

# WEC modeling in irregular waves using Sparse Identification of Nonlinear Dynamics (SINDy)

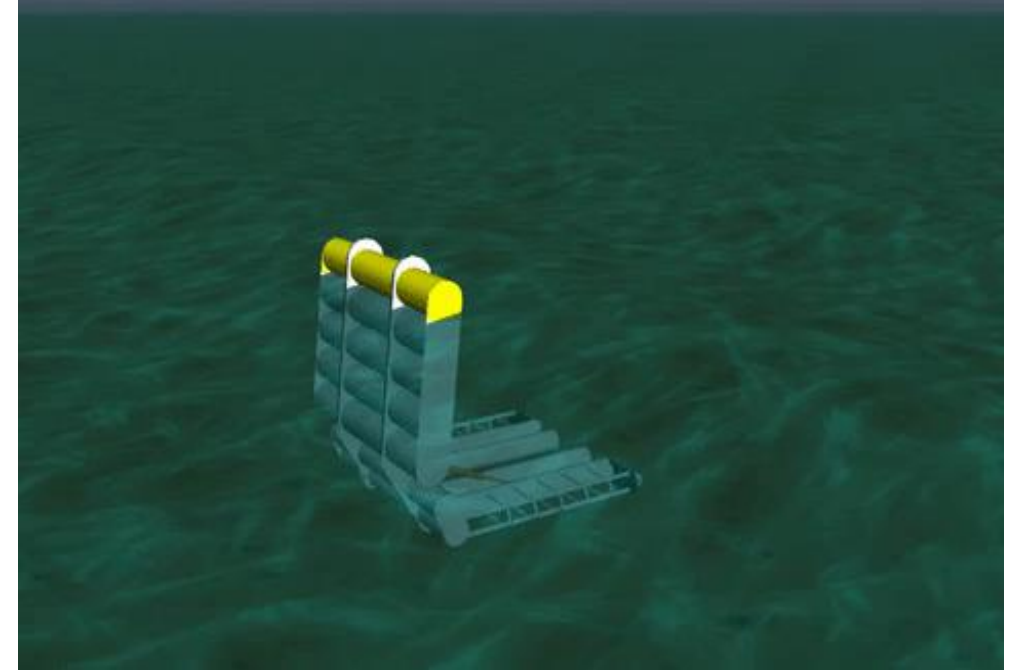
Brittany Lydon, Brian Polagye, and Steve Brunton  
University of Washington  
Seattle, WA, USA



# Oscillating Surge Wave Energy Converter (OSWEC)

## Modeling challenges:

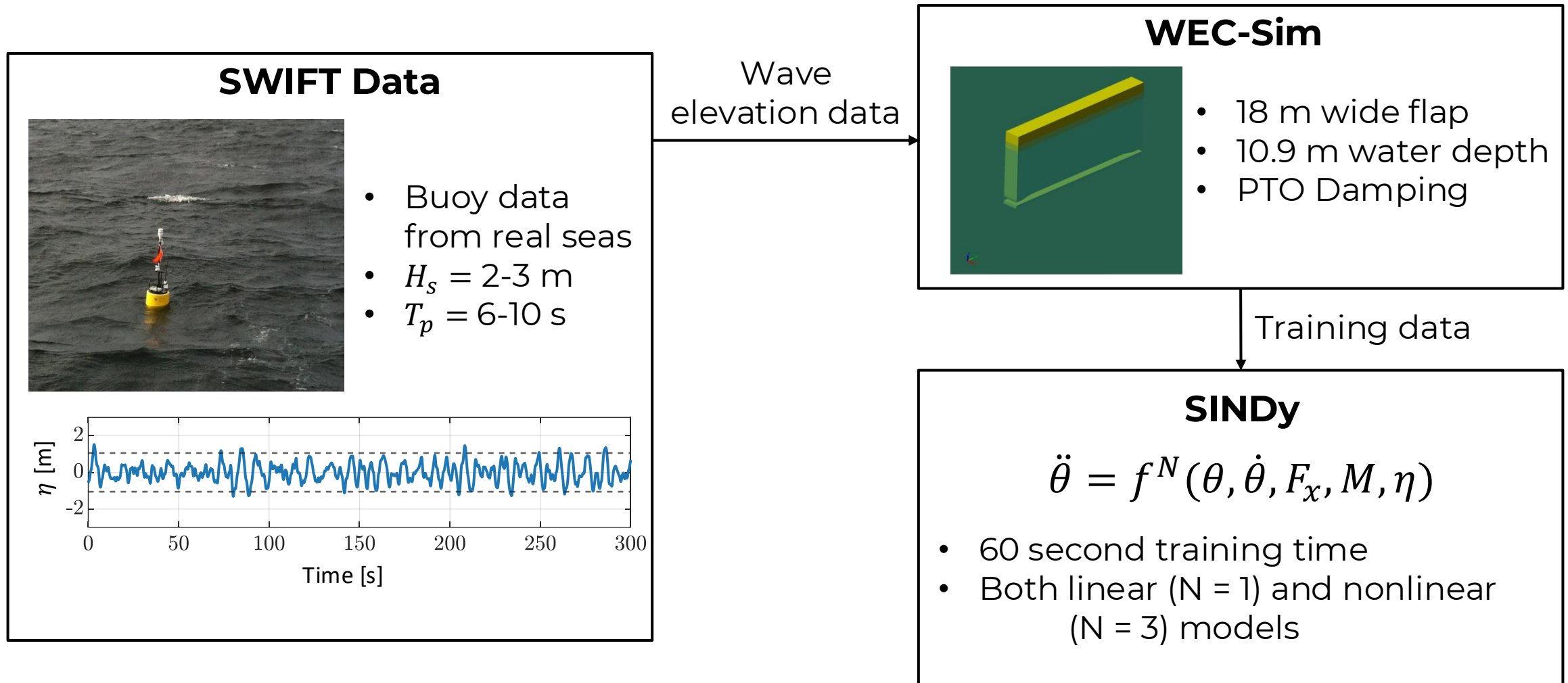
- OSWEC behavior in irregular waves is high-dimensional and complex
  - Changing sea states
  - Non-periodic
  - Stochastic
- Time-domain models have limitations
  - Requires significant computation time
  - Requires knowledge of wave field



Maine Marine Composites, 2014

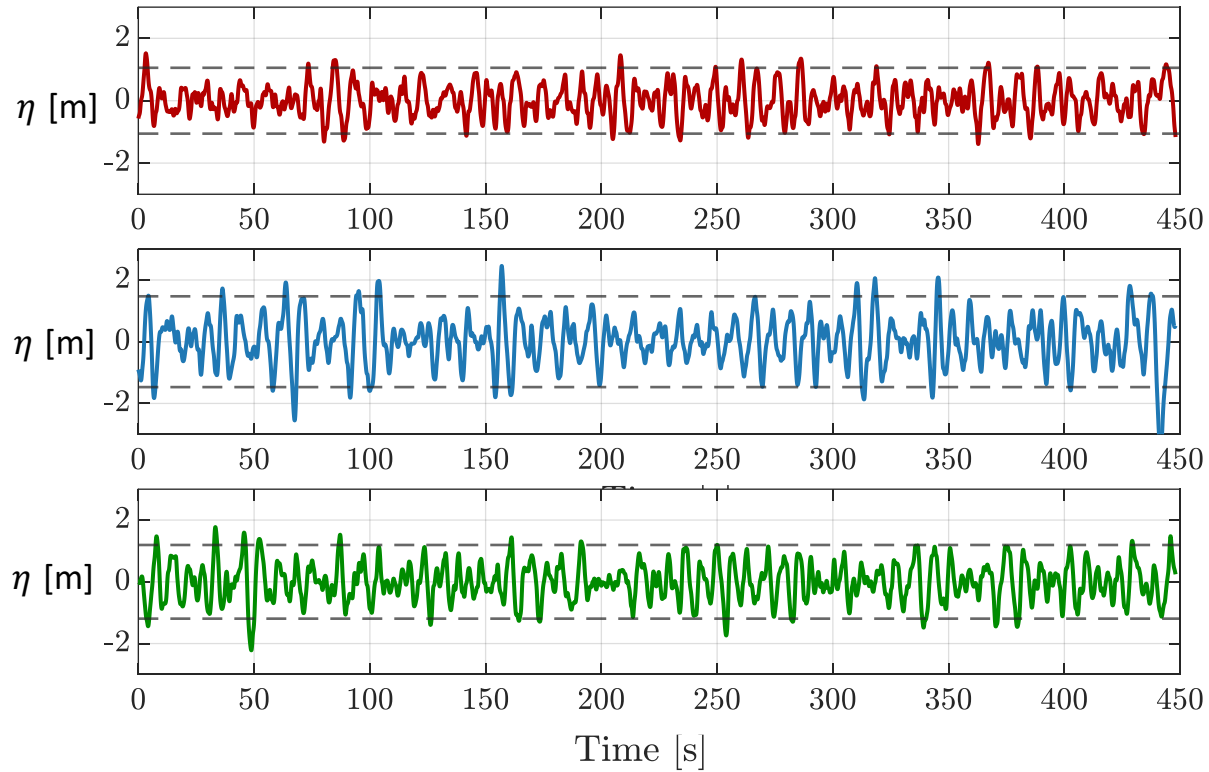
**Goal:** Use **data-driven methods** to build **generalizable** models for OSWEC behavior in **irregular** seas in the **time domain**

# Methods: Workflow

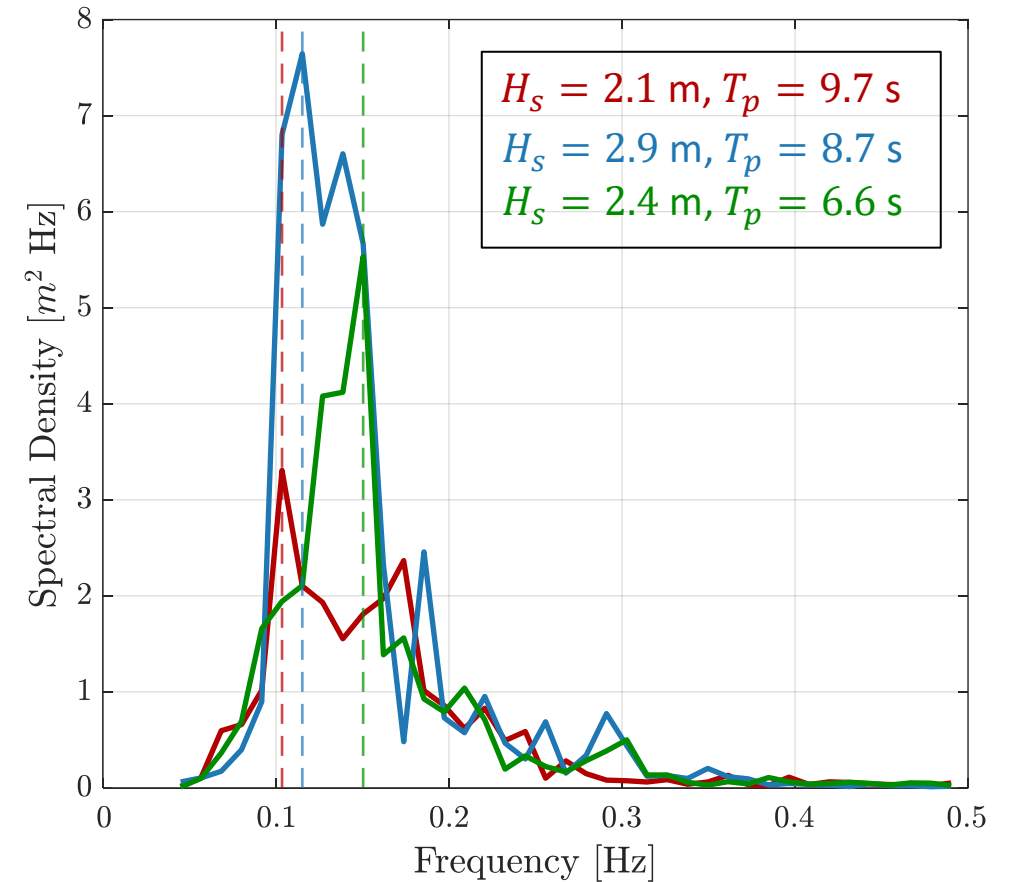


# Methods: SWIFT Data

Buoy Time Series



Power Spectrum



# Methods: SINDy workflow

Step 1: Collect data & choose state variables

$$\ddot{\theta} = \Lambda^N(\theta, \dot{\theta}, F_x, M, \eta)\xi$$

Diagram illustrating the SINDy workflow equation:

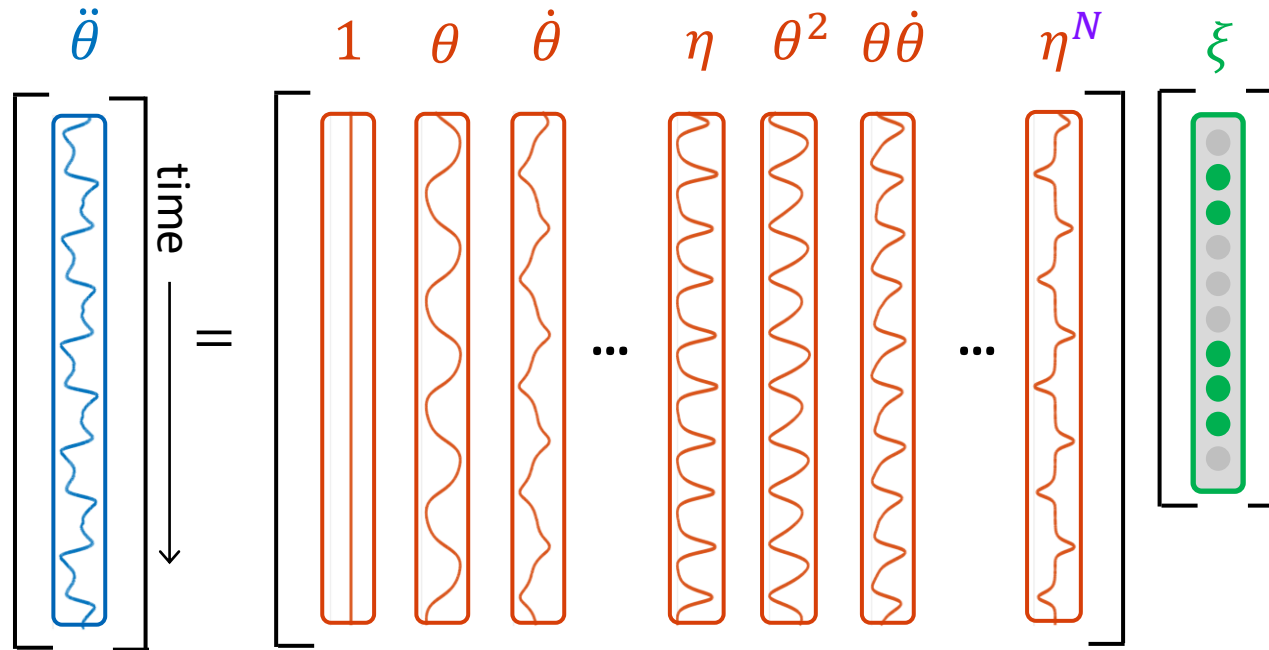
- $\ddot{\theta}$ : Modelled Variable (from data)
- $\Lambda^N$ : Function Library (from data), where  $N$  is the maximum polynomial order
- $(\theta, \dot{\theta}, F_x, M, \eta)$ : States (from data)
- $\xi$ : function weights (what SINDy solves for)

# Methods: SINDy workflow

Step 1: Collect data & choose state variables

$$\ddot{\theta} = \Lambda^N(\theta, \dot{\theta}, F_x, M, \eta)\xi$$

Step 2: Build matrix equation



Step 3: Choose parameters, solve for  $\xi$

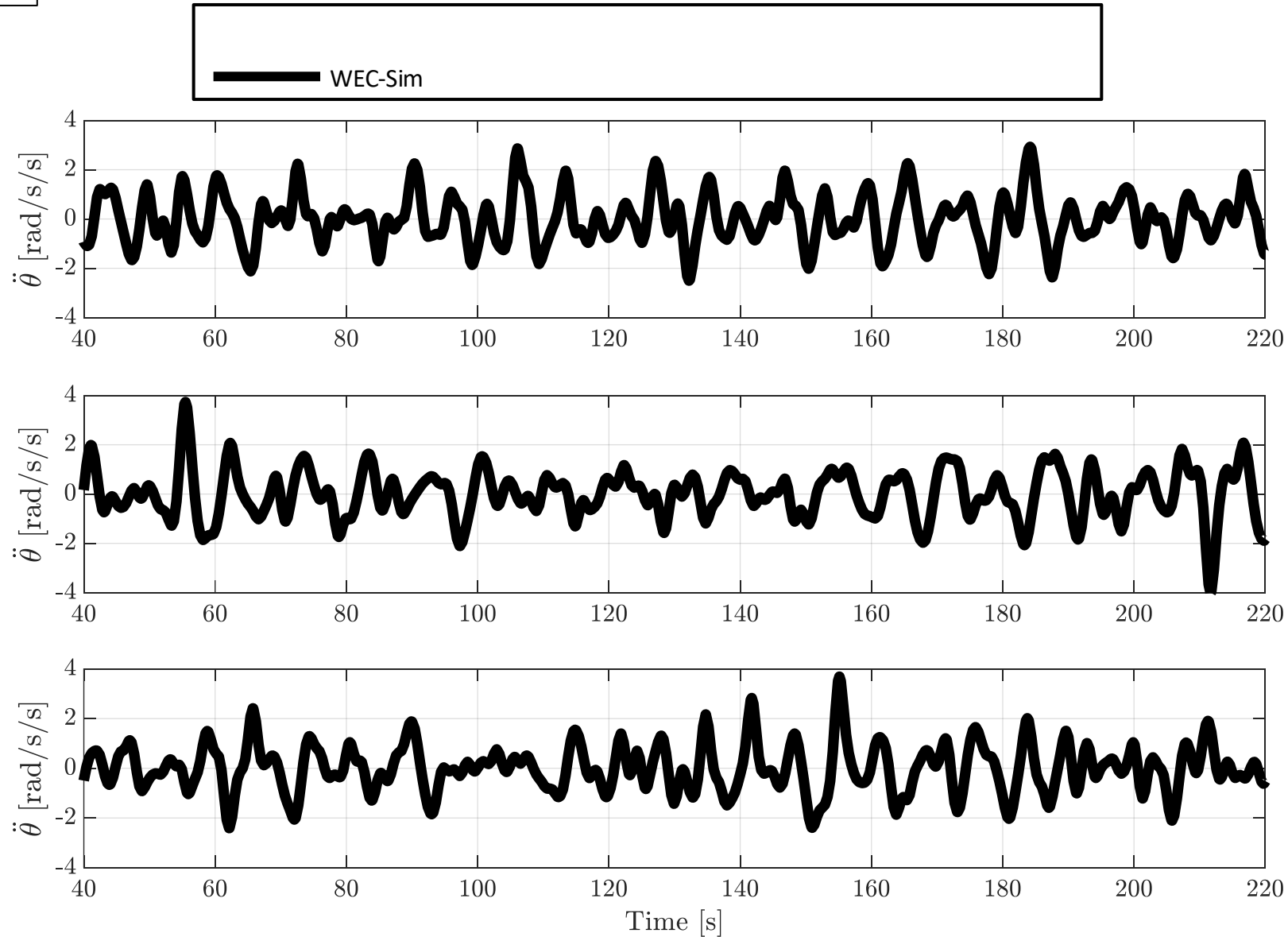
$$\min_{\xi} \left[ \|\ddot{\theta} - \Lambda \xi\|_2 + \lambda \|\xi\|_1 \right]$$

# Results: SINDy Model

$$H_s = 2.1 \text{ m}, T_p = 9.7 \text{ s}$$

$$H_s = 2.9 \text{ m}, T_p = 8.7 \text{ s}$$

$$H_s = 2.4 \text{ m}, T_p = 6.6 \text{ s}$$

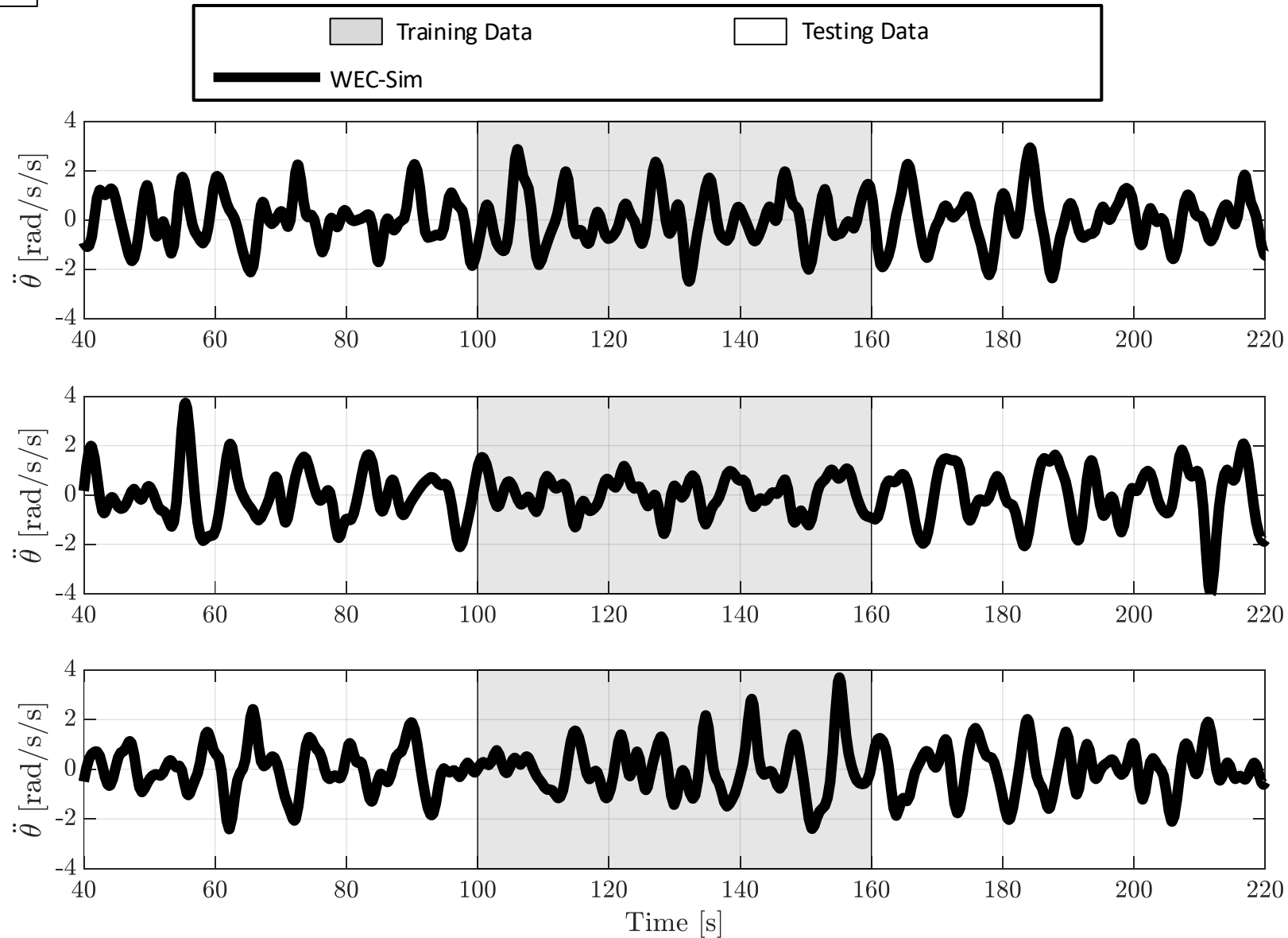


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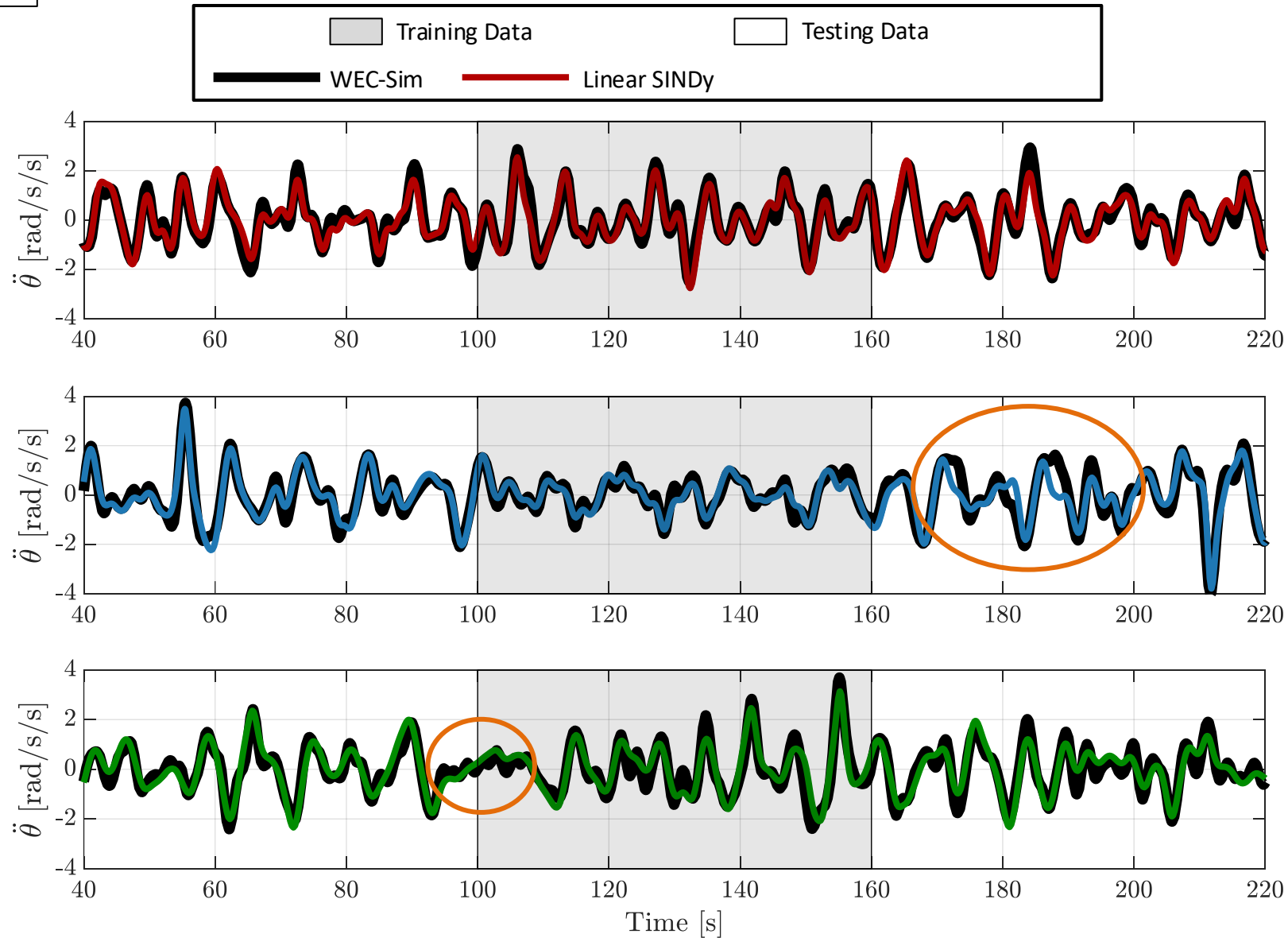


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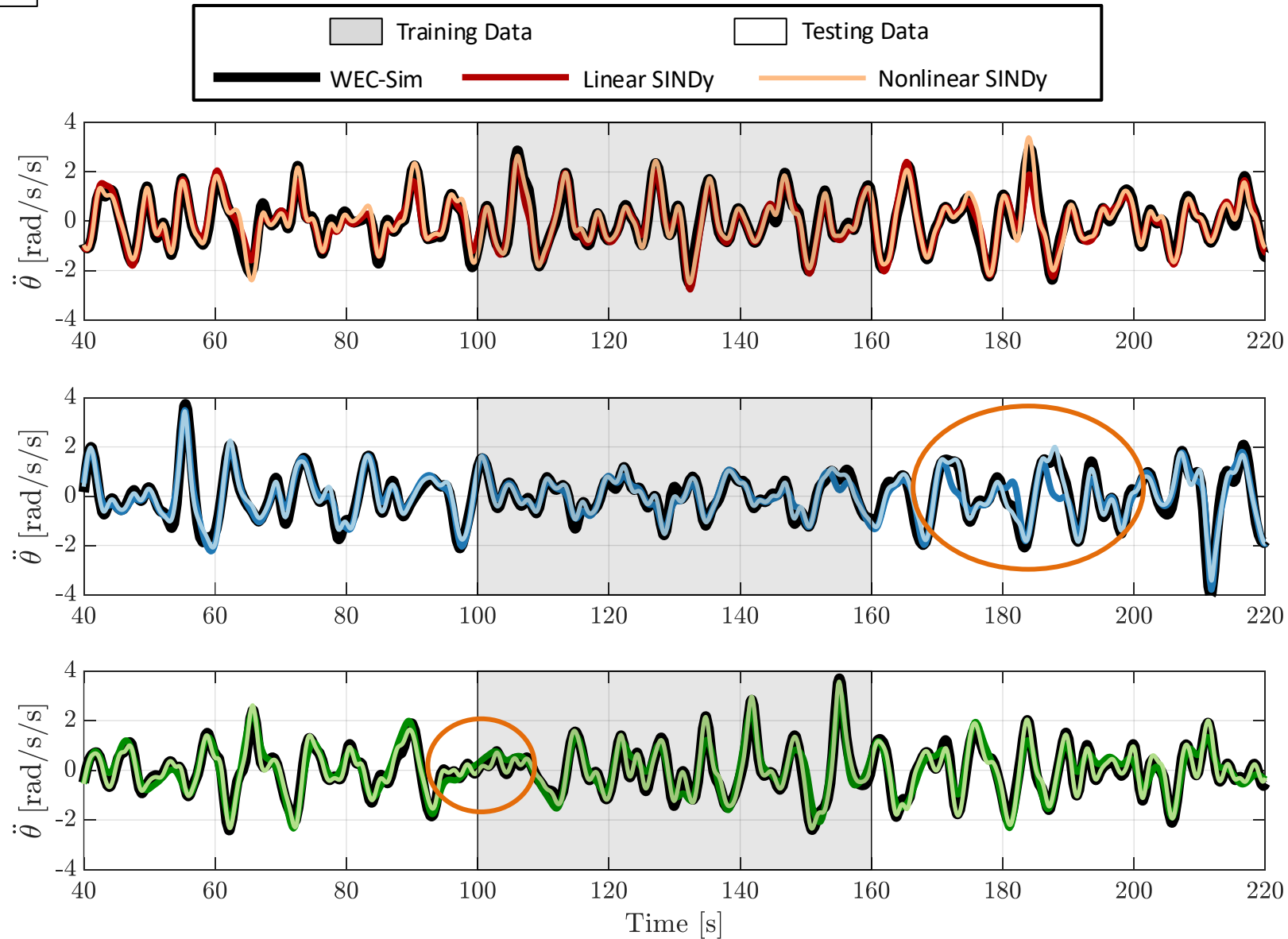


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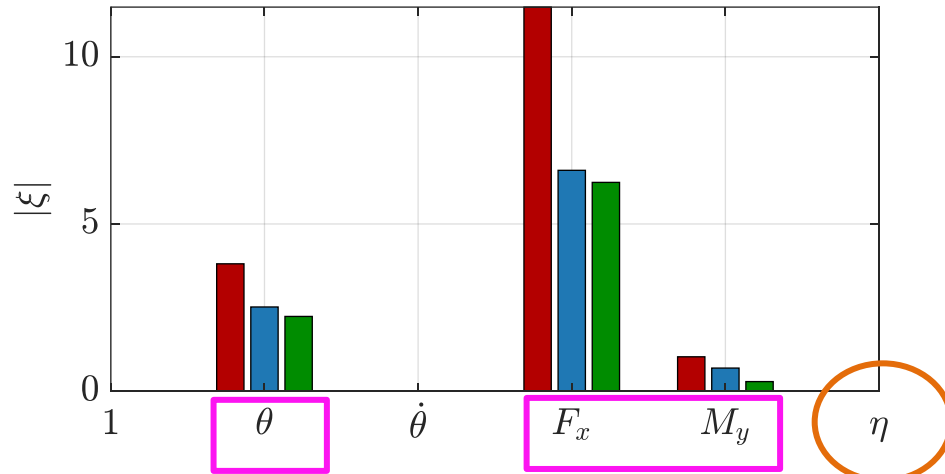
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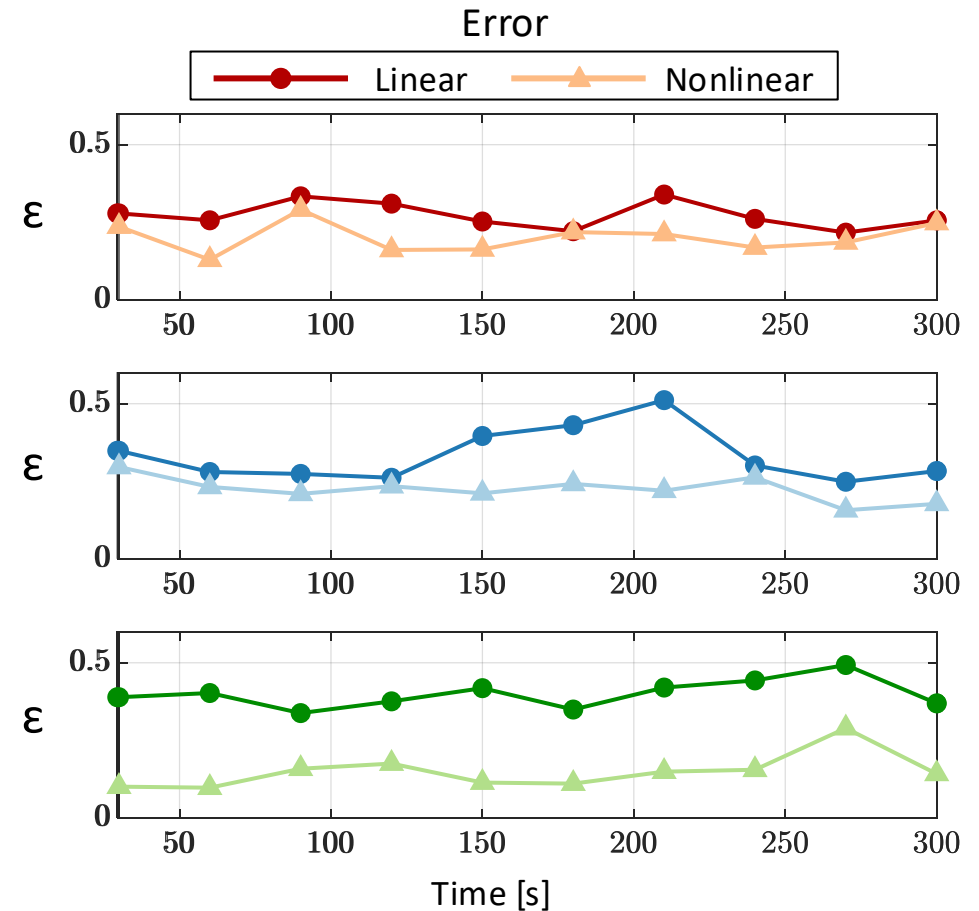
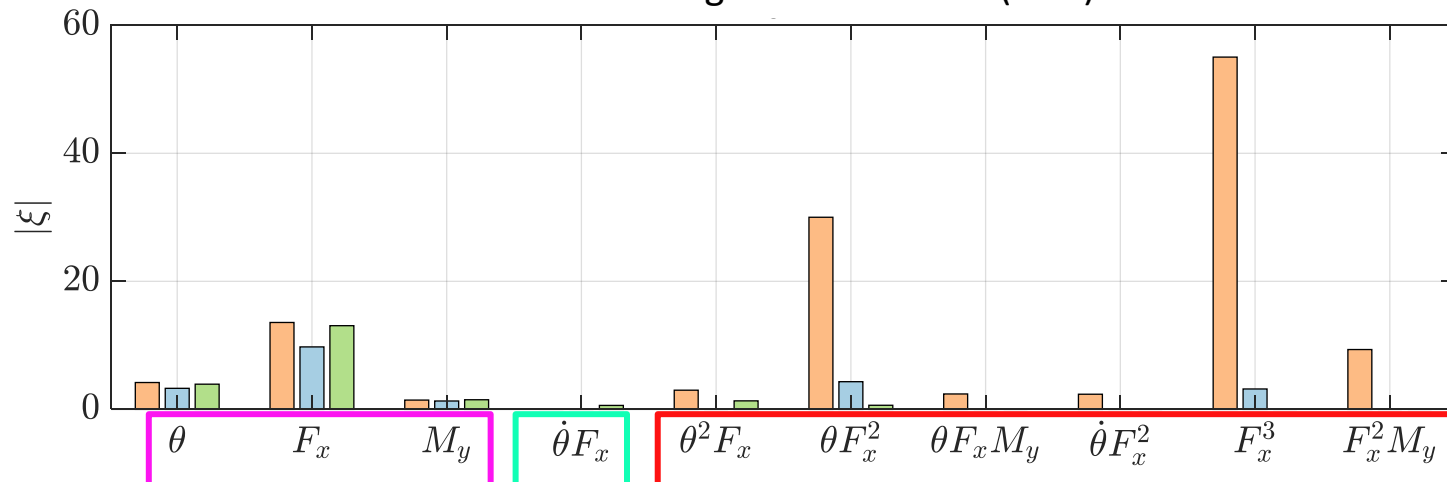
$$\ddot{\theta}_{SINDy} = \Lambda^N(\theta, \dot{\theta}, F_x, M, \eta) \xi$$

$$\varepsilon = \frac{\|\ddot{\theta} - \ddot{\theta}_{SINDy}\|_2}{\|\ddot{\theta}\|_2} \Big|_{30 \text{ s}}$$

Function Weights – Linear (N=1)

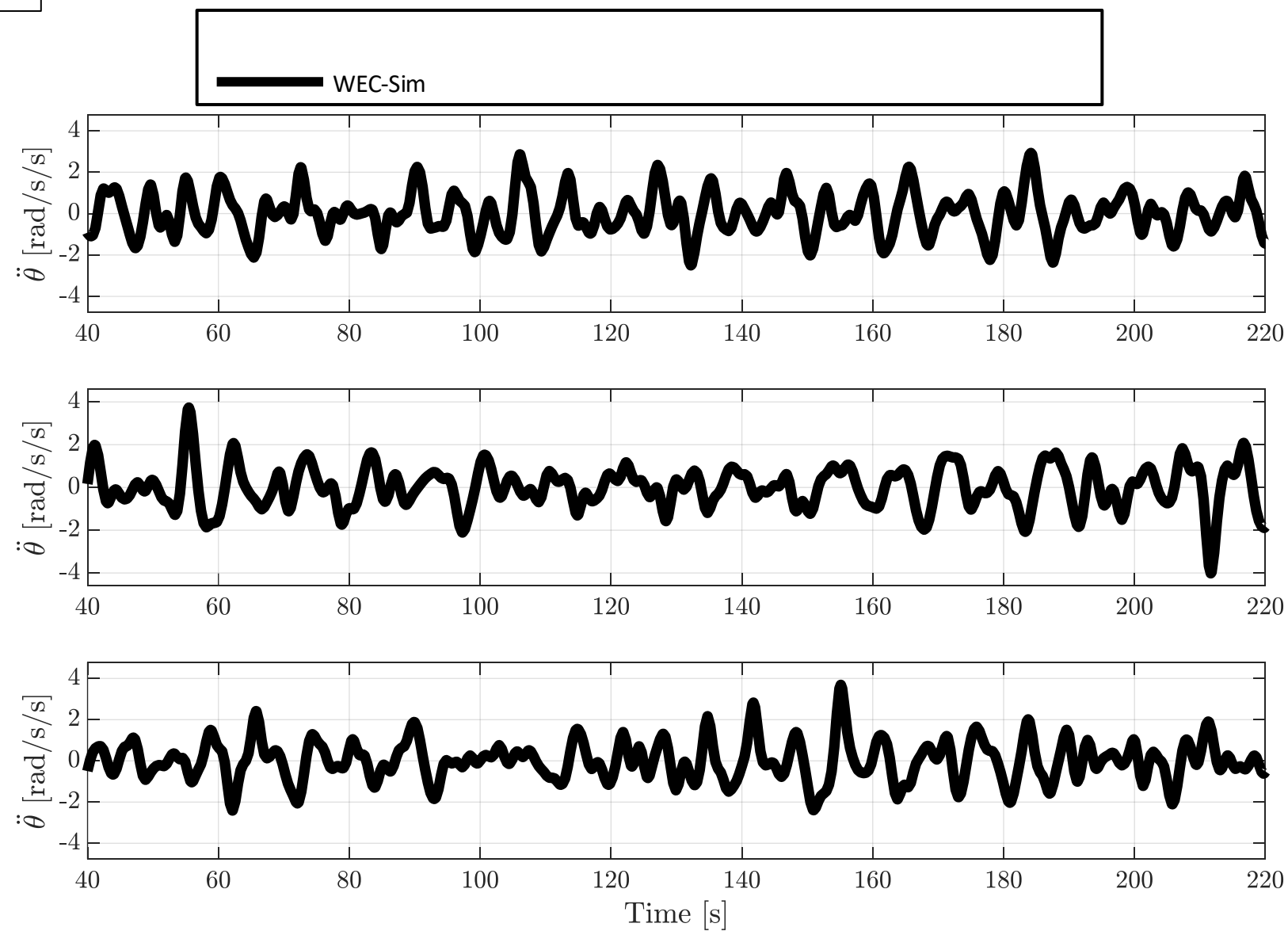


Function Weights – Nonlinear (N=3)



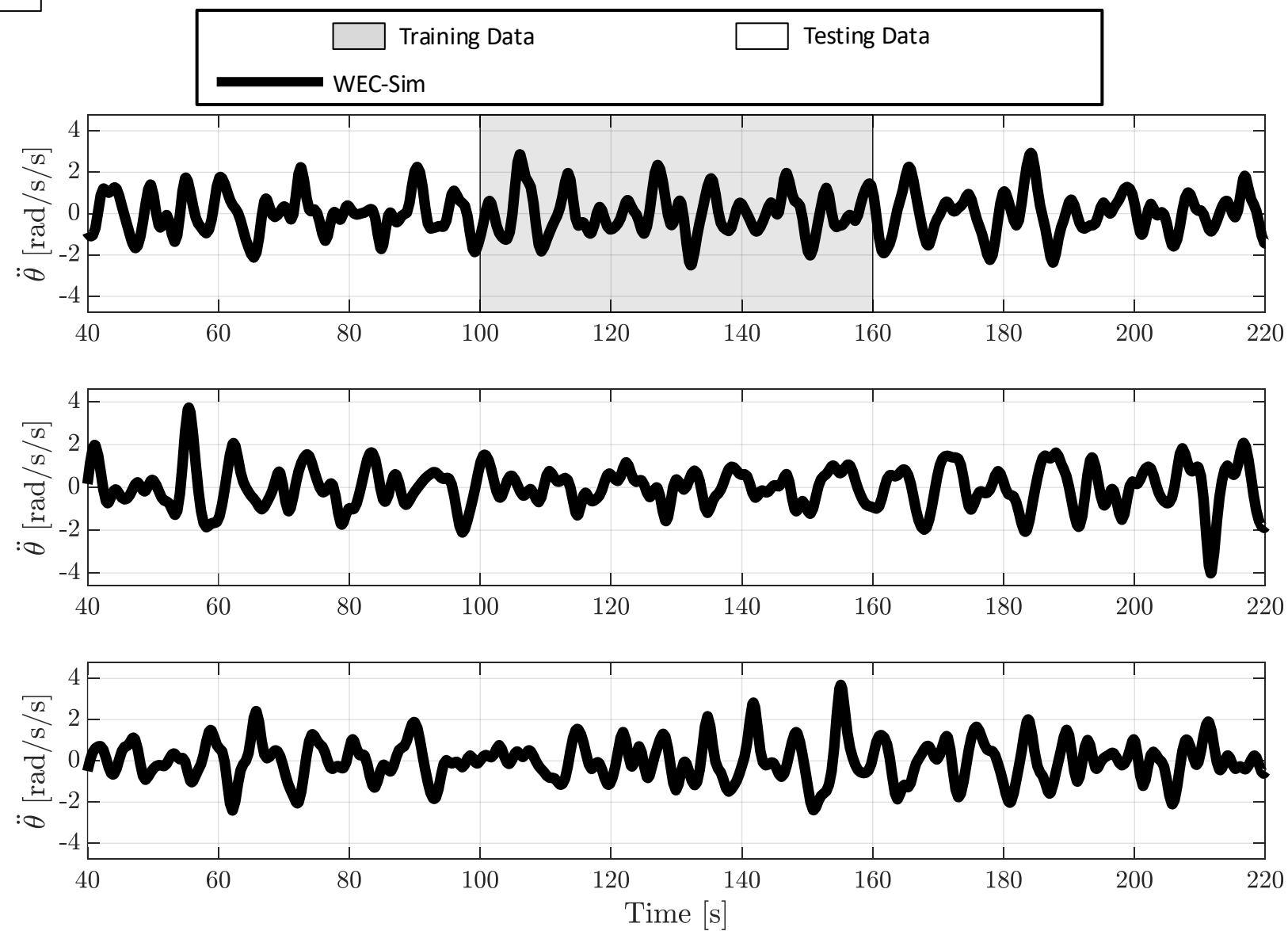
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# Results: Generalization



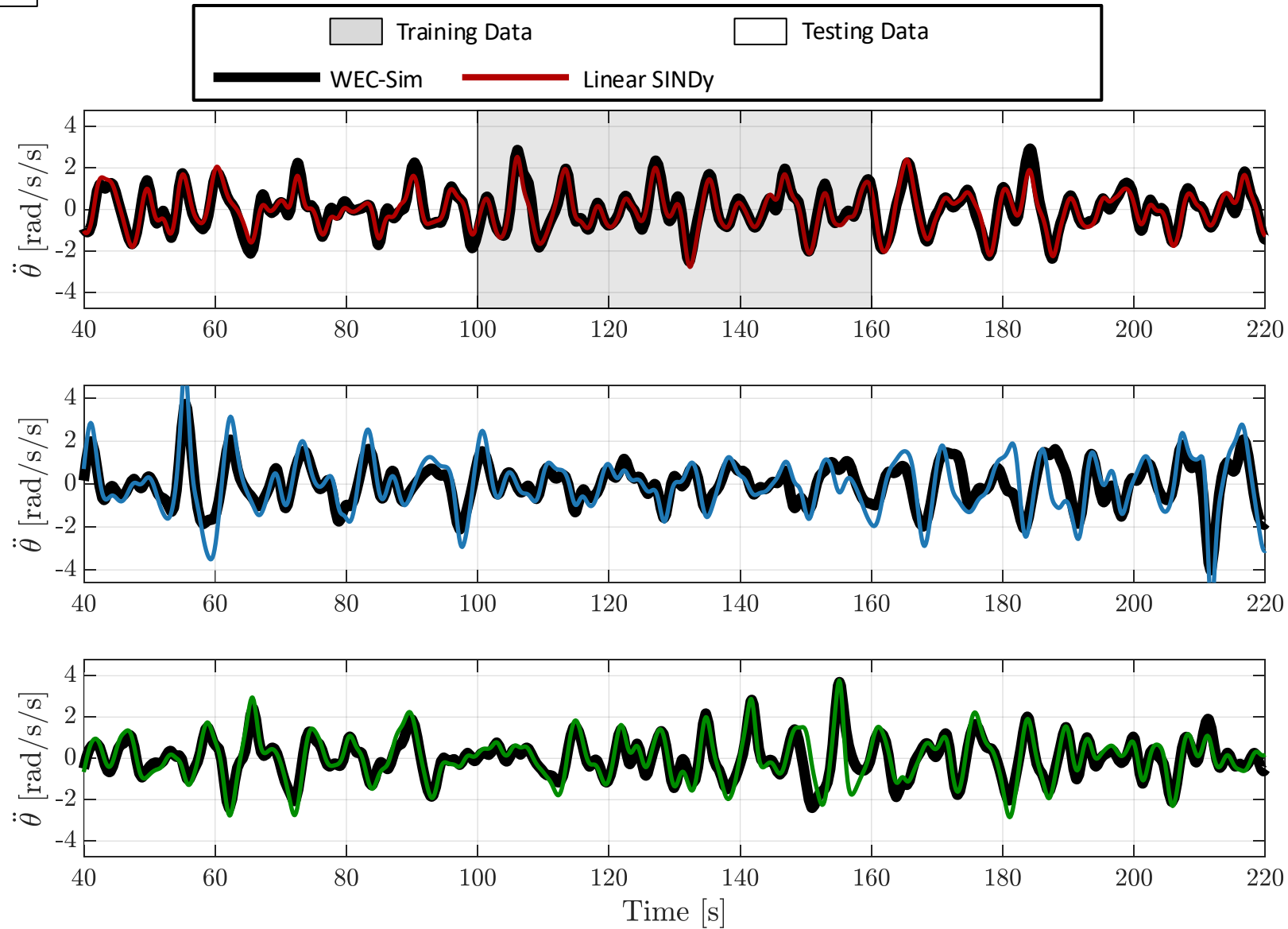
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# Results: Generalization



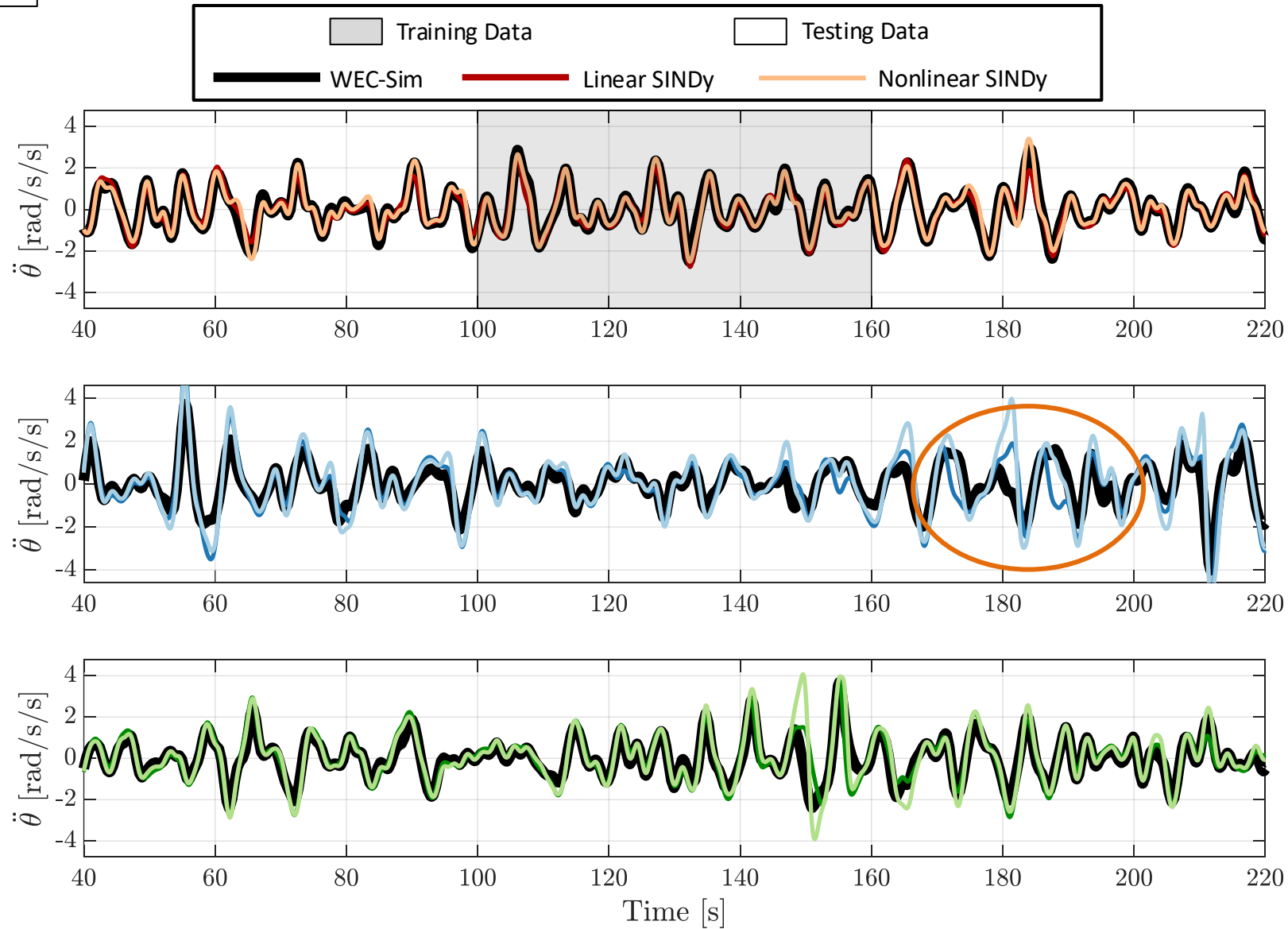
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# Results: Generalization



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# Results: Generalization



# Conclusions

- SINDy can create models for OSWEC acceleration in irregular waves
  - Without using incident wave field
  - Both linear and nonlinear models capture dynamics well
  - Variety of sea states
- Composition of nonlinear models is mostly cubic
- Linear models could be slightly more generalizable than nonlinear models

# Future work: Experimental Comparison

Experimental Device



SWEL Wave Tank at NREL



# Acknowledgements

Advisors: Dr. Brian Polagye and Dr. Steve Brunton

Colleagues at MREL

Funding

- Naval Facilities Engineering Command (NAVFAC)
- National Science Foundation Graduate Research Fellowship Program



An underwater scene with a deep blue background. In the upper left, there's a bright, wavy surface of water with many small, white bubbles and light rays filtering through. The rest of the image is a darker blue with numerous small, white bubbles rising from the bottom right towards the center.

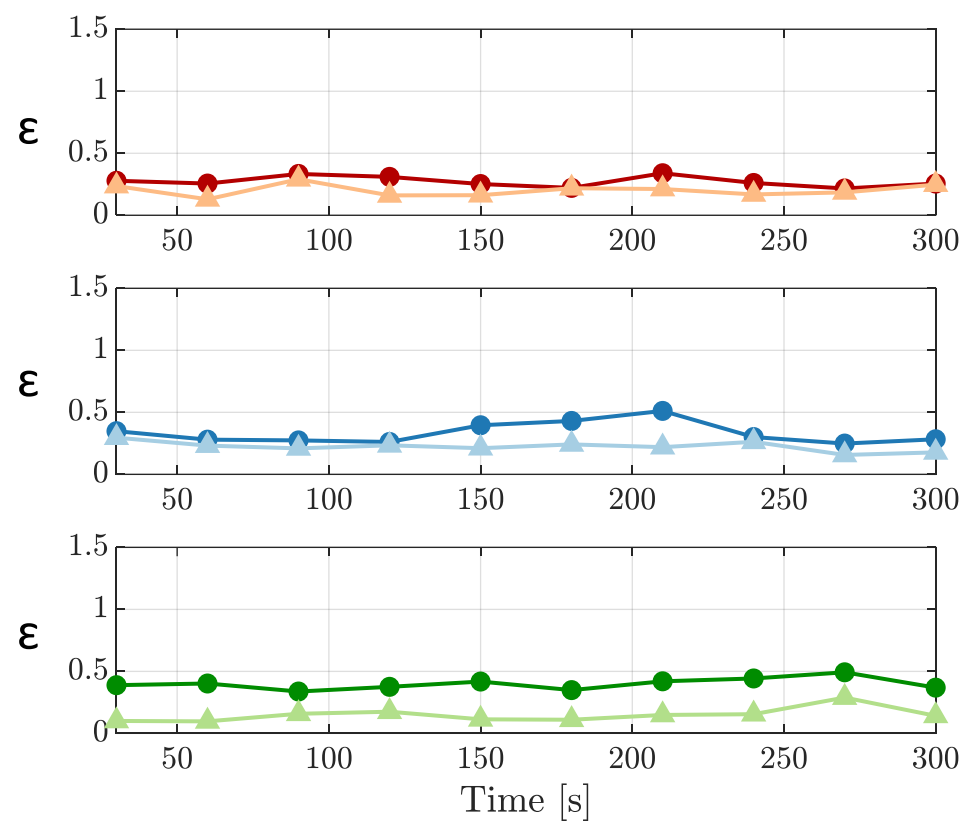
[BrittLyd@uw.edu](mailto:BrittLyd@uw.edu)  
[pmec.us](http://pmec.us)

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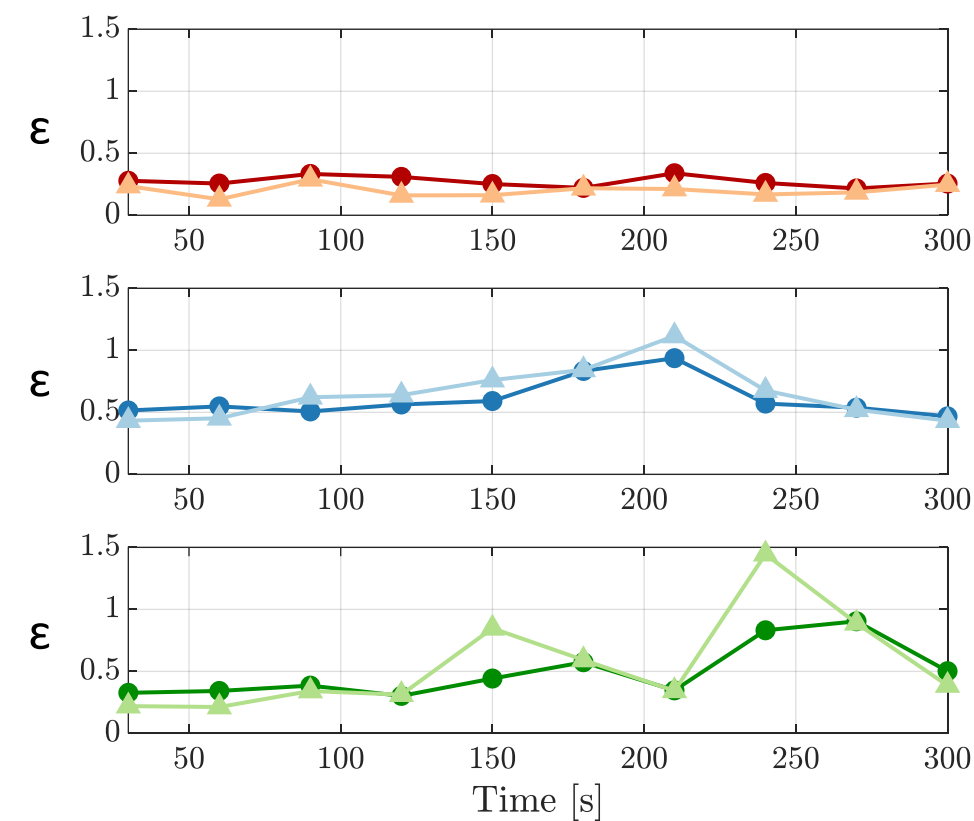
# Results: Generalization

Linear Nonlinear

Using Coefficients from Same Model

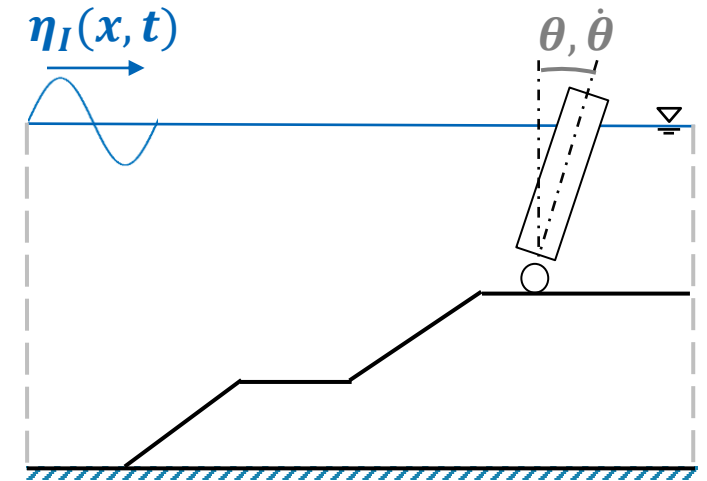
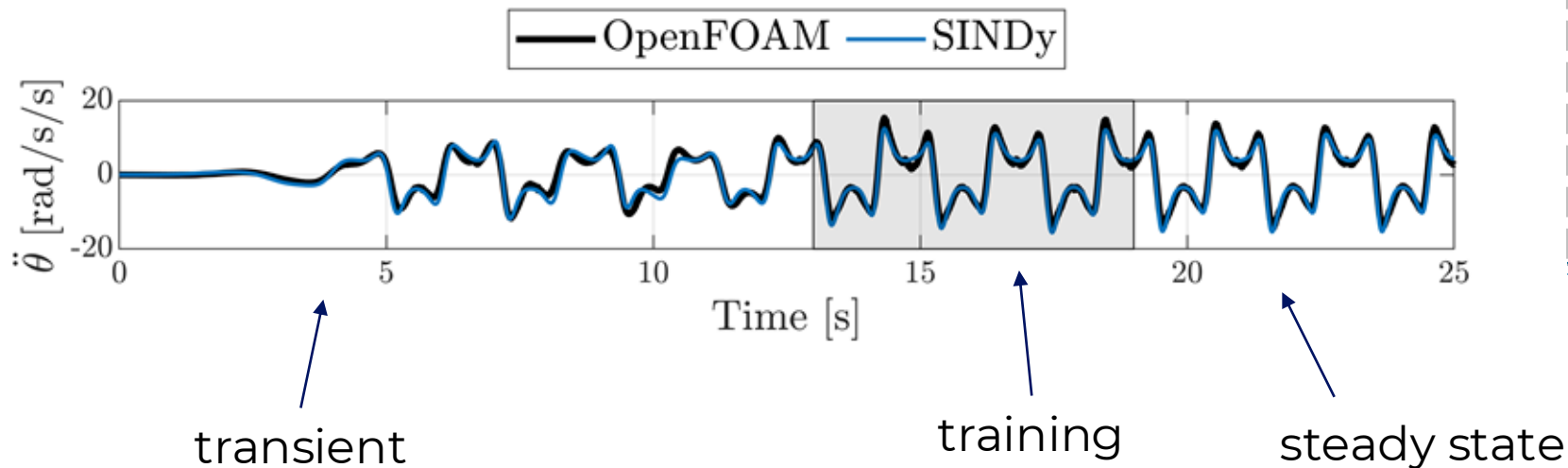


Using Coefficients from First Model



# Ex: Nonlinear kinematics in regular waves

$$\ddot{\theta} = -8.7\theta + 1.8\dot{\theta} + 4.3\theta^3 - 8.2\theta^2\dot{\theta} - 2.4\theta\dot{\theta}^2$$



Based on experiments run at Queen's University, Schmitt & Elsaesser, 2015

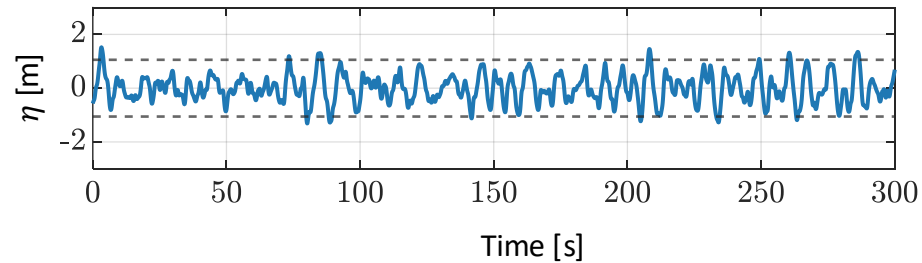
Lydon, Brittany, Brian Polagye, and Steven Brunton. **"Nonlinear WEC modeling using Sparse Identification of Nonlinear Dynamics (SINDy)."** Proceedings of the European Wave and Tidal Energy Conference. Vol. 15. 2023.

# Methods: Workflow

## SWIFT Data

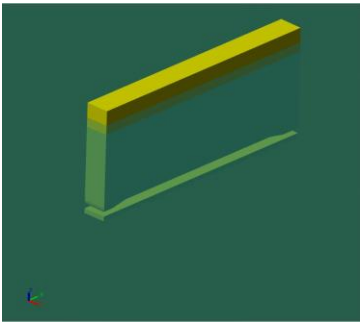


- Buoy data from real seas<sup>1</sup>



Wave  
elevation  
data

## WEC-Sim



- 18 m wide flap
- 10.9 m water depth
- PTO Linear Damping

Training data

## SINDy

$$\ddot{\theta} = f^N(\theta, \dot{\theta}, F_x, M, \eta)$$

- 60 second training time
- Both linear (N = 1) and nonlinear (N = 3) models

<sup>1</sup>Thomson, Jim. "Wave breaking dissipation observed with "SWIFT" drifters." Journal of Atmospheric and Oceanic Technology 29.12 (2012): 1866-1882.

# Sparse Identification of Nonlinear Dynamics (SINDy)

**Main idea:** Generate parsimonious nonlinear reduced order models using only data

$$\frac{d}{dt} \mathbf{x} = f(\mathbf{x}, t)$$

dynamics (from data)  $\rightarrow \dot{\mathbf{x}} = \text{nonlinear sparse} \mathbf{A}(\mathbf{x}) \boldsymbol{\xi} \leftarrow \text{function weights (what SINDy solves for)}$

$\min_{\boldsymbol{\xi}} \left[ \underbrace{\|\dot{\mathbf{x}} - \mathbf{A}(\mathbf{x}) \boldsymbol{\xi}\|_2}_{\text{promotes accuracy}} + \underbrace{\lambda \|\boldsymbol{\xi}\|_1}_{\text{promotes sparsity}} \right]$

nonlinear function library  $\mathbf{A}(\mathbf{x})$  (from data) states  $\mathbf{x}$