, t) + \mathcal{G}(x, t)u, \\ y &= s(x, t),\end{aligned}$$

where $x \in \mathcal{X} \subset \mathbb{R}^n$ is the **state vector**, $u \in \mathbb{R}$ is the **control input**, $y \in \mathbb{R}$ is the **output**. The functions $\mathcal{F}(x, t)$ and $\mathcal{G}(x, t)$ are assumed to be: **smooth, unknown, bounded**, $\forall x \in \mathcal{X}$. A sliding mode is established when $s(x, t) = 0$ with $x \in \mathcal{X}$.

Dynamics of the Sliding Variable

$$\dot{s} = \frac{\partial s}{\partial x} \dot{x} + \frac{\partial s}{\partial t} = \underbrace{\frac{\partial s}{\partial t} + \frac{\partial s}{\partial x} \mathcal{F}(x, t)}_{f(\cdot)} + \underbrace{\frac{\partial s}{\partial x} \mathcal{G}(x, t) u}_{g(\cdot)}$$

Objective: enforce $s(x, t) = 0$ despite uncertainties.

Integral Sliding Mode Control

To achieve this objective and compensate the effect of uncertainties from $t \geq 0$, a robust controller can be designed in spite of perturbations and uncertainties. According to Utkin[†], the control law is defined as

Control Law

$$u = u_0 + u_1,$$

$$u_0 = -ks, \quad u_1 = -\rho \operatorname{sign}(\sigma)$$

- u_0 handles nominal dynamics.
- u_1 enforces robustness against disturbances.

[†] V. Utkin and J. Shi: *Integral sliding mode in systems operating under uncertainty conditions*, CDC, Kobe, Japan, 1996, pp. 4591–4596.

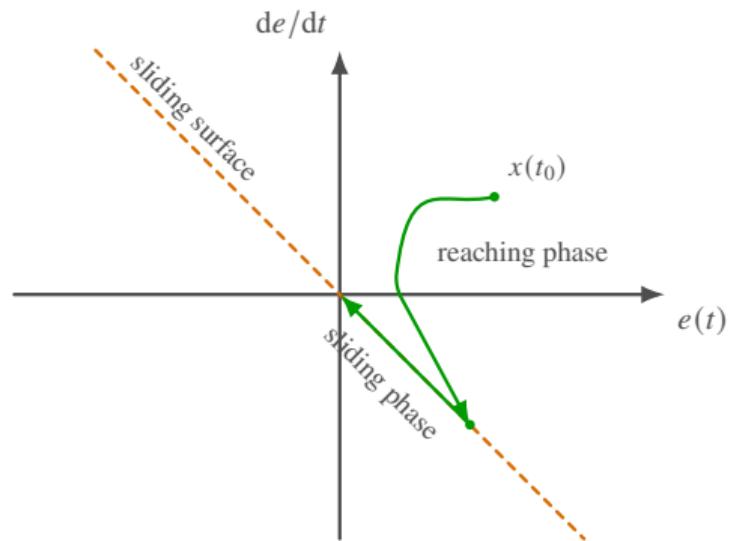
Integral Sliding Mode Control

Integral Sliding Variable

$$\sigma = s + z,$$

where $s = e$ and z is defined such that $z(0) = -s(0)$ (i.e., $\sigma(0) = 0$) and

$$\dot{z} = -[f(\cdot) + g(\cdot) u_0].$$



This formulation guarantees that the sliding motion with respect to σ starts from the *initial time*, eliminating the reaching phase typical of conventional sliding mode controllers[†].

[†] V. Utkin and J. Shi: *Integral sliding mode in systems operating under uncertainty conditions*, CDC, Kobe, Japan, 1996, pp. 4591-4596.

Data-Based Function Approximation

Designing an ISM control requires system dynamics*. However, due to their complexity and strong aerodynamic-hydrodynamic coupling, many real-world systems like FOWTs are difficult to model.

Functions Approximation

$$\begin{aligned}f(\cdot) &= W_f^\top h_f(\Phi_f^\top s) + \varepsilon_f, \\g(\cdot) &= W_g^\top h_g(\Phi_g^\top s) + \varepsilon_g,\end{aligned}$$

W_f, W_g, Φ_f, Φ_g : the ideal NN weights. $\varepsilon_f(x), \varepsilon_g(x)$: the approximation errors.

* Pan, C. Yang, L. Pan, and H. Yu: *Integral sliding mode control: Performance, modification, and improvement*, IEEE Transactions on Industrial Informatics, vol. 14, no. 7, pp. 3087–3096, 2018.

Data-Based Function Approximation

Sigmoid Activation Function

$$h(\alpha) = \frac{1}{1 + e^{-\alpha}}$$

Chosen for smooth derivatives and fast online learning.

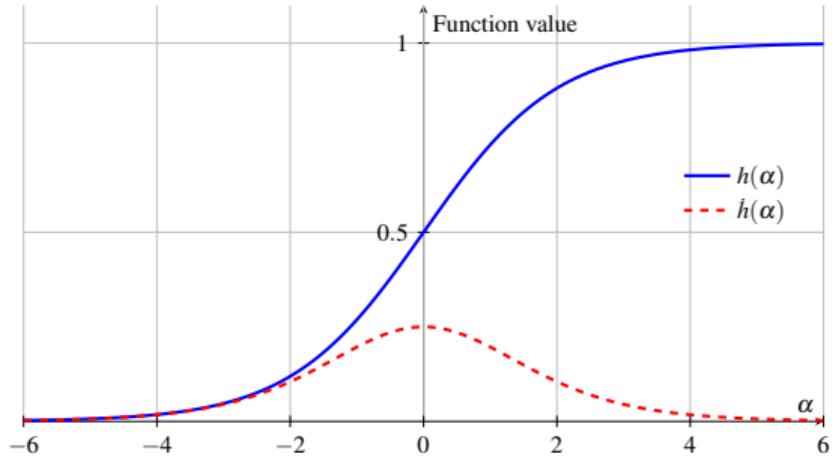


Figure: The sigmoid function $h(\cdot)$ (solid blue line) and its derivative $\dot{h}(\cdot)$ (dashed red line), illustrating smoothness and boundedness properties desirable for stability analysis in control systems.

Assumptions

Boundedness Assumption

The functions $f(\cdot)$ and $g(\cdot)$ are continuous and bounded, satisfying

$$f(\cdot) \in [-f_m, f_M], \quad g(\cdot) \in [g_m, g_M] \quad \forall x \in \mathcal{X}$$

where f_m, f_M, g_m , and g_M are positive but unknown constants.

Weights Boundedness

The NN weights W_f , W_g , Φ_f , and Φ_g , as well as the corresponding approximation errors ε_f and ε_g , are assumed to be bounded. That is, there exist positive constants \bar{W}_f , \bar{W}_g , $\bar{\Phi}_f$, $\bar{\Phi}_g$, $\bar{\varepsilon}_f$, and $\bar{\varepsilon}_g$ such that

$$\|W_f\| \leq \bar{W}_f, \quad \|\Phi_f\| \leq \bar{\Phi}_f, \quad |\varepsilon_f| \leq \bar{\varepsilon}_f,$$

$$\|W_g\| \leq \bar{W}_g, \quad \|\Phi_g\| \leq \bar{\Phi}_g, \quad |\varepsilon_g| \leq \bar{\varepsilon}_g$$

z-dynamics with NN approximators

Weight Approximation Errors

$$\tilde{W}_f = W_f - \hat{W}_f, \quad \tilde{\Phi}_f = \Phi_f - \hat{\Phi}_f,$$

$$\tilde{W}_g = W_g - \hat{W}_g, \quad \tilde{\Phi}_g = \Phi_g - \hat{\Phi}_g$$

Key Idea

Neural Network (NN) approximators are applied within the ISMC framework. Since the true functions $f(\cdot)$ and $g(\cdot)$ are **unknown**, the dynamics of the integral term z are approximate.

Approximated z-Dynamics

$$\dot{\hat{z}} = -\left(\hat{f}(\cdot) + \hat{g}(\cdot) u_0\right) \quad \text{data-based approximation}$$

$$= -\left(\hat{W}_f^\top h_f(\hat{\Phi}_f^\top s) + \hat{W}_g^\top h_g(\hat{\Phi}_g^\top s) u_0\right)$$

Theorem

Theorem

Consider the nonlinear uncertain system $\dot{s} = f + g u$, controlled by the law $u = -ks - \rho \operatorname{sign}(\sigma)$, where $\sigma = s + \hat{z}$, with $\hat{z}(0) = -s(0)$ and \hat{z} being derived from $\dot{\hat{z}} = -(\hat{f}(\cdot) + \hat{g}(\cdot)u_0)$, updated according to the adaptation protocols given in the sequel.

If the assumptions hold, and the NN estimators employ the logistic sigmoid activation function $h(\alpha) = \frac{1}{1+e^{-\alpha}}$, with derivative $\dot{h}_f = \hat{h}_f \circ (1 - \hat{h}_f)$, then the sliding variable remains at $\sigma(t) = 0$ for all $t \geq 0$.

Takeaway

In other words: the controller ensures stability of the closed-loop system, thanks to NN approximation and ISMC.

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In other words: the controller ensures **stability of the closed-loop system**, thanks to NN approximation and ISMC.

Lyapunov candidate

Considering the following **Lyapunov candidate function**

Lyapunov Function

$$\begin{aligned} V = & \frac{1}{2}\sigma^2 + \frac{1}{2}\text{tr}(\tilde{W}_f^\top \Gamma_f^{-1} \tilde{W}_f) + \frac{1}{2}\text{tr}(\tilde{W}_g^\top \Gamma_g^{-1} \tilde{W}_g) \\ & + \frac{1}{2}\text{tr}(\tilde{\Phi}_f^\top \Theta_f^{-1} \tilde{\Phi}_f) + \frac{1}{2}\text{tr}(\tilde{\Phi}_g^\top \Theta_g^{-1} \tilde{\Phi}_g) \end{aligned}$$

Then, differentiating with respect to time, and substituting the control input and . . .

Adaptation laws

The NN weights are proposed to be updated based on the adaptation laws as

Adaptation laws.

$$\begin{aligned}\dot{\hat{W}}_f &= \Gamma_f \sigma \hat{h}_f, \\ \dot{\hat{W}}_g &= -\Gamma_g \sigma k s \hat{h}_g, \\ \dot{\hat{\Phi}}_f &= \Theta_f \sigma (\hat{W}_f^\top \dot{\hat{h}}_f)^\top s, \\ \dot{\hat{\Phi}}_g &= -\Theta_g \sigma k s (\hat{W}_g^\top \dot{\hat{h}}_g)^\top s.\end{aligned}$$

Let $\Gamma_f, \Gamma_g, \Theta_f, \Theta_g \succ 0$ be constant learning-rate matrices.

These update laws ensure online adaptation of the NN parameters in response to the evolving system state.

Sketch of Proof 1/2

Sketch of Proof 1/2.

- 1 Using equations, we reach

$$\dot{\sigma} = \dot{s} + \dot{z} = (W_f^\top h_f - \hat{W}_f^\top \hat{h}_f) + ks(\hat{W}_g^\top \hat{h}_g - W_g^\top h_g) - \rho \operatorname{sign}(\sigma)(W_g^\top h_g + \varepsilon_g) + \varepsilon_f$$

- 2 Substitute the update laws; the cross-terms cancel by construction.
- 3 To guarantee the negative definiteness of \dot{V} , the gain ρ is chosen to dominate the remaining terms.



Sketch of Proof 2/2

Stability Result

Therefore, under the proposed gain design, the Lyapunov derivative satisfies

$$\dot{V} \leq -\eta|\sigma|, \quad \eta > 0.$$

Since the integral sliding variable is initialized with $\hat{z}(0) = -s(0)$, it follows that $\sigma(0) = 0$, and thus the sliding condition is enforced from the initial time instant and maintained for all $t \geq 0$.

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Why Floating Offshore Wind?

Problem

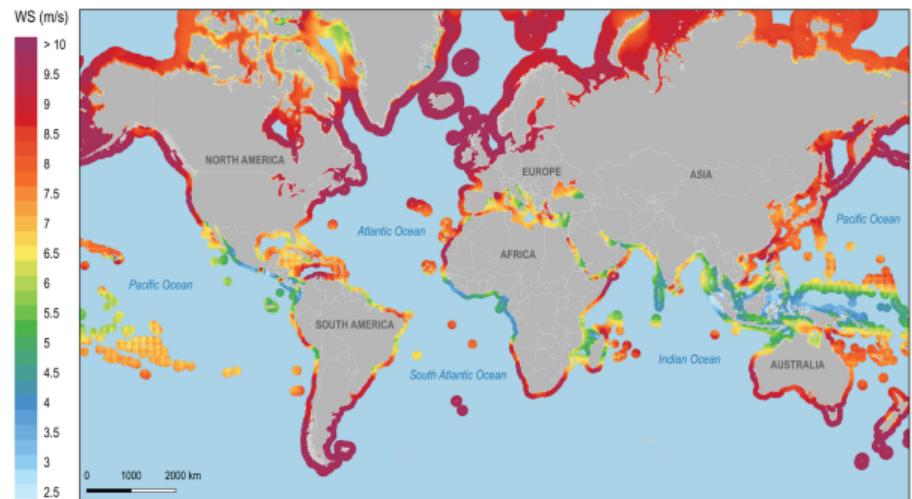
Wind resources mainly in > 60 m depth
 Fixed-bottom turbines costly & impractical

Solution

Floating platforms → access stronger offshore winds

Challenges

High DOFs → oscillations, negative damping
 Wind–wave interactions → complex control
 Standard pitch control is insufficient



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ESMAP
 Energy Sector Management Assistance Program

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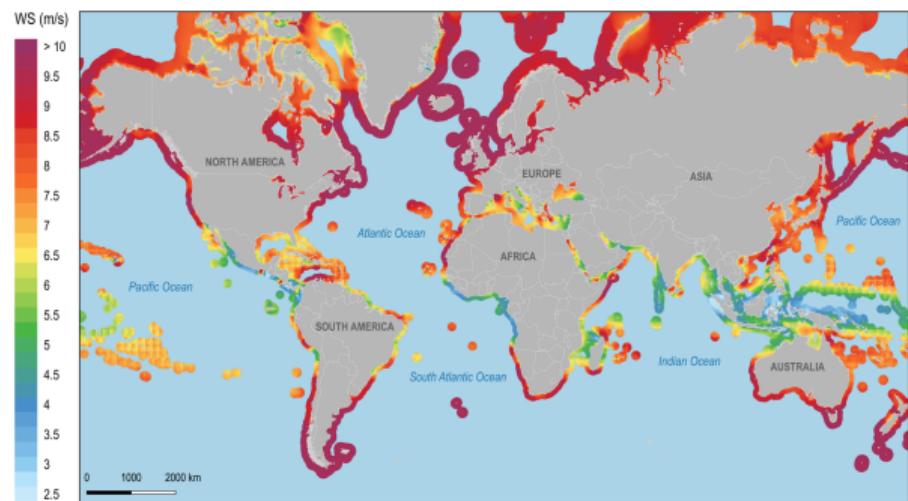
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Typical Floater and WTG 20 MW

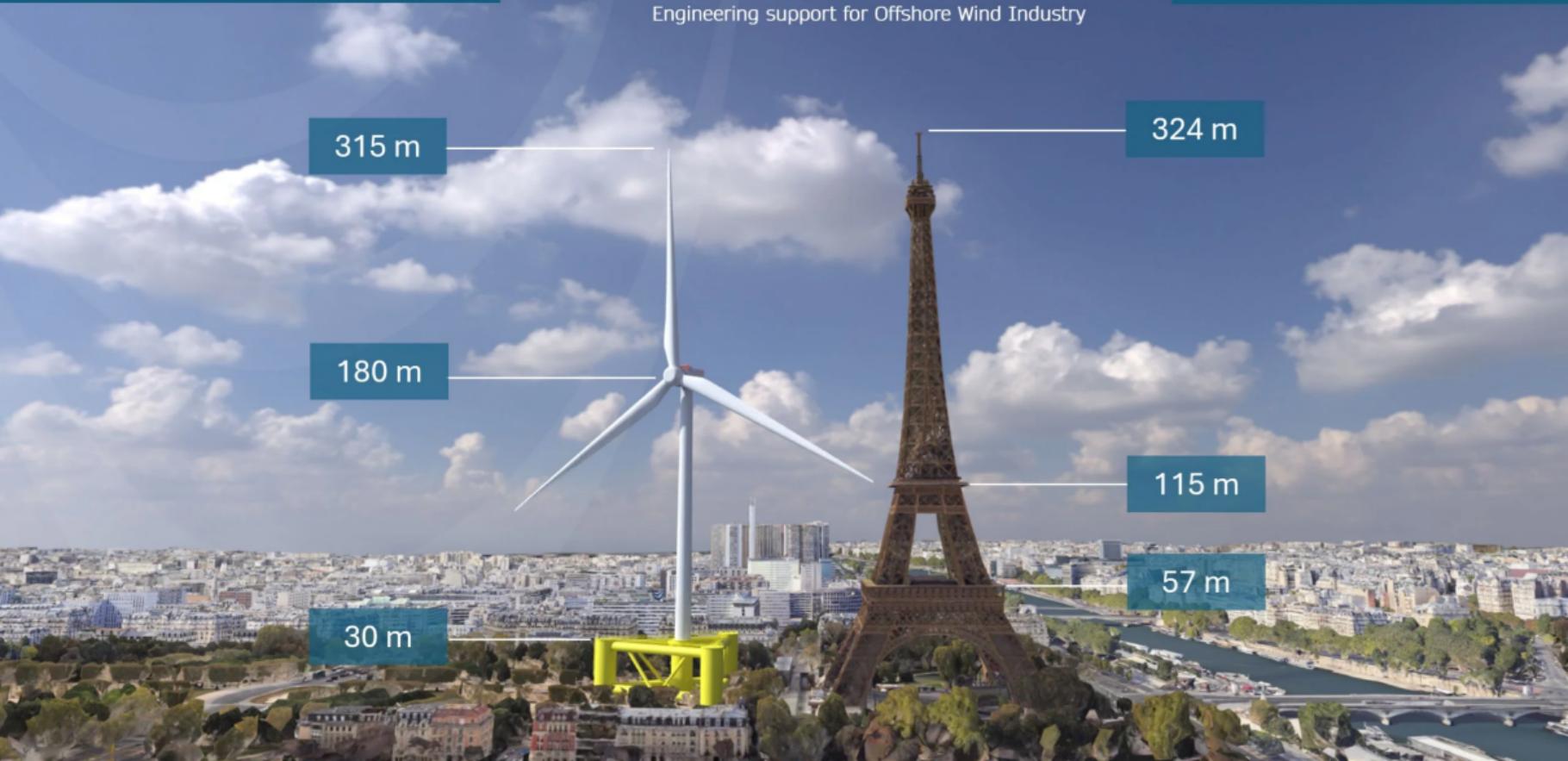


Flowindus

Engineering support for Offshore Wind Industry



Eiffel Tower,
Paris, France



Typical Floater for WTG 20 MW

Camp Nou,
Barcelona, Spain



Floater
100 x 90 m

Football Pitch
105 x 68 m



Flowindus

Engineering support for Offshore Wind Industry

The Challenge of Floating Wind Turbines

Why is Control Difficult?

- Floating platforms introduce more **degrees of freedom (DOF)**.
- Complex coupling between **wind, waves, and structure**.
- **Accurate models** are hard to obtain and maintain.

Our Objective

Design a controller that:

- Requires **no system model**
- Learns in **real time**
- Remains **robust to disturbances**

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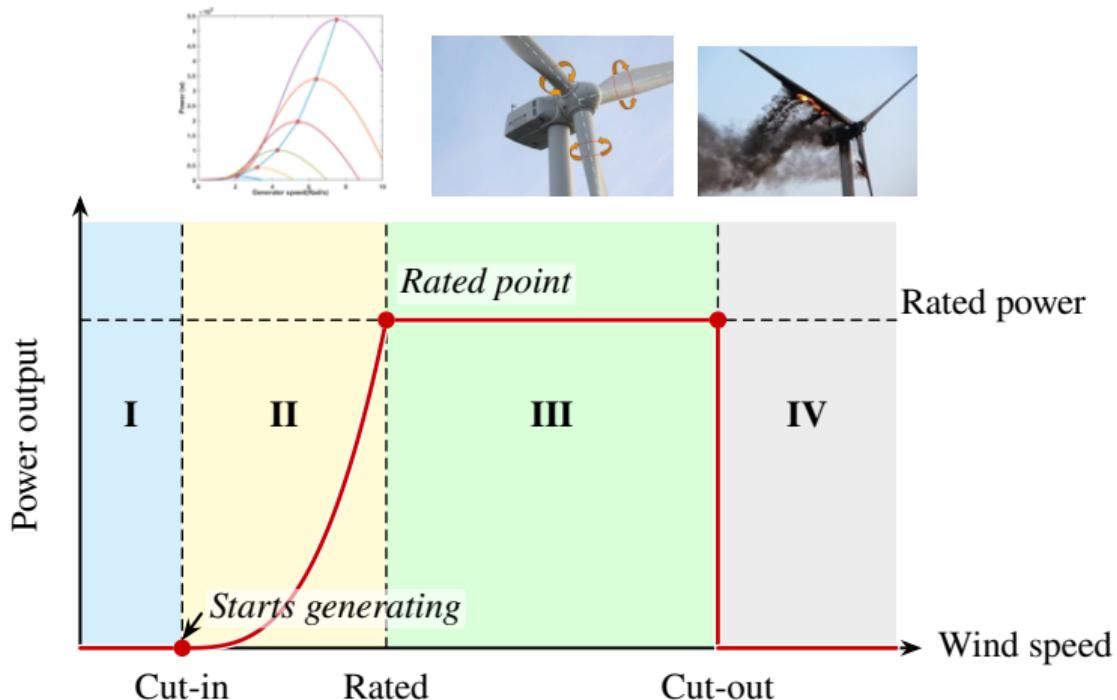
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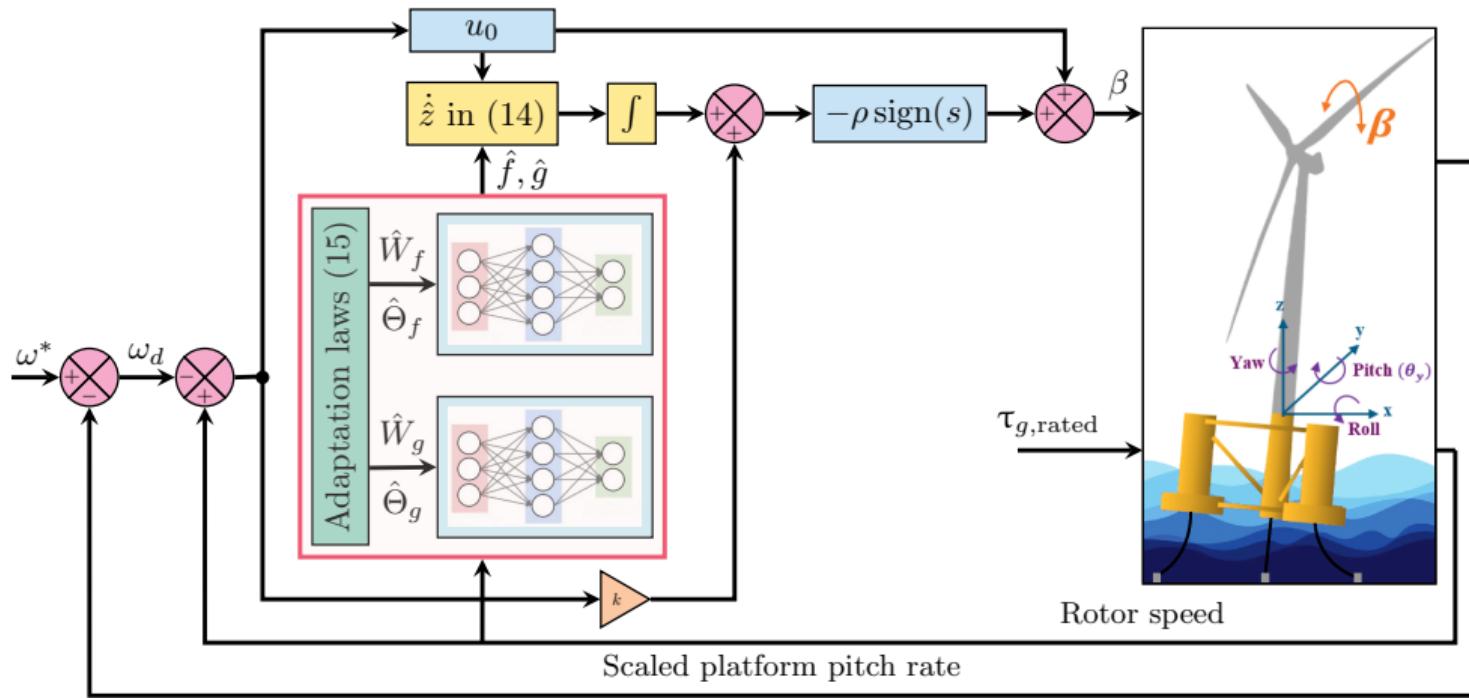
- Requires **no system model**
- Learns **in real time**
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Control Objective

- Region I: Start up
- Region II: MPPT
- **Region III: maintain rated power, reducing fatigue loads**
- Region IV: Survival mode



Conceptual Diagram: How It All Works



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Simulation Setup

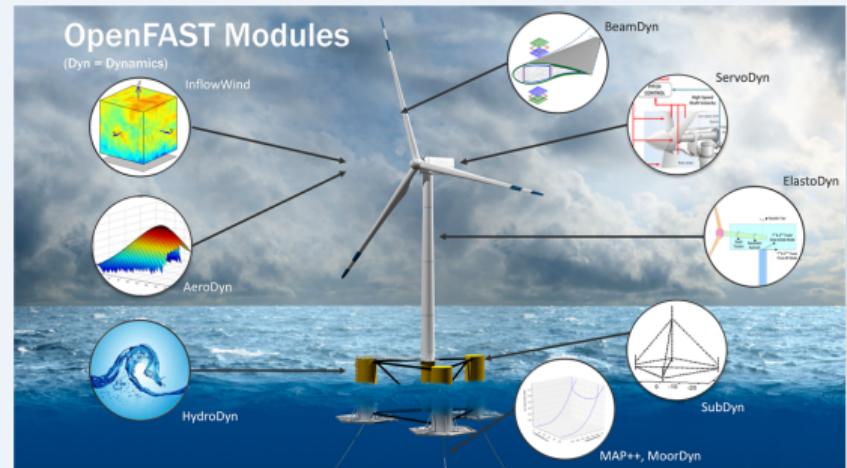
Framework

- OpenFAST + MATLAB/Simulink
- ROSCO[†], Classic ISMC, Data-based ISMC

Operating Conditions

- Wind speed:** 18 m/s (turbulent)
- Wave height:** 3.25 m (irregular)
- Simulation time:** 1000 s
- DoFs:** all 24 activated

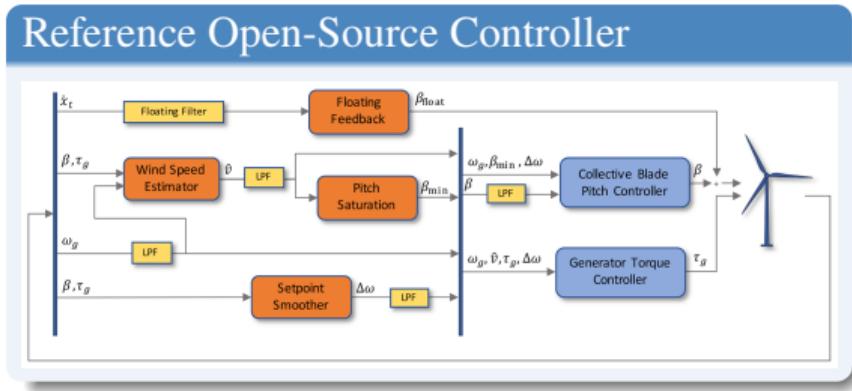
OpenFAST Simulator Overview



[†] Abbas *et al.*: A reference open-source controller for fixed and floating offshore wind turbines, Wind Energ. Sci., 7, 53–73, 2022

What is ROSCO?

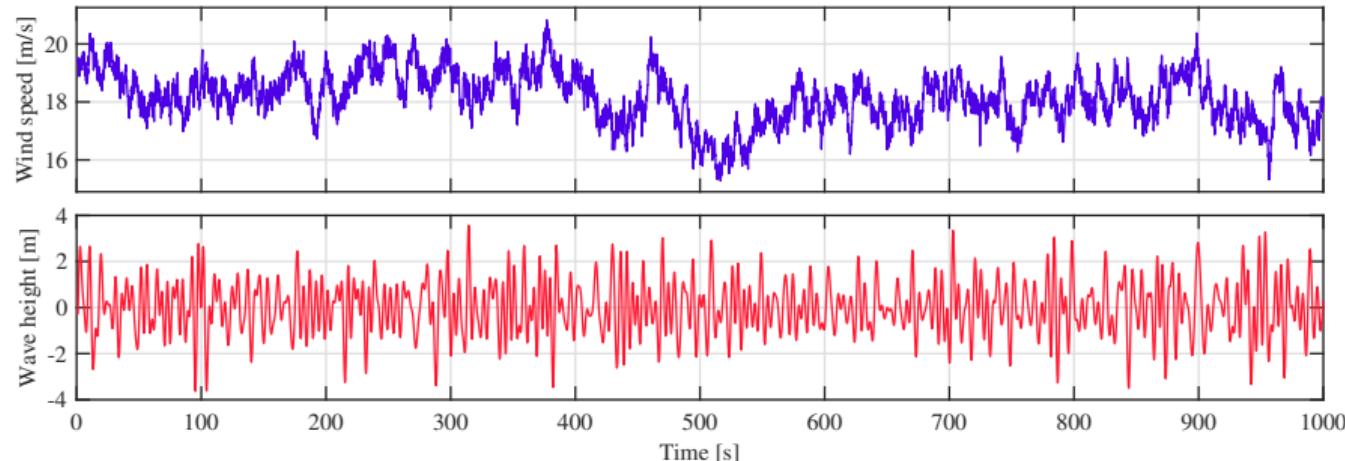
- Developed by the **National Renewable Energy Laboratory (NREL)**
- **ROSCO** (Reference Open-Source Controller) is an open-source control framework
- Demonstrated superior performance for controlling **floating offshore wind turbines** compared to other controllers



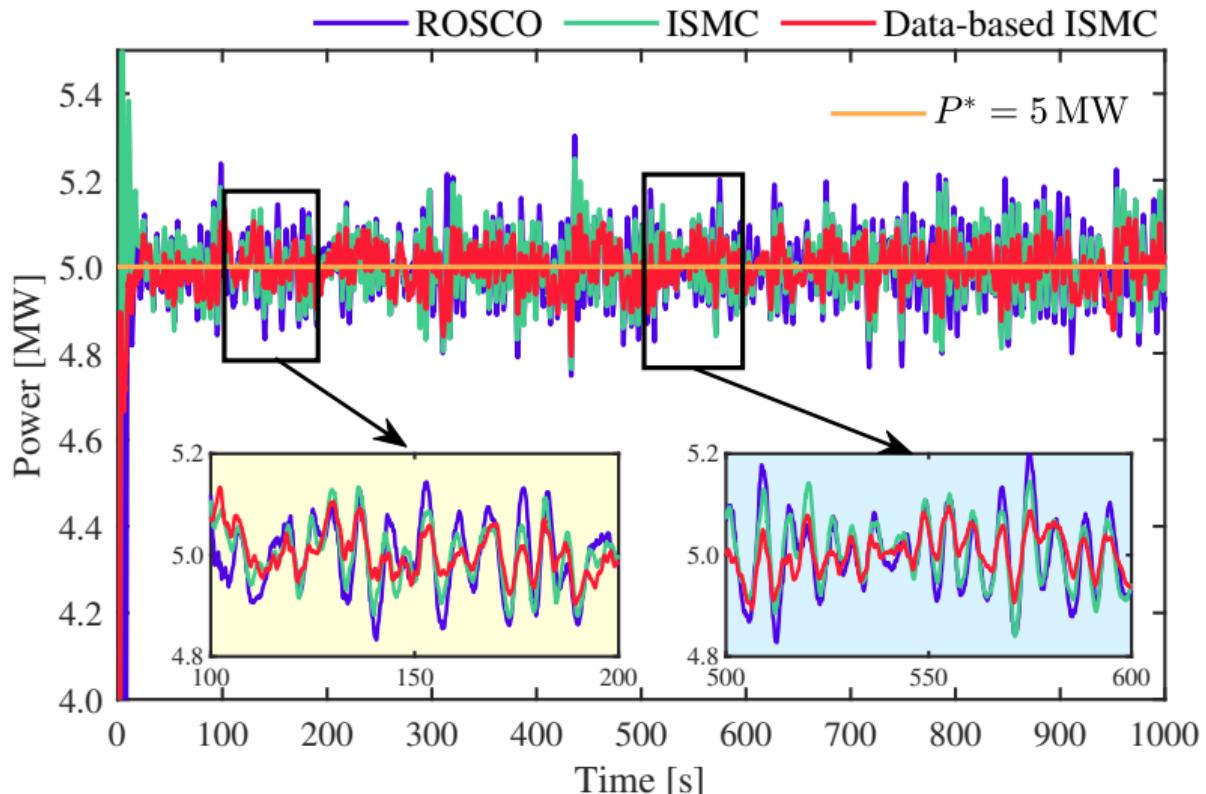
Abbas *et al.*: A reference open-source controller for fixed and floating offshore wind turbines, Wind Energ. Sci., 7, 53–73, 2022

Wind and Wave Conditions

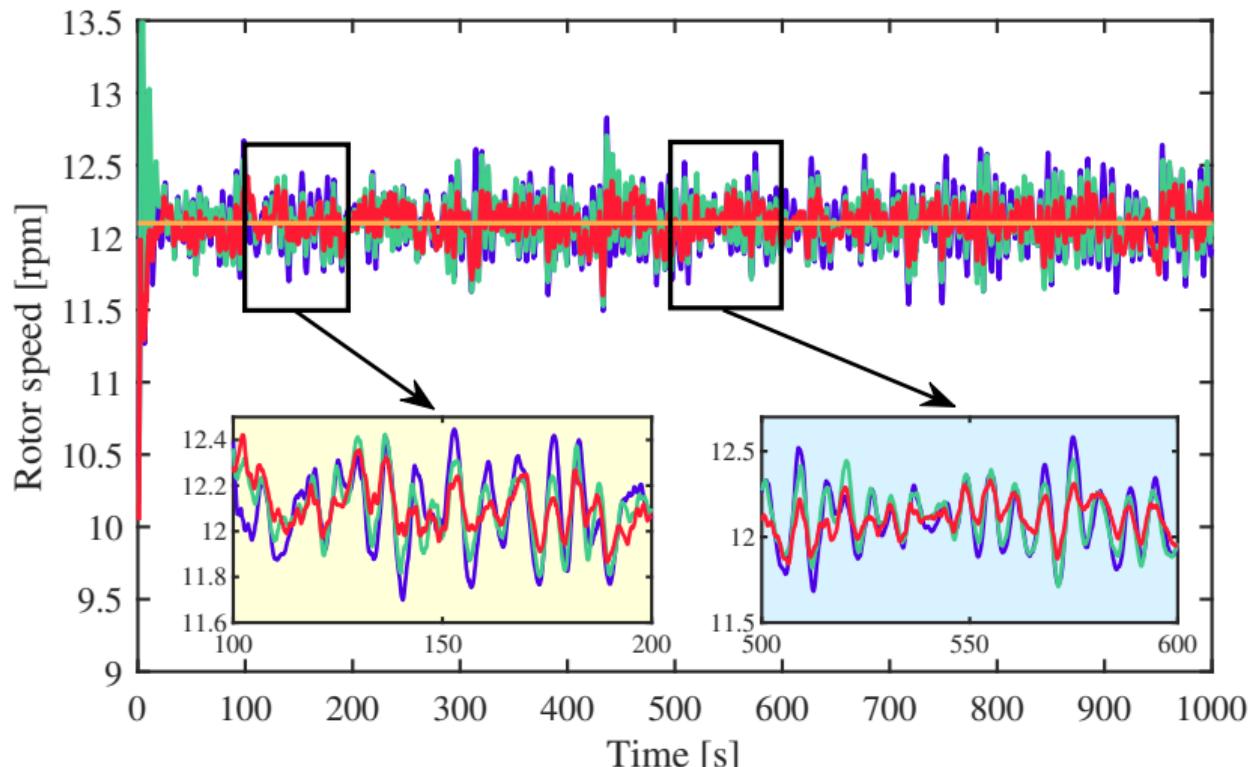
- **Wind:** Turbulent wind speed generated by **TurbSim** with a mean velocity of 18 m.s^{-1} , following the **Kaimal turbulence model**.
- **Wave:** Irregular wave conditions generated with the **HydroDyn** module in OpenFAST, based on the **Pierson–Moskowitz spectrum**, with a significant wave height of 3.25 m.



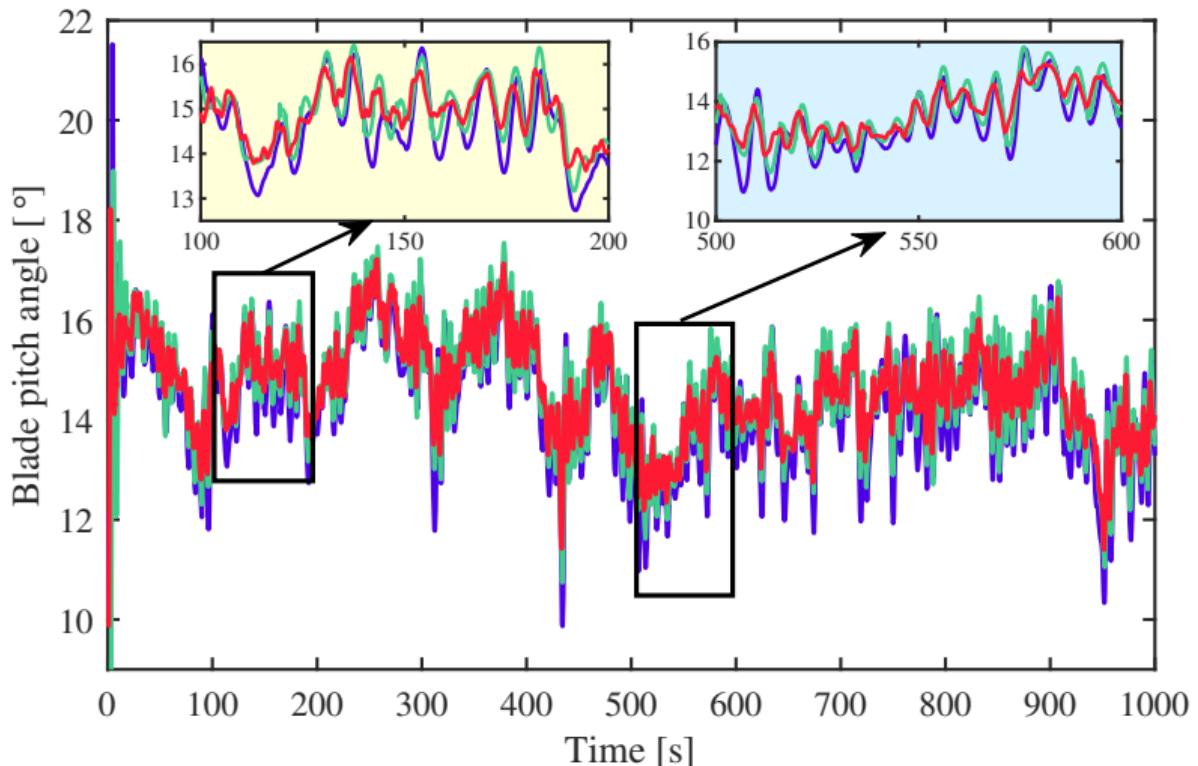
Tracking Performance – Power



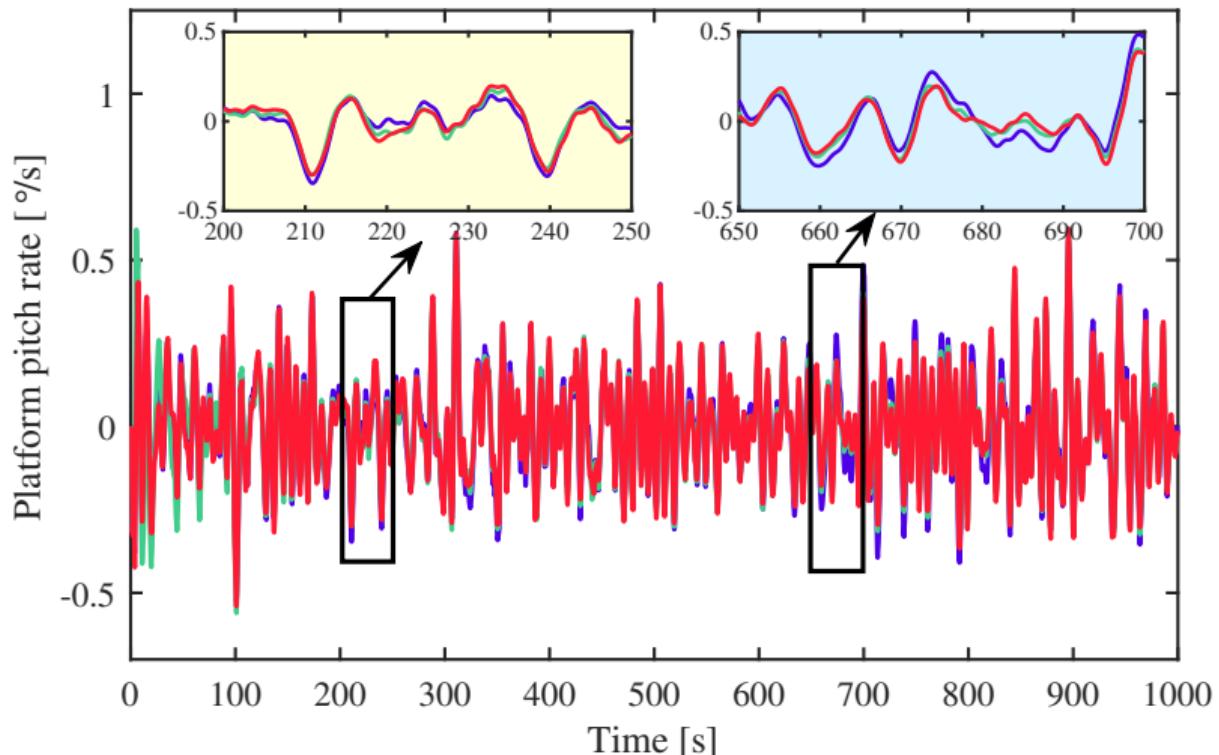
Tracking Performance – Rotor Speed



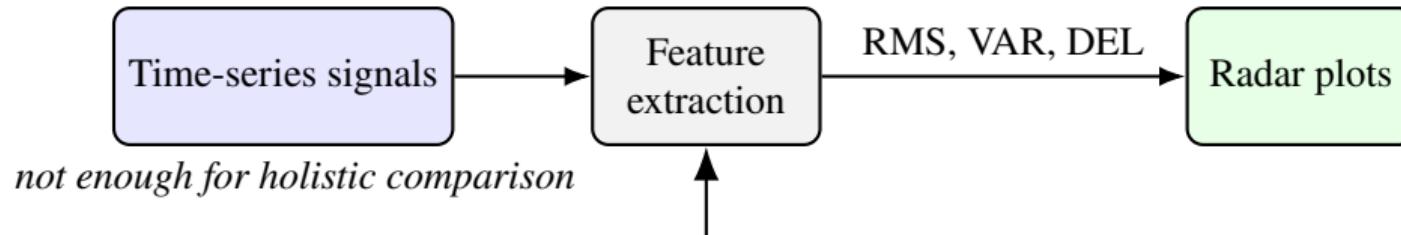
Blade Pitch Variation



Platform Pitch Rate



From Time Series to Comparable Metrics



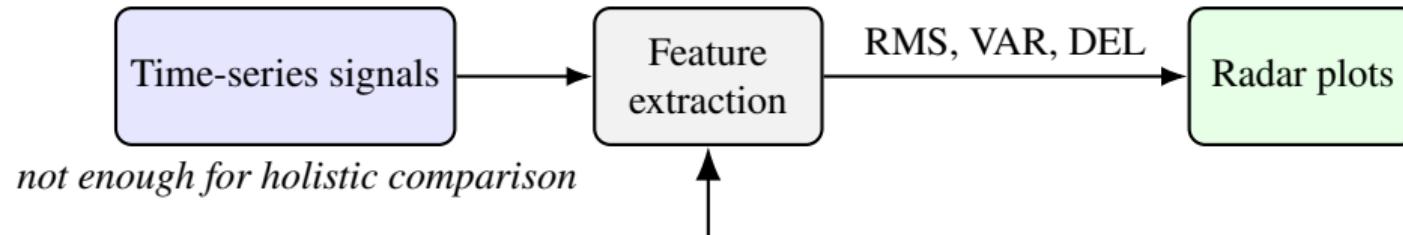
Root Mean Square (RMS) of platform roll, pitch, yaw, and pitch rate.

Variation $\sum |y_{t+1} - y_t|$ of the signal. Higher values \Rightarrow more activity (chattering).

Damage Equivalent Load (DEL) of Fatigue loads: tower bases, blade roots, fair-lead forces & anchor forces of mooring lines.

The next slides use radar plots to compare these normalized indicators across controllers.

From Time Series to Comparable Metrics



Root Mean Square (RMS) of pitch, yaw,

Variation

For these metrics, lower is better.

activity (chattering).

Equivalent (DEL) of Fatigue

loads: tower bases, blade roots, fair-lead forces & anchor forces of mooring lines.

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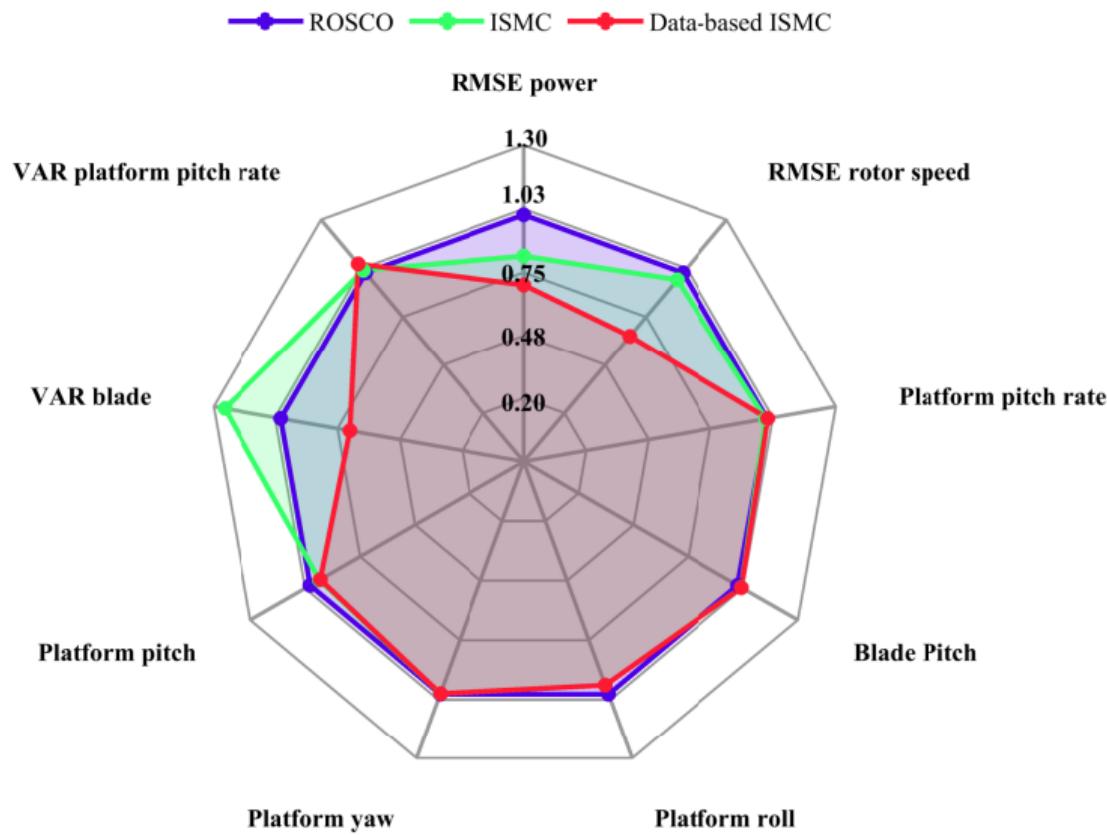


Figure: Comparing the performance metrics.

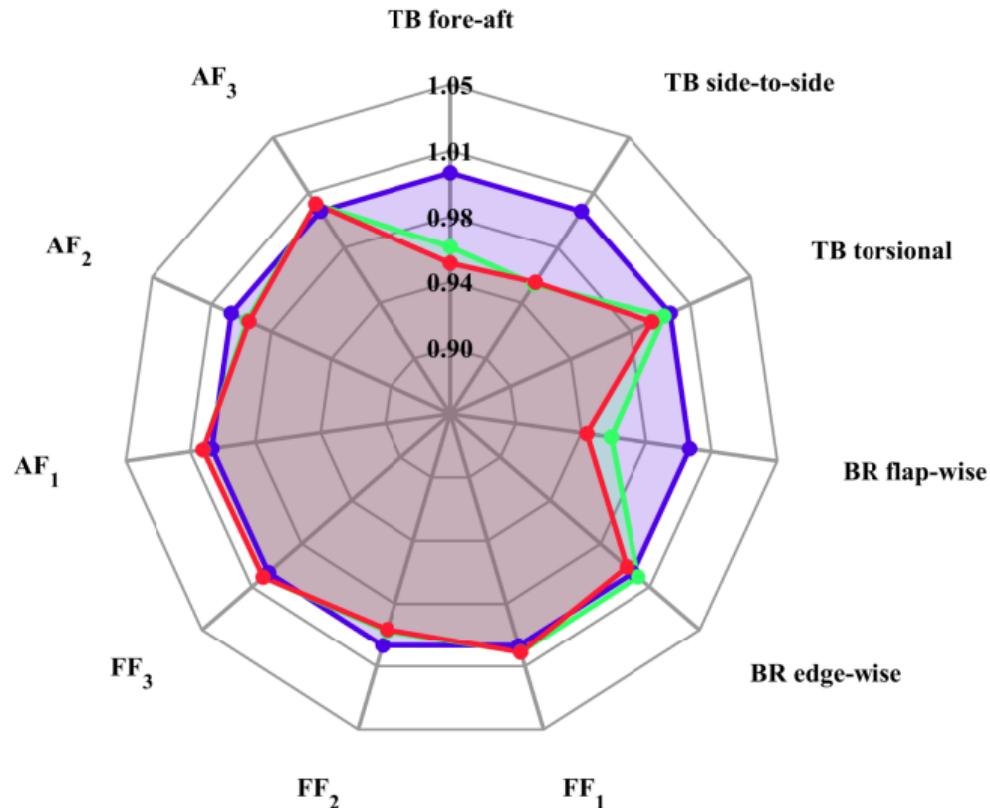


Figure: Comparing the structural forces.

Conclusion & Future Work

✓ Conclusion

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“In God we trust; all others must bring data.”

— W. Edwards Deming

Thanks for your attention!

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