Data-Based ISMC of FOWTs with Unknown Dynamics

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Outline

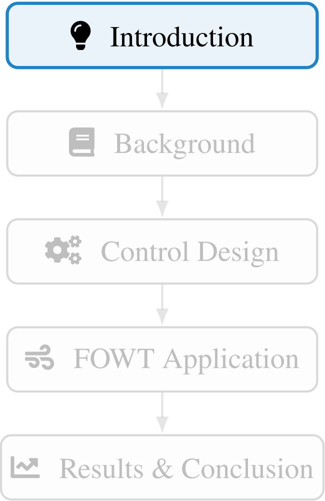
1 Introduction
- About Me
- Motivation

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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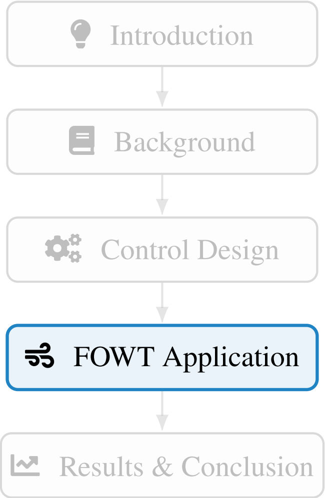

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Roadmap

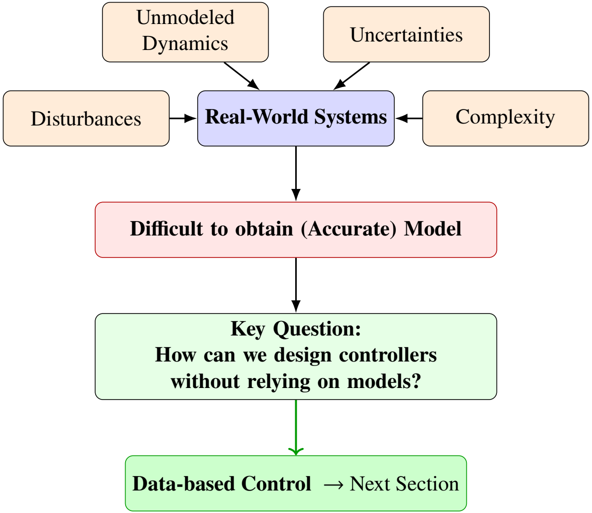
1. Introduction & Motivation
2. Background: ISMC & Neural Approximators
3. Problem Formulation & Proposed Solution
4. Application: Floating Offshore Wind Turbines
5. Simulation Setup & Results & Discussion

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.

IEEE CSS

IFAC INTERNATIONAL FEDERATION OF AUTOMATIC CONTROL

NSF

digital futures

Roadmap

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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.

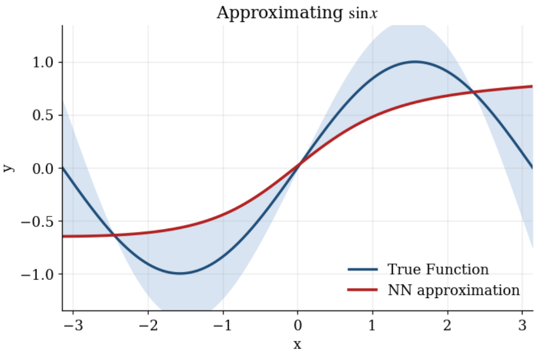
- System identification[2]
- State estimation and observers[3]
- Inverse dynamics / feedforward control[3]
- Learning optimal control laws[4]
- Model predictive / constrained control[5]

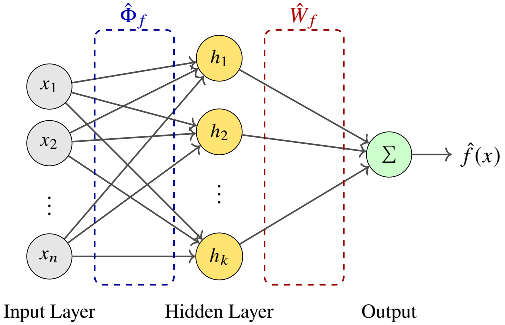
1. Scarselli *et al.*, *Universal approximation using feed-forward neural networks: A survey of some existing methods, and some new results*, Neural Networks, 11(1), 15–37, 1998.
2. Kuschewski *et al.*, *Application of feedforward neural networks to dynamical system identification and control*, IEEE 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

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

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

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

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

$$u = u_0 + u_1,$$

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

- 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.

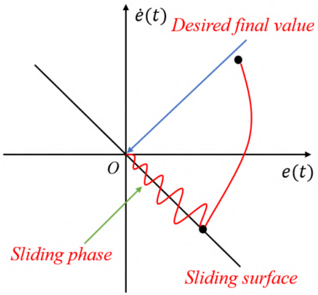
Integral Sliding Mode Control

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

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



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

$$f(\cdot) = W_f^\top h_f(\Phi_f^\top s) + \varepsilon_f,$$
$$g(\cdot) = W_g^\top h_g(\Phi_g^\top s) + \varepsilon_g,$$

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.

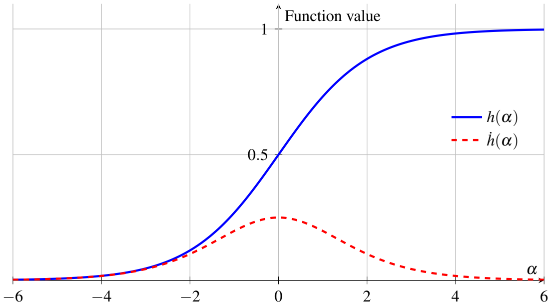


Figure: The sigmoid function $h(\cdot)$ (solid blue line) and its derivative $\dot{h}(\cdot)$ (dashed red line), illustrating smoothness and boundedness properties desirable for stability analysis in control systems.

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

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

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

z–dynamics with NN approximators

Weight Approximation Errors

$$\tilde{W}_f = W_f - \hat{W}_f, \qquad \tilde{\Phi}_f = \Phi_f - \hat{\Phi}_f,$$
$$\tilde{W}_g = W_g - \hat{W}_g, \qquad \tilde{\Phi}_g = \Phi_g - \hat{\Phi}_g$$

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

$$\dot{\hat{z}} = -\big(\hat{f}(\cdot) + \hat{g}(\cdot)\, u_0\big) \qquad \text{data–based approximation}$$
$$= -\Big(\hat{W}_f^\top h_f(\hat{\Phi}_f^\top s) + \hat{W}_g^\top h_g(\hat{\Phi}_g^\top s)\, u_0\Big)$$

Theorem

Theorem

Consider the nonlinear uncertain system $\dot{s} = f + g\,u$, controlled by the law $u = -ks - \rho\,\mathrm{sign}(\sigma)$, where $\sigma = s + \hat{z}$, with $\hat{z}(0) = -s(0)$ and $\hat{z}$ being derived from $\dot{\hat{z}} = -\big(\hat{f}(\cdot) + \hat{g}(\cdot)u_0\big)$, 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 $\dot{\hat{h}}_f = \hat{h}_f \circ (1 - \hat{h}_f)$, 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.

Lyapunov candidate

Considering the following **Lyapunov candidate function**

Lyapunov Function

$$V = \frac{1}{2}\sigma^2 + \frac{1}{2}\operatorname{tr}\left(\tilde{W}_f^\top \Gamma_f^{-1} \tilde{W}_f\right) + \frac{1}{2}\operatorname{tr}\left(\tilde{W}_g^\top \Gamma_g^{-1} \tilde{W}_g\right) + \frac{1}{2}\operatorname{tr}\left(\tilde{\Phi}_f^\top \Theta_f^{-1} \tilde{\Phi}_f\right) + \frac{1}{2}\operatorname{tr}\left(\tilde{\Phi}_g^\top \Theta_g^{-1} \tilde{\Phi}_g\right)$$

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.

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

Let $\Gamma_f, \Gamma_g, \Theta_f, \Theta_g \succ 0$ be constant learning–rate matrices.
These update laws ensure online adap-tation 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

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

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.

$\square$

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

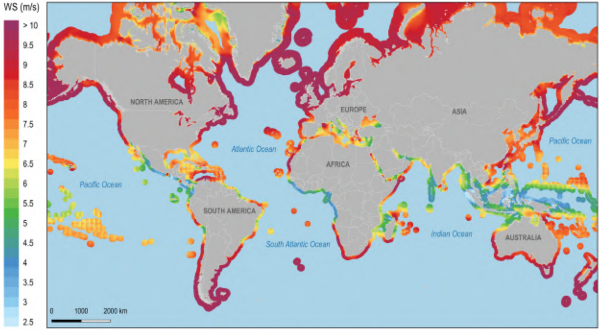
Floating platforms $\rightarrow$ access stronger offshore winds

Challenges

High DOFs $\rightarrow$ oscillations, negative damping

Wind–wave interactions $\rightarrow$ complex control

Standard pitch control is insufficient



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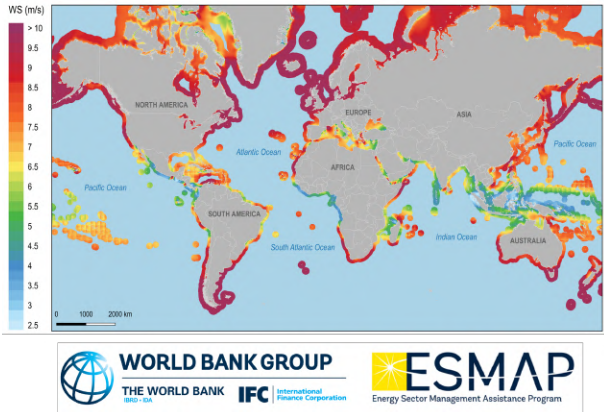
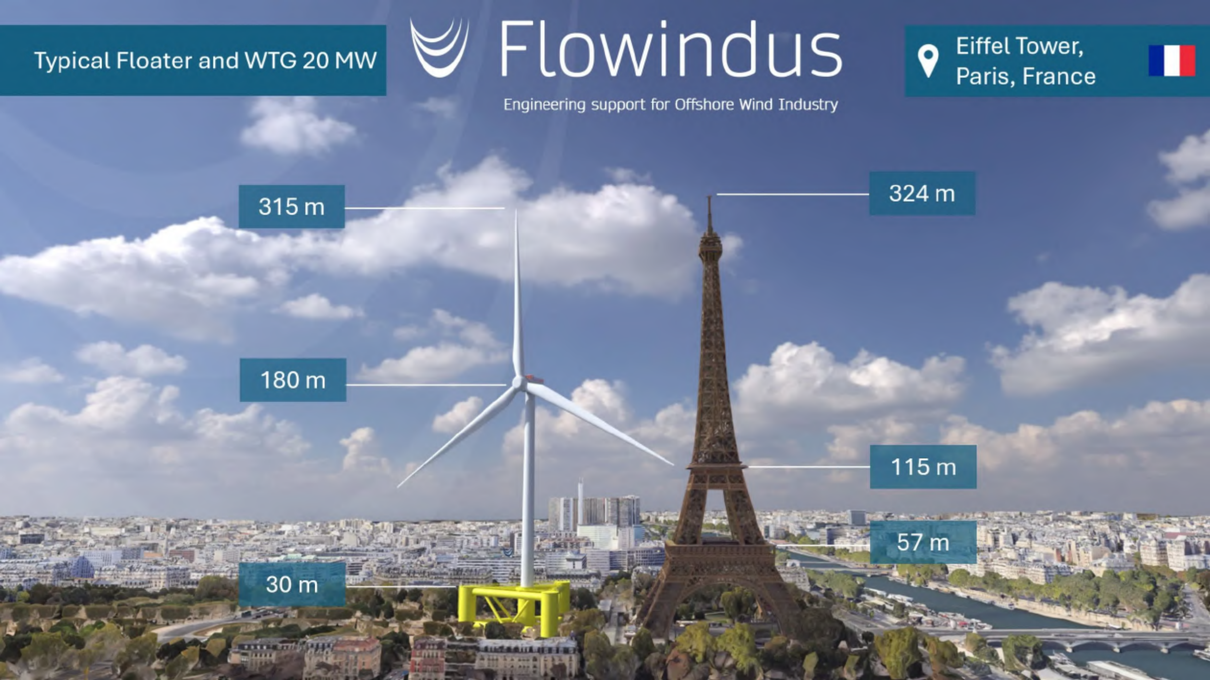
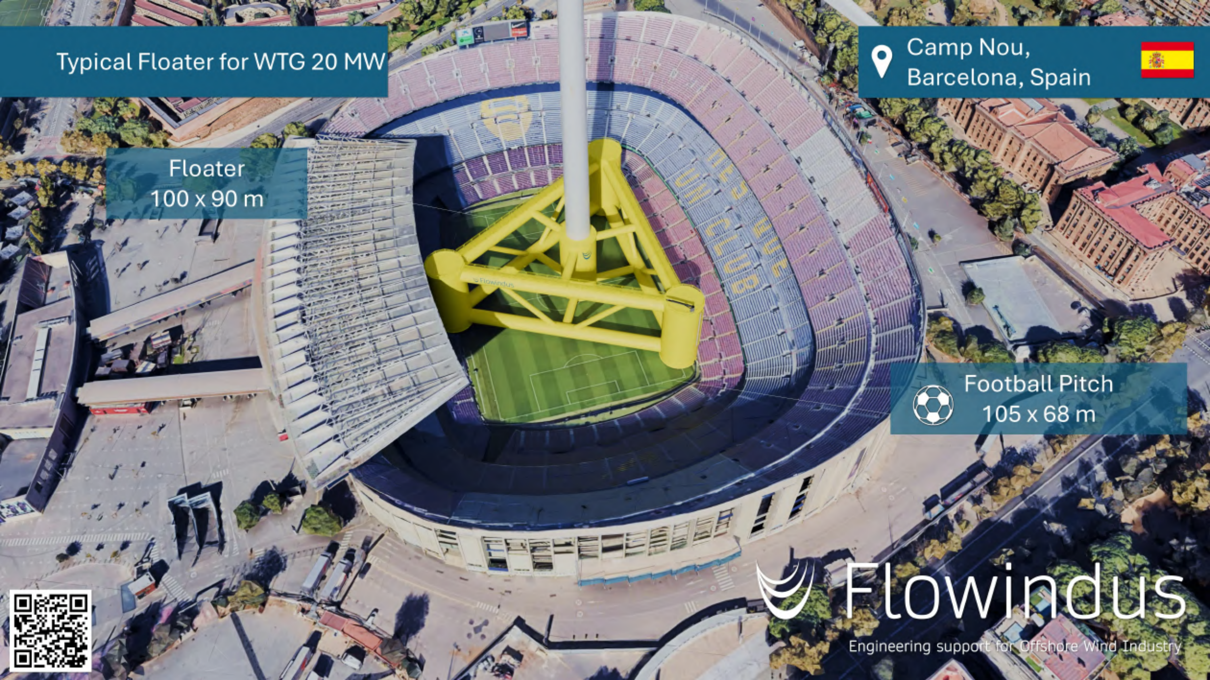



Typical Floater and WTG 20 MW
Flowindus
Engineering support for Offshore Wind Industry
Eiffel Tower,
Paris, France
315 m
180 m
30 m
324 m
115 m
57 m


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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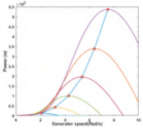
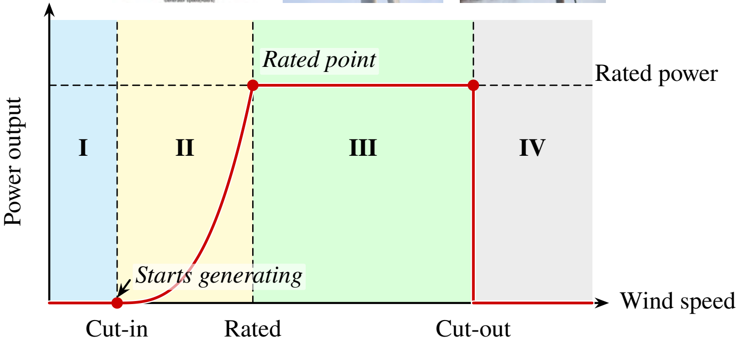
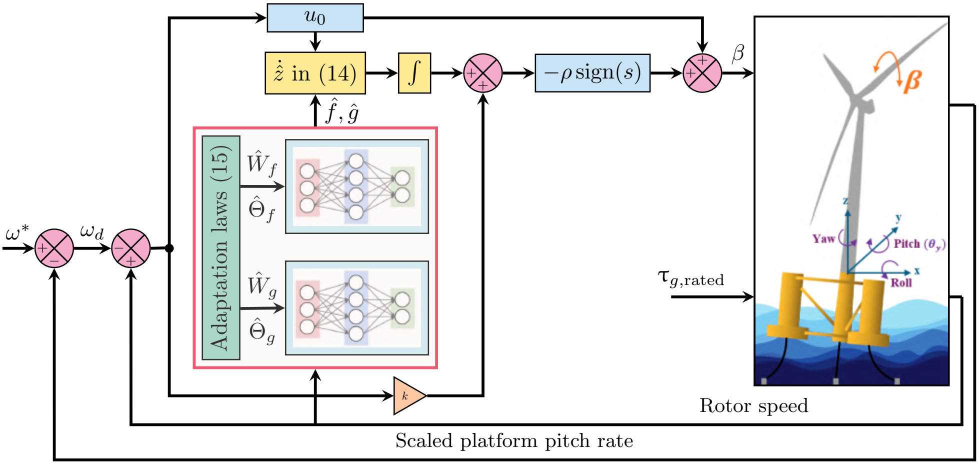
Control Objective

- 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

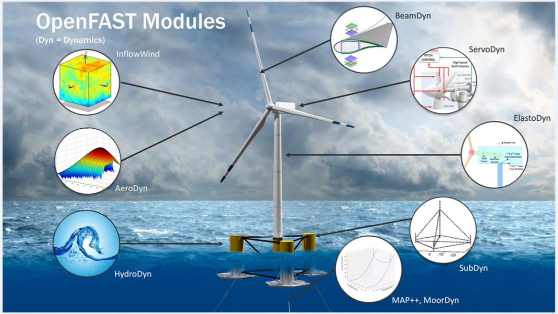
Framework

- **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



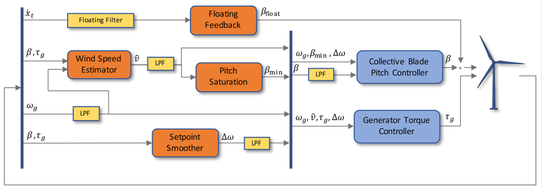
[†] Abbas *et al.*: *A reference open-source controller for fixed and floating offshore wind turbines*, Wind Energ. Sci., 7, 53–73, 2022

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

NATIONAL RENEWABLE ENERGY LABORATORY

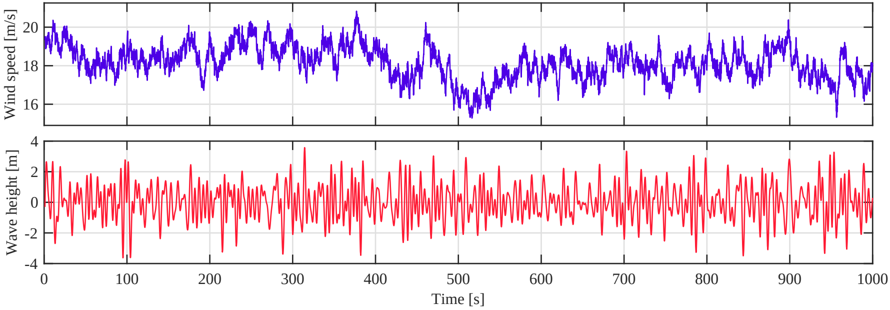
Reference Open-Source Controller



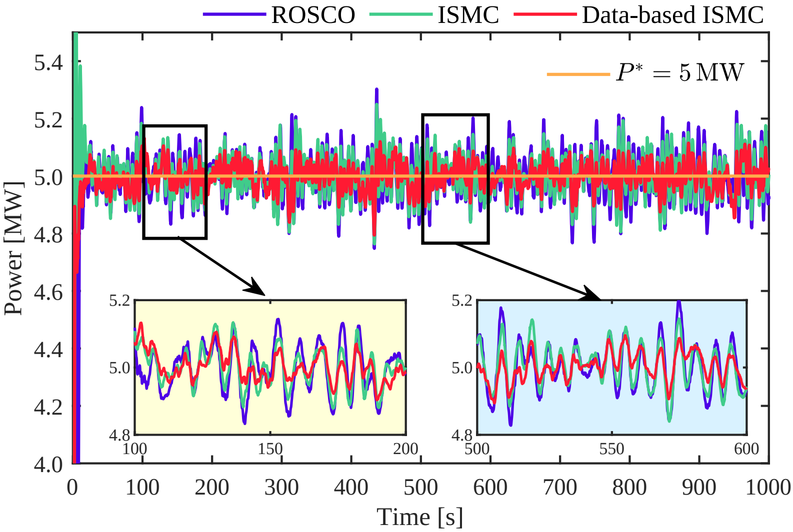
Abbas *et al.*: *A reference open-source controller for fixed and floating offshore wind turbines*, Wind Energ. Sci., 7, 53–73, 2022

Wind and Wave Conditions

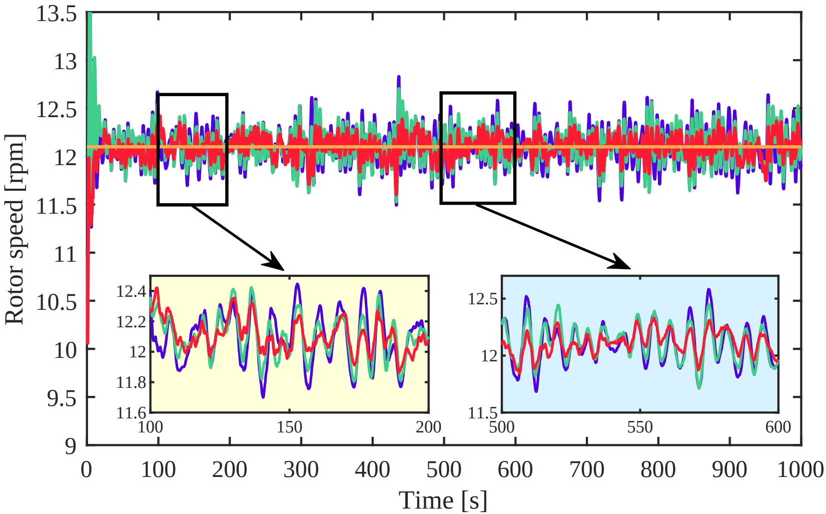
- **Wind:** Turbulent wind speed generated by **TurbSim** with a mean velocity of 18 $\mathrm{m.s^{-1}}$, following the **Kaimal turbulence model**.
- **Wave:** Irregular wave conditions generated with the **HydroDyn** module in OpenFAST, based on the **Pierson–Moskowitz spectrum**, with a significant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



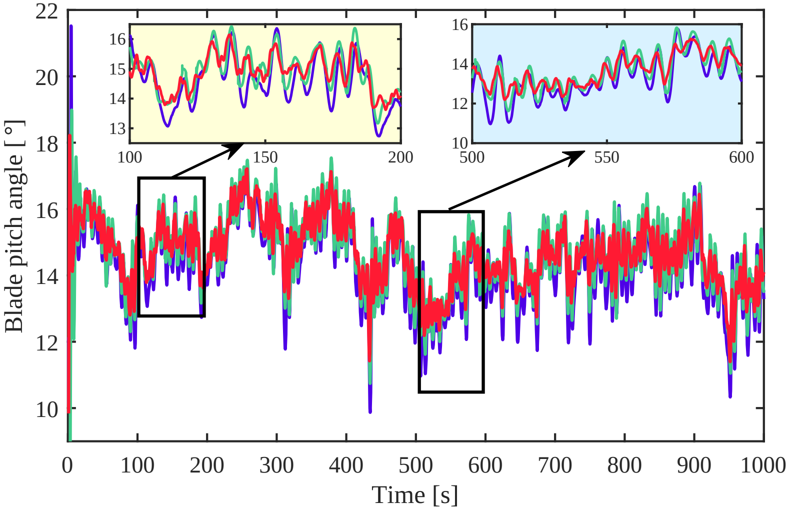
Tracking Performance – Power



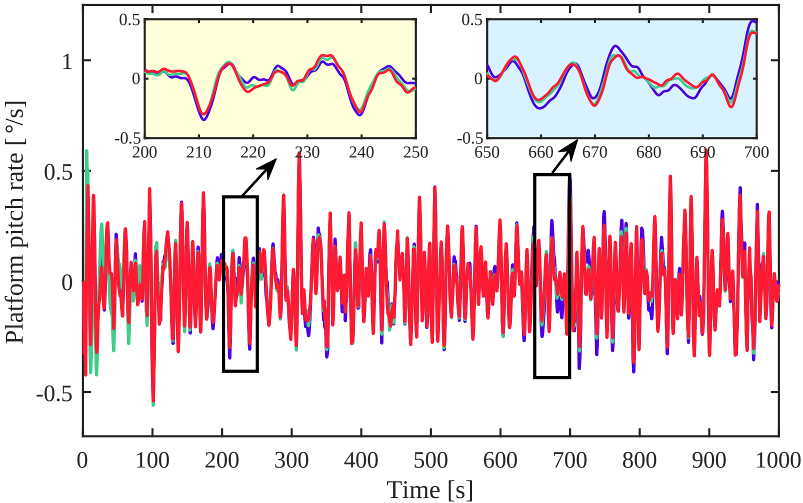
Tracking Performance – Rotor Speed



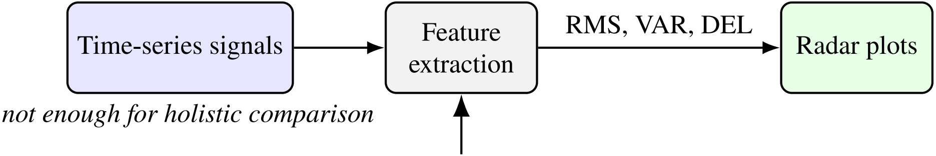
Blade Pitch Variation



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

Time-series signals → Feature extraction → (RMS, VAR, DEL) → Radar plots

not enough for holistic comparison

Root Mean Square (RMS) of pl... pitch, yaw, ...

Variation ... activity (chattering).

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

For these metrics, lower is better.

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

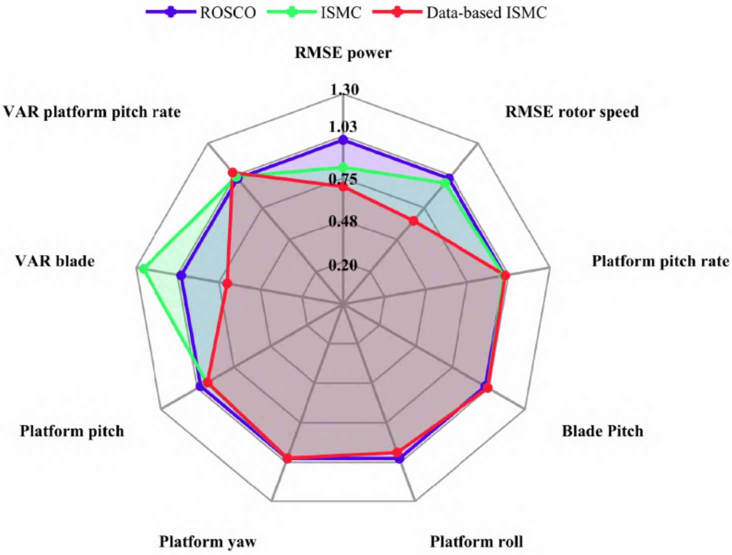


Figure: Comparing the performance metrics.

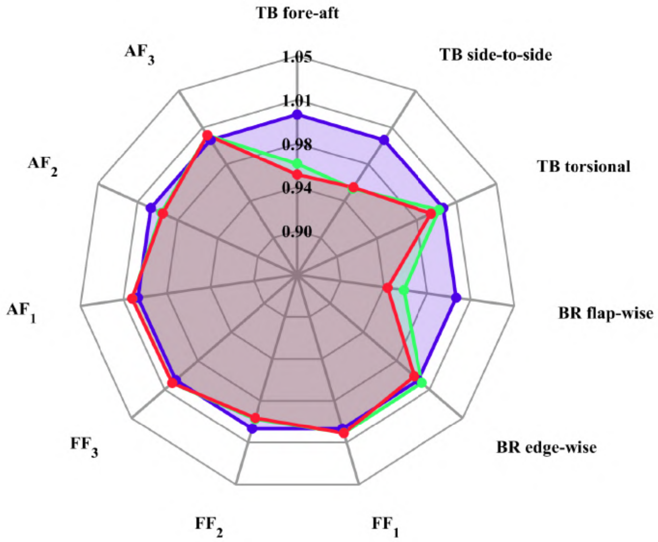


Figure: Comparing the structural forces.

Conclusion & Future Work

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- **Data-based ISMC** with adaptive NNs for FOWTs.
- **No explicit model required**; Lyapunov-based adaptation ensures closed-loop stability.
- In OpenFAST (Region III): tighter power tracking and reduced structural loads.
- Practical and robust: online learning, bounded errors, resilient to unmodeled dynamics.

Future Work

- Explore **higher–order sliding mode (HOSM)** methods (e.g., super–twisting).
- **Physics–informed learning:** embed known dynamics; learn only residual.
- Evaluate advanced **NN architectures** (LSTM, RNN, etc.).

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"In God we trust; all others must bring data."

— W. Edwards Deming

Thanks for your attention!

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Scan to visit the DENSE website

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