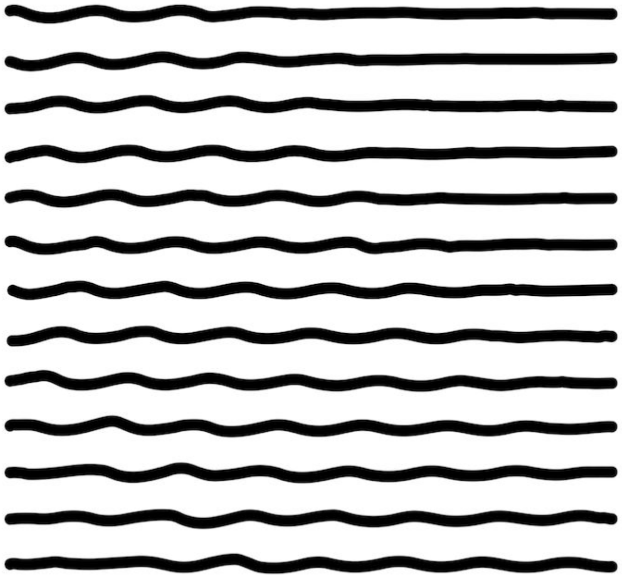
MASTERS THESIS DEFENSE

REAL TIME PHASE-RESOLVED WAVE PREDICTION

FOR THE ACTIVE CONTROL OF FLOATING STRUCTURES

SHAWN ALBERTSON



Friday April 21, 2023, 1 PM

Real time phase-resolved nonlinear wave prediction for the active control of floating structures

Shawn Albertson
Prof. Jason Dahl
Prof. Stéphan Grilli

U.S. DEPARTMENT OF ENERGY

THE UNIVERSITY OF RHODE ISLAND

Overview

- Context and motivation
- Phase resolved nonlinear wave prediction
- Active control of floating structures

Why floating wind?

Illustration by Josh Bauer, National Renewable Energy Laboratory (NREL)

Source:
BBC News
via YouTube

Existing control systems are not good enough

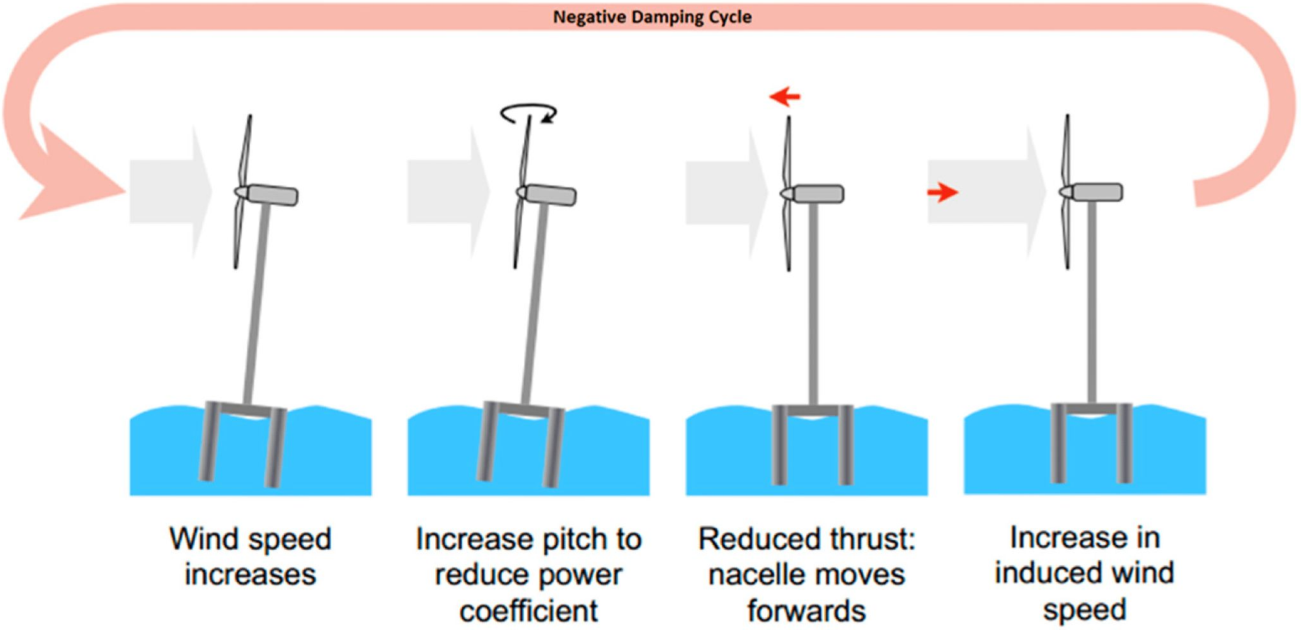
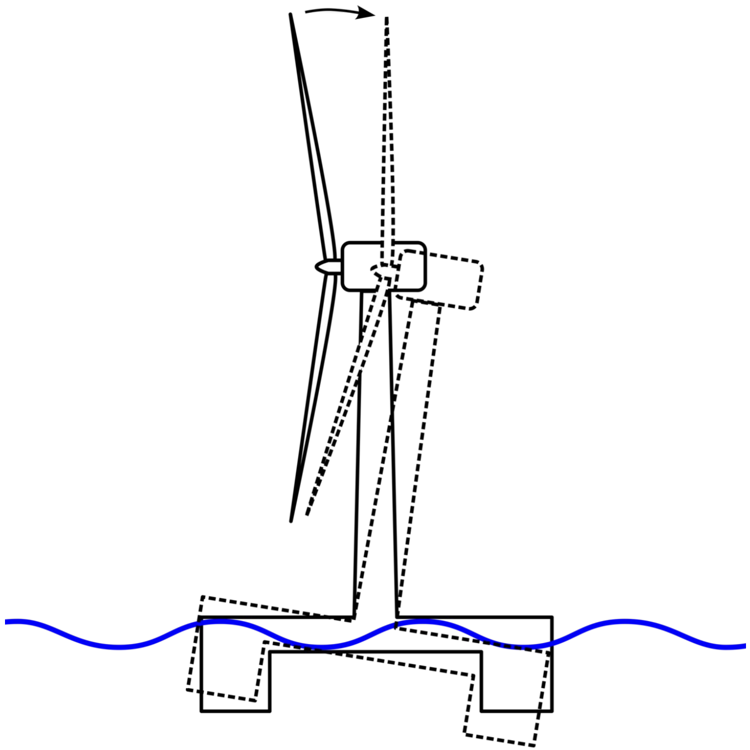


Image by Ward (2019)

An improved control system

Model based controller

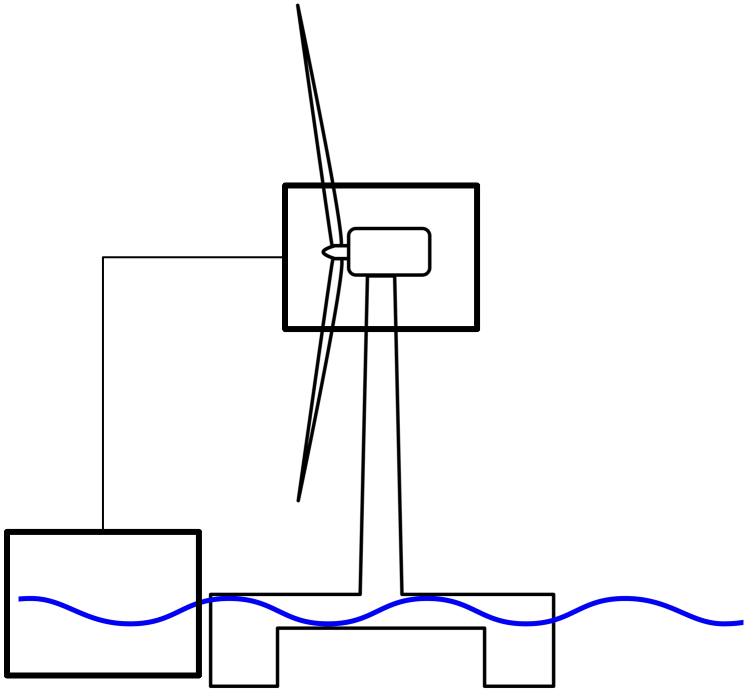


An improved control system

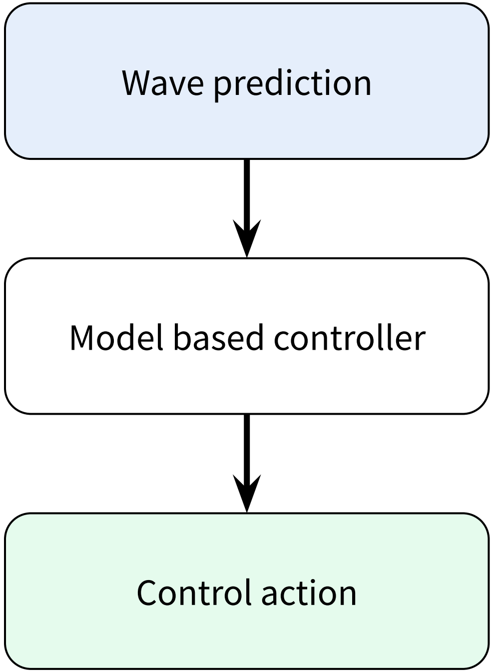
Wave prediction

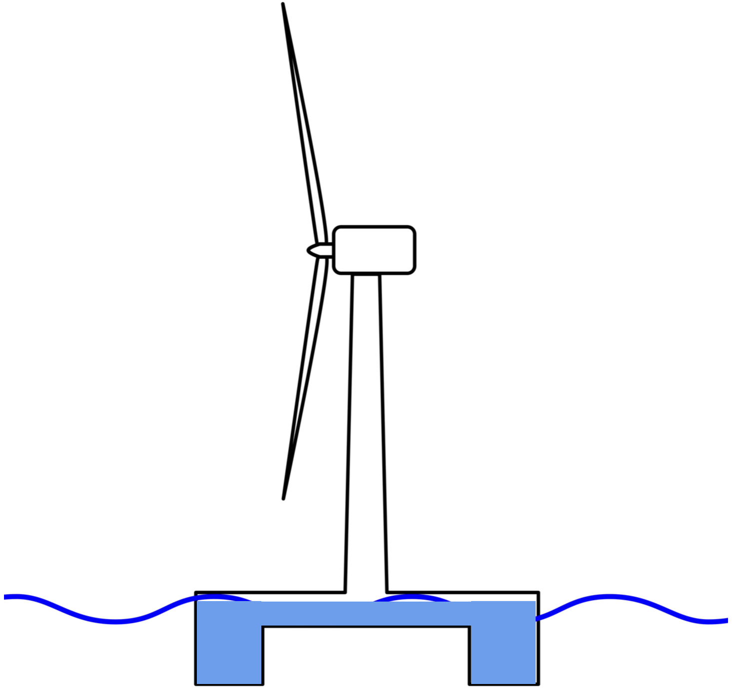
↓

Model based controller



An improved control system





An improved control system

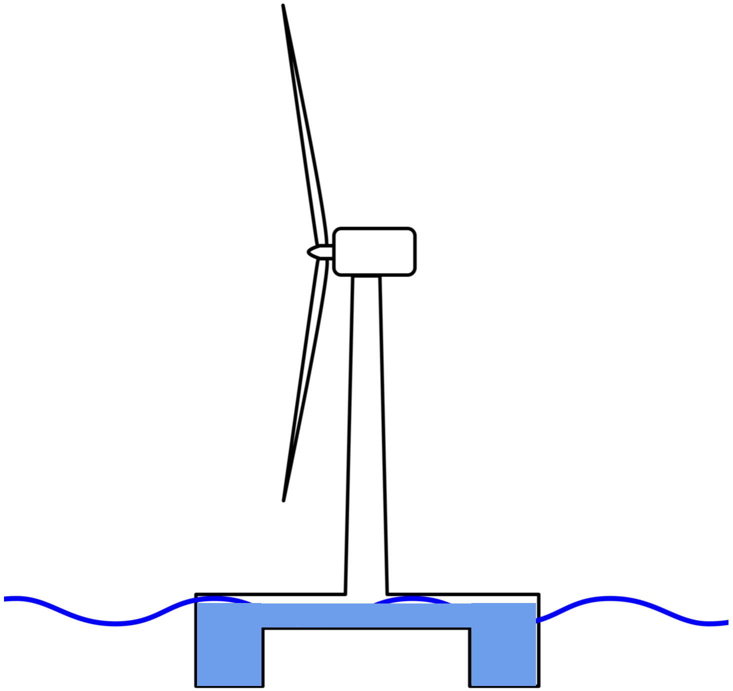
Wave prediction

↓

Model based controller

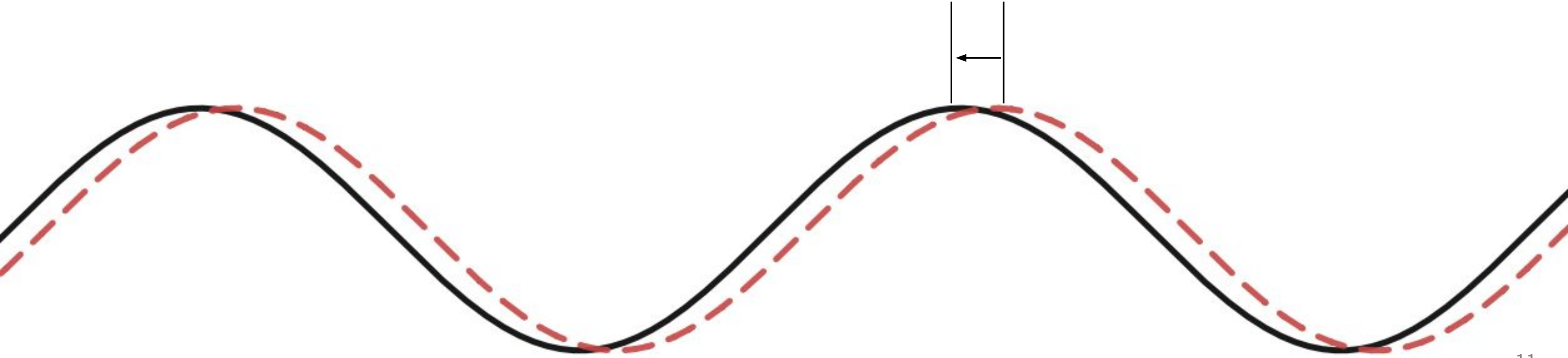
↓

Control action



Requirements of the wave forecast

- Fast enough for real time
- Good phase agreement
- Balance between **physical fidelity** and **operational efficiency**



The future of a wave?

Simplest, first order

- Linear wave models

too cold

The future of a wave?

Simplest, first order

- Linear wave models

too cold

Higher order

- Higher order spectral (HOS) methods (Dommermuth & Yue)
- Higher order Eulerian (Stokes)
- Neural networks (Mohaghegh)

too hot

The future of a wave?

Simplest, first order

- Linear wave models

too cold

Higher order

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too hot

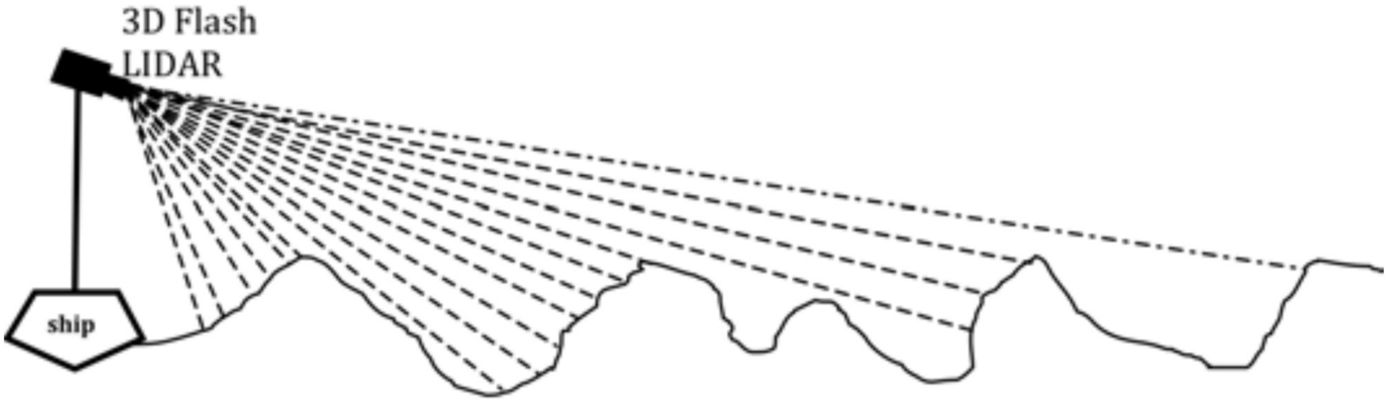
Efficient with higher order properties

- Lagrangian models (Nouguier, Guérin)

just right

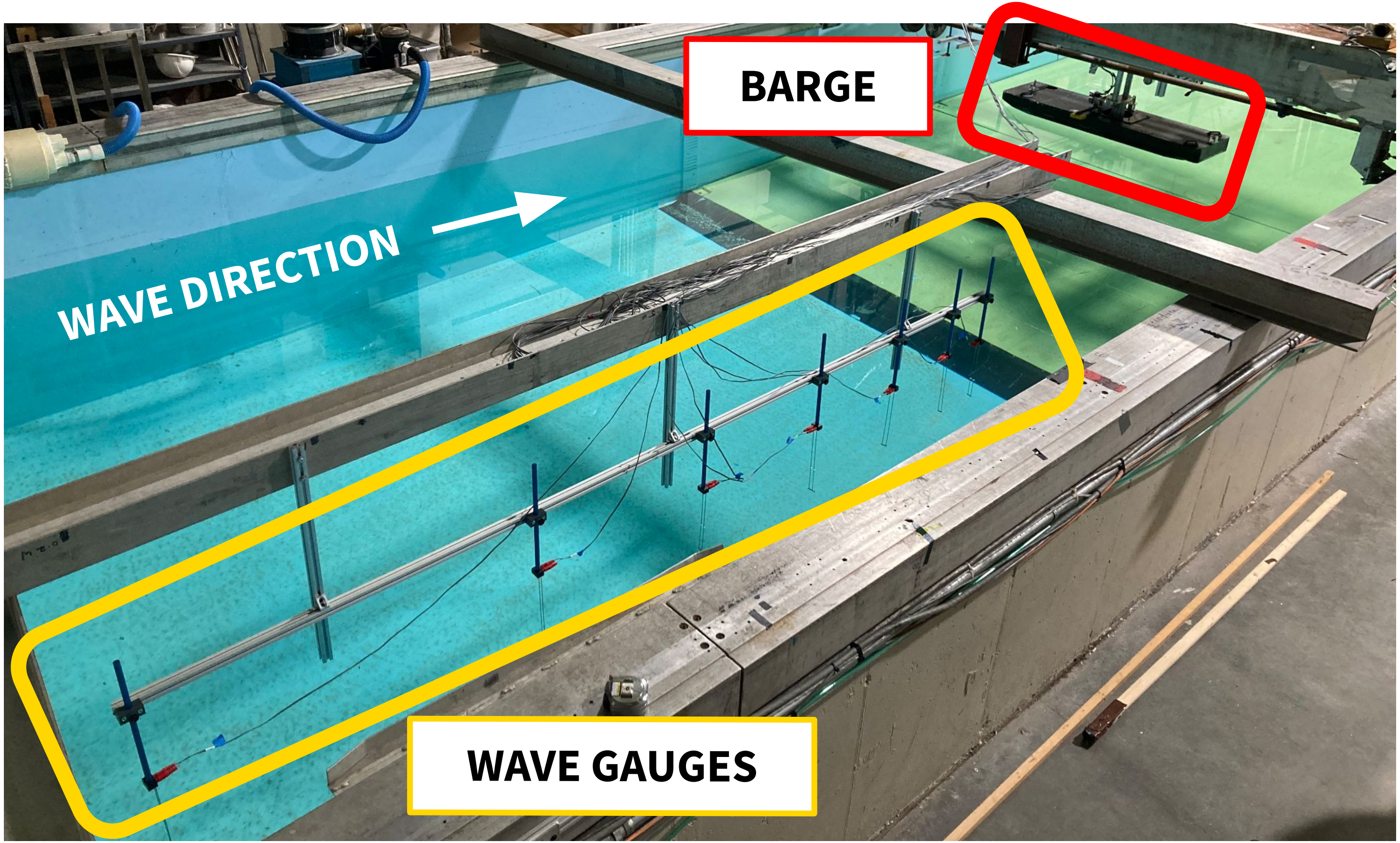
Objective

- Develop and test wave forecast algorithms using the Lagrangian models
  - Use LiDAR-like upstream wave measurements
- Couple them with a control mechanism to modify the floating structure's motion

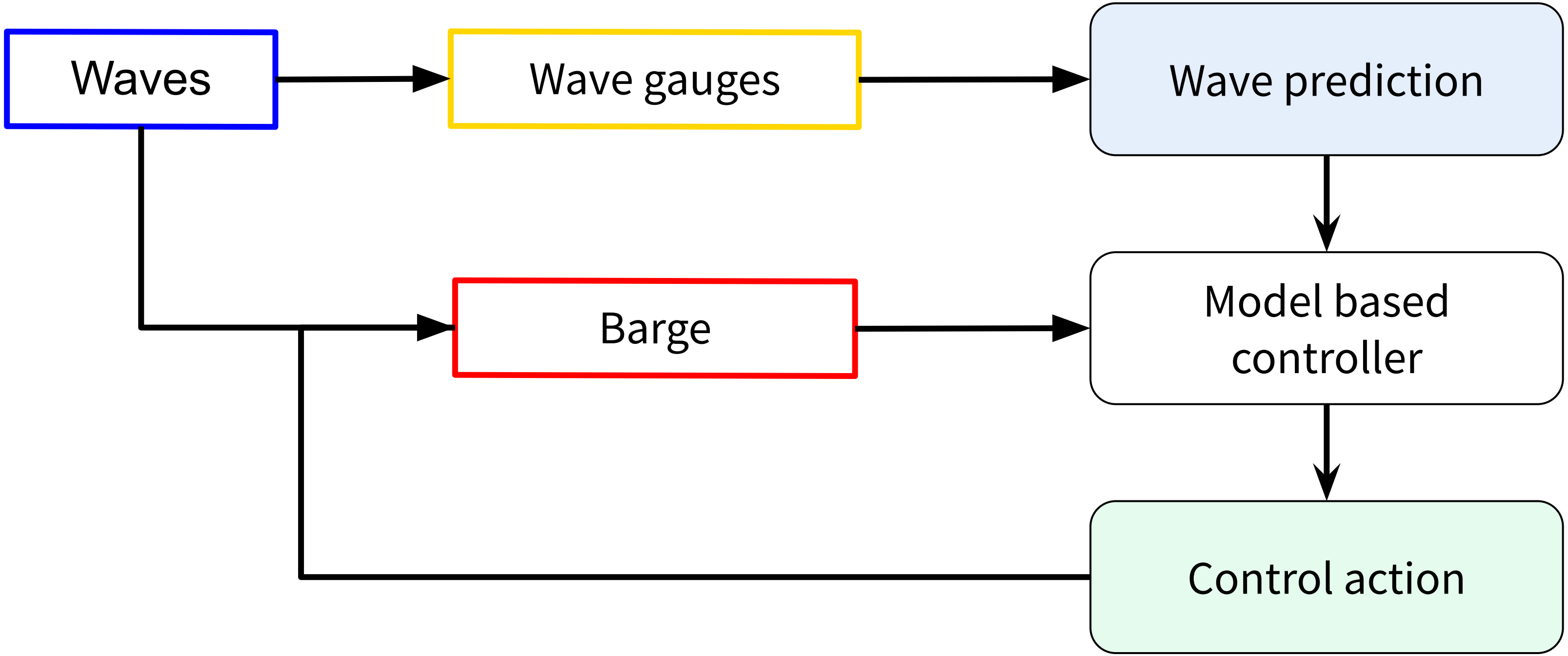


International Offshore and Polar Engineering Conference, I. S. of O. and P. E. (Ed.). (2011). *The proceedings of the twenty-first (2011) International Offshore and Polar Engineering Conference: Maui, Hawaii, USA, June 19-24, 2011*. International Society of Offshore and Polar Engineers.

Lab experiment

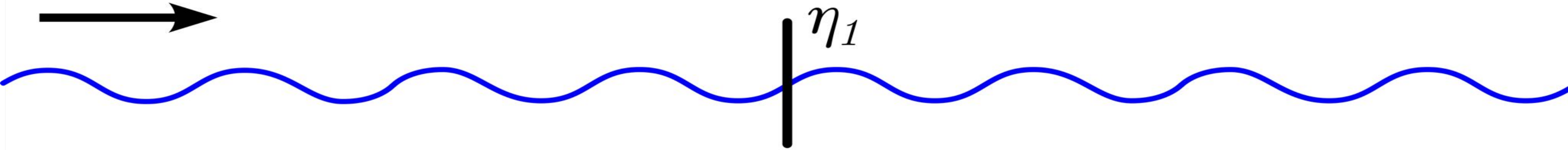


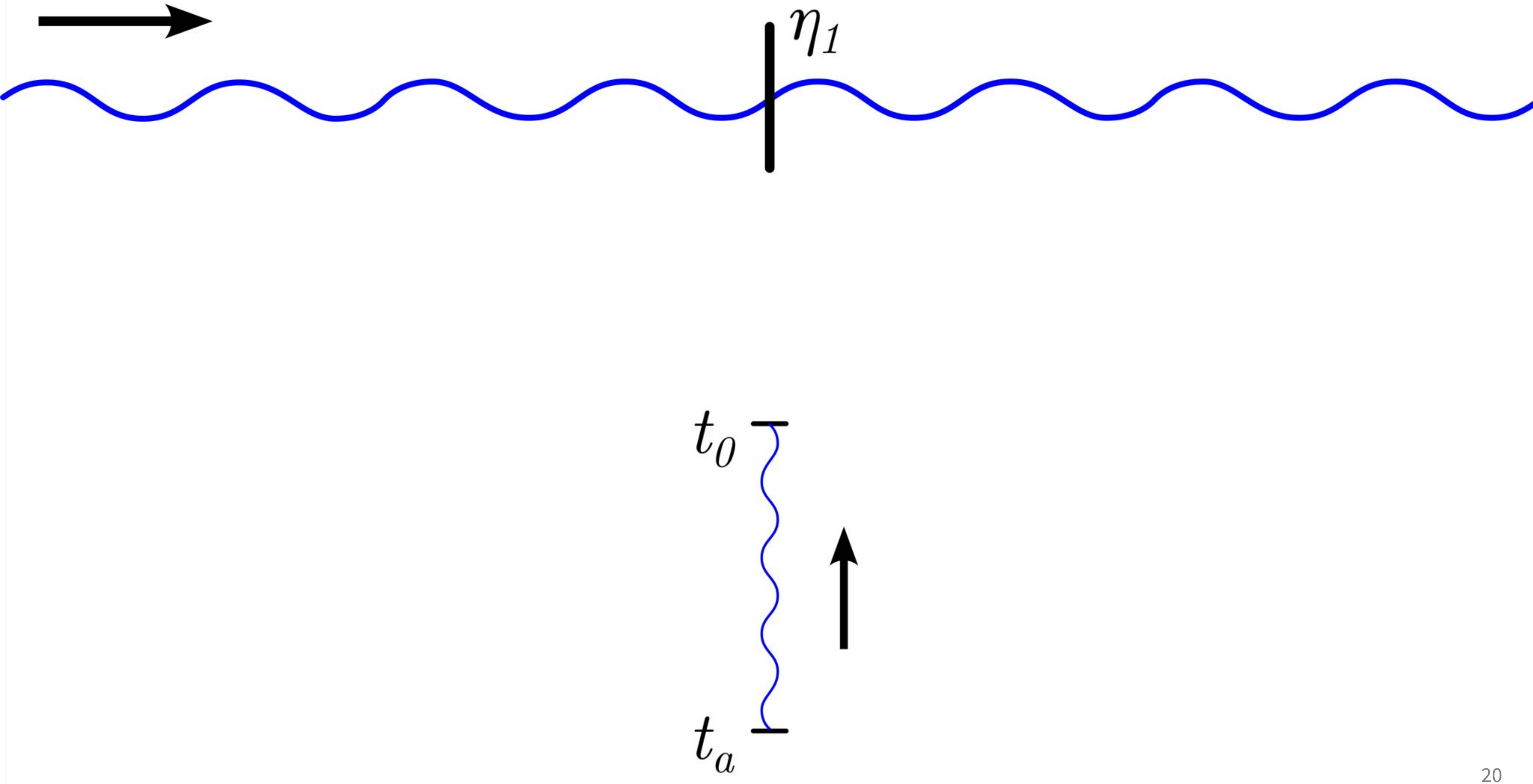
System overview

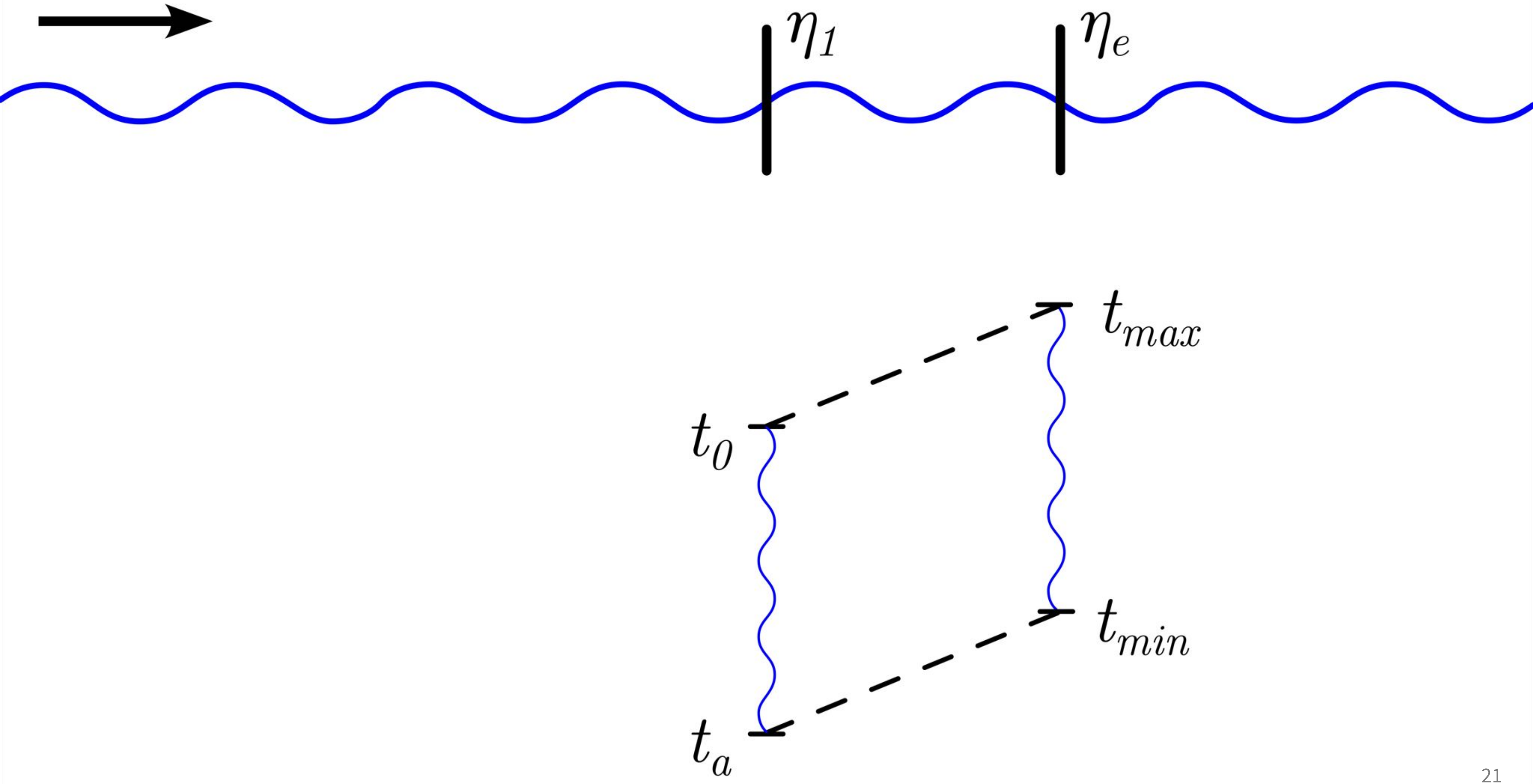


Fundamental of wave forecasting

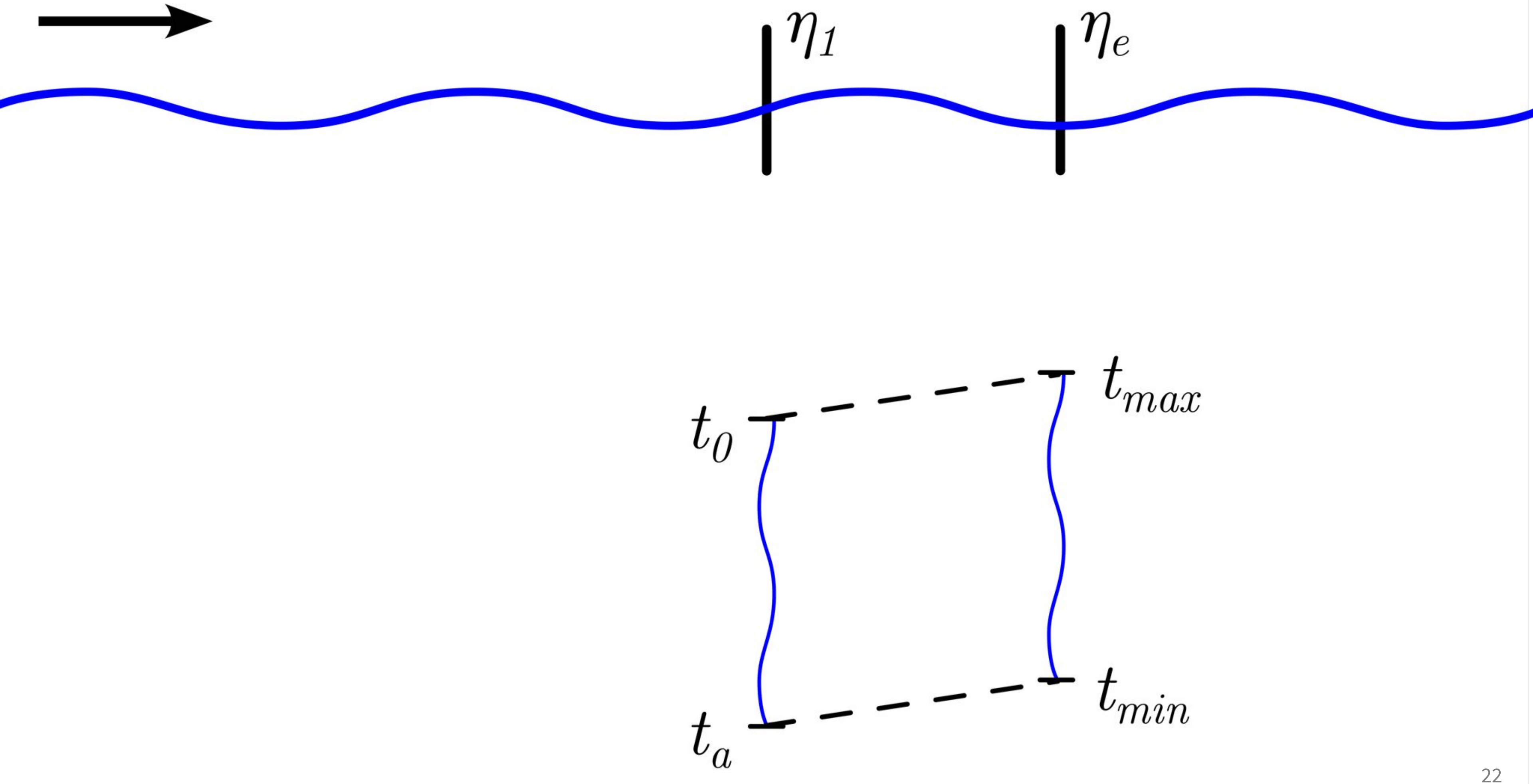
given a wave…

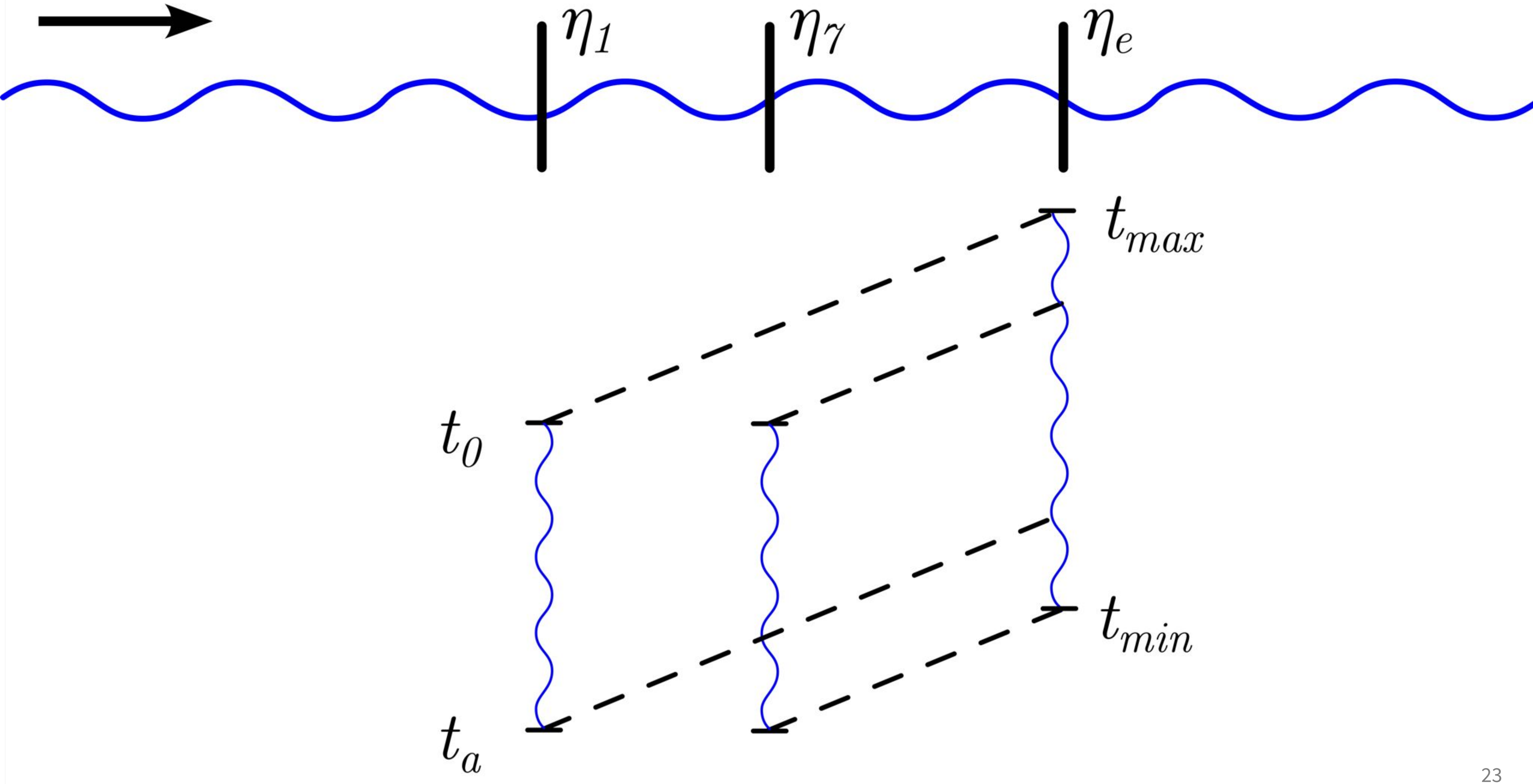

η_1

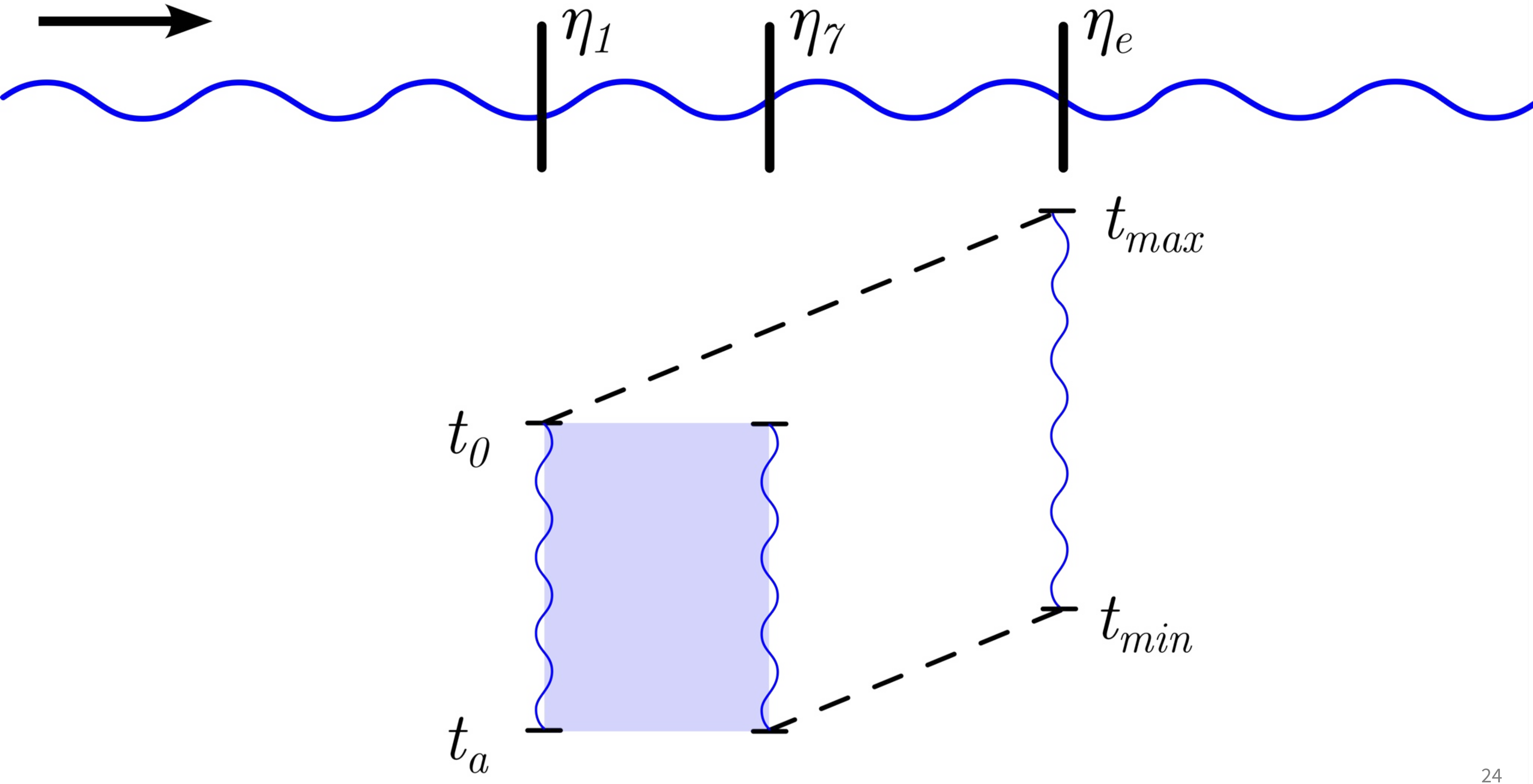

η_1
t_0
t_a



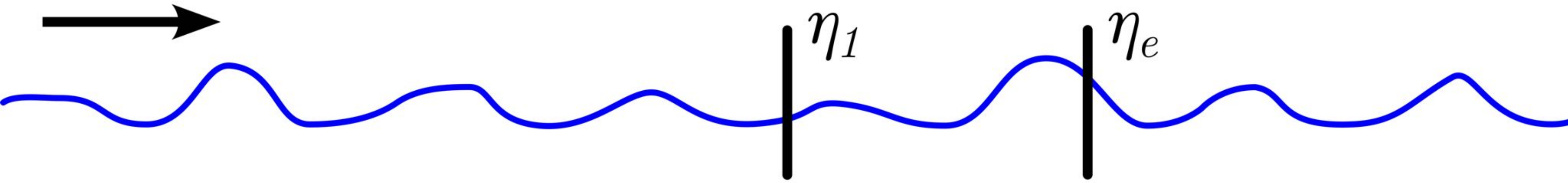
η_1
η_e
t_{max}
t_0
t_{min}
t_a

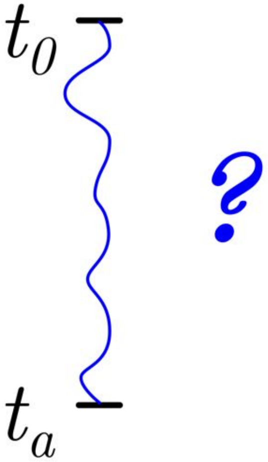

η_1
η_e
t_0
t_{max}
t_a
t_{min}

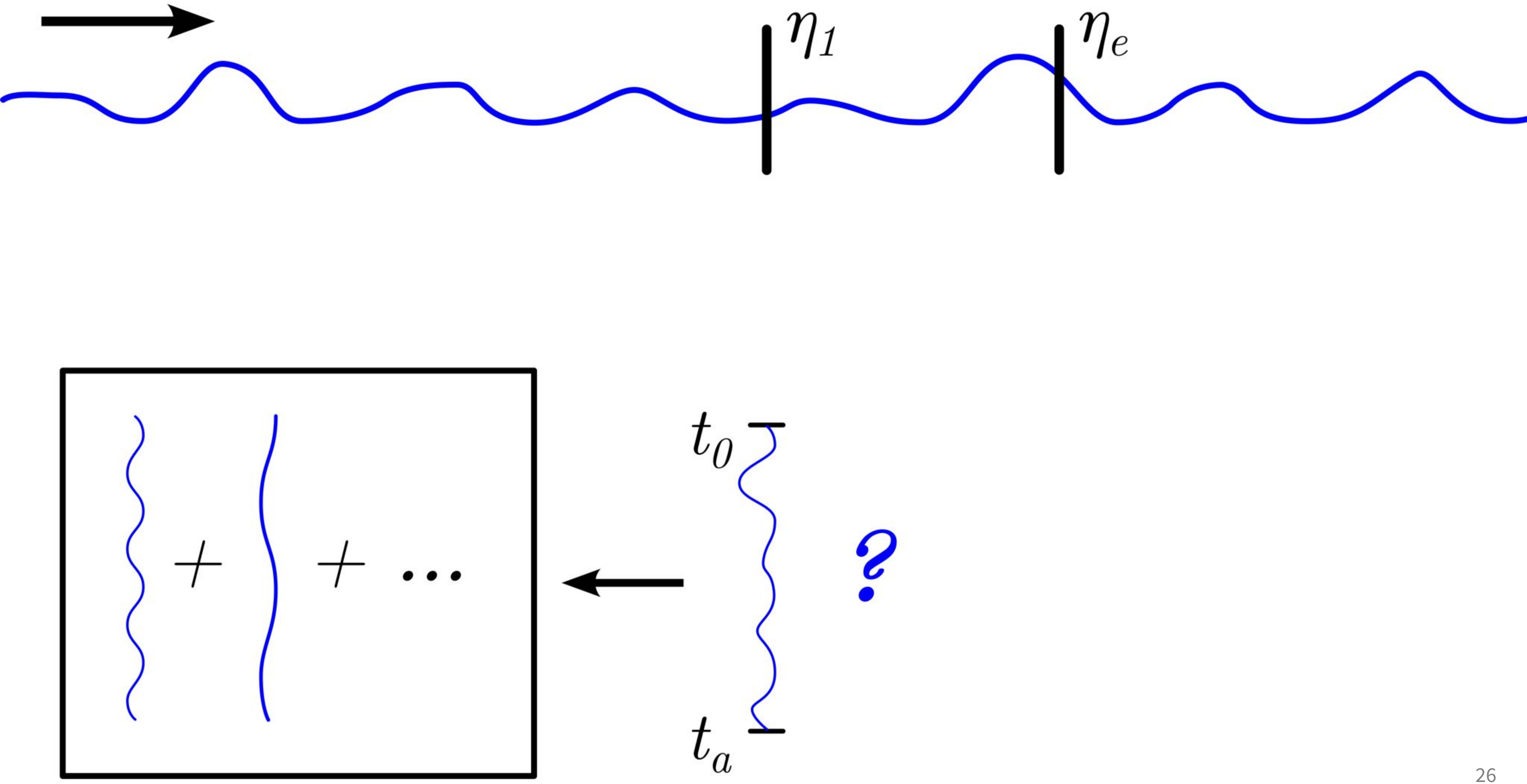

η_1
η_7
η_e
t_{max}
t_0
t_{min}
t_a



η_1
η_7
η_e
t_{max}
t_0
t_{min}
t_a


η_1
η_e


t_0
?
t_a



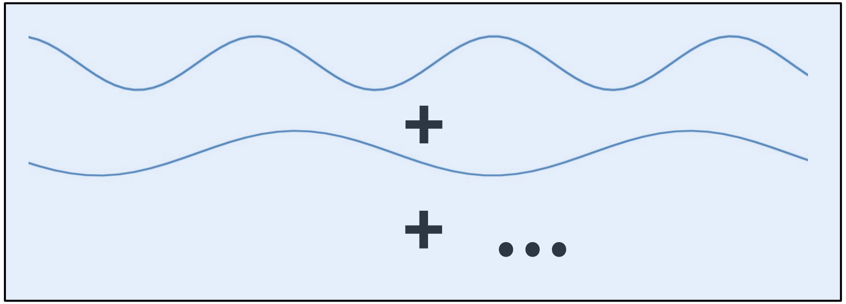
η_1
η_e
$+$
$+ \cdots$
t_0
t_a
?

Model an irregular sea state?

- Surface representation
  - N → number of frequencies considered
  - k → wavenumbers
  - ω → frequencies

$$\tilde{\eta}(x,t) = \sum_{n=1}^{N} \{a_n \cos \Psi_n + b_n \sin \Psi_n\}\,;\, \Psi_n = (k_n x - \omega_n t)$$

$\tilde{\eta}(x,t)$ =



$\omega^2 = gk$

Model an irregular sea state?

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- Find weights that minimize difference between **measured** and **reconstructed** surfaces

$$C = \frac{1}{L}\sum_{l=1}^{L}(\tilde{\eta}_l - \eta_l)^2$$

Model an irregular sea state!

$\omega^2 = gk$

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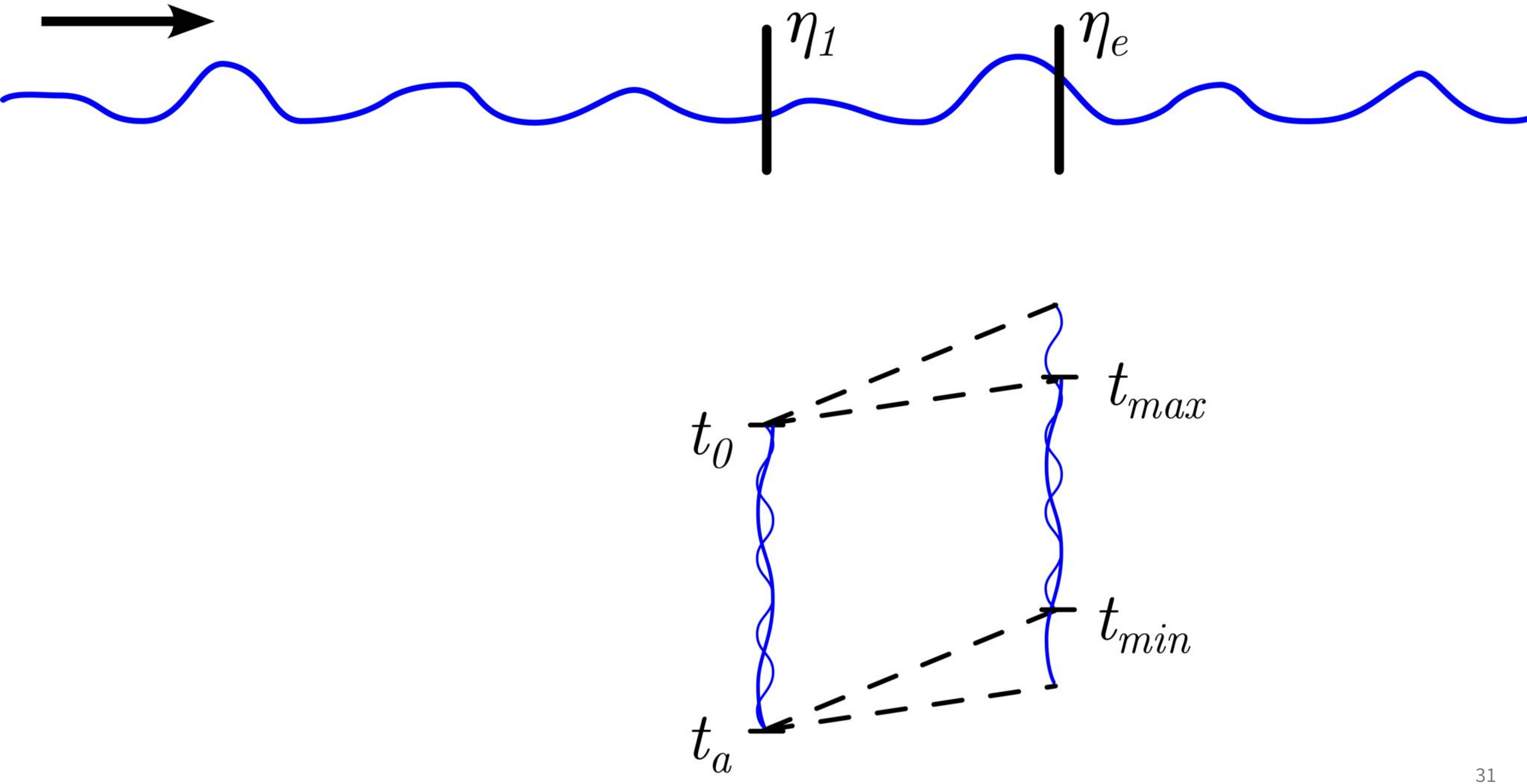
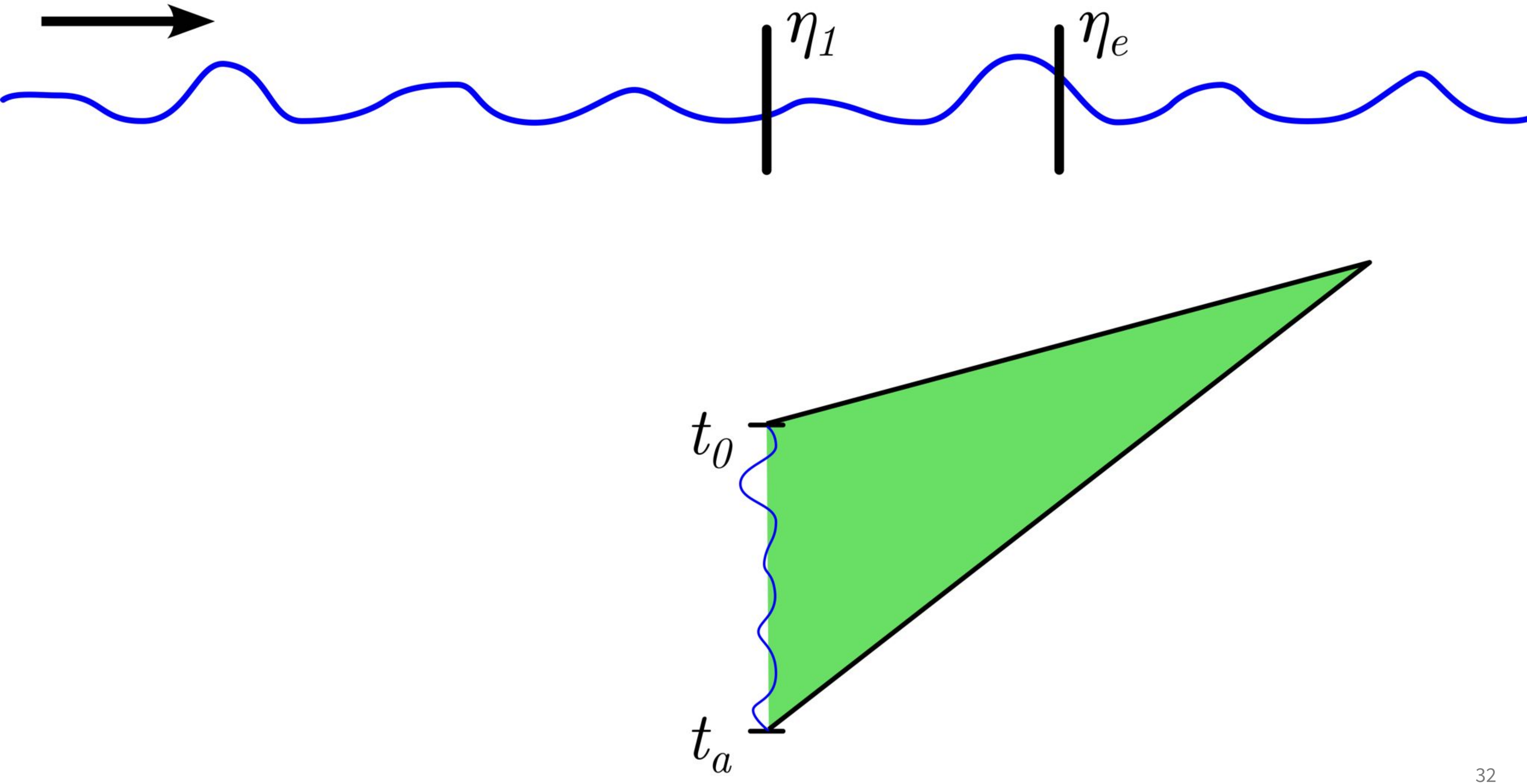
- Find weights that minimize difference between **measured** and **reconstructed** surfaces

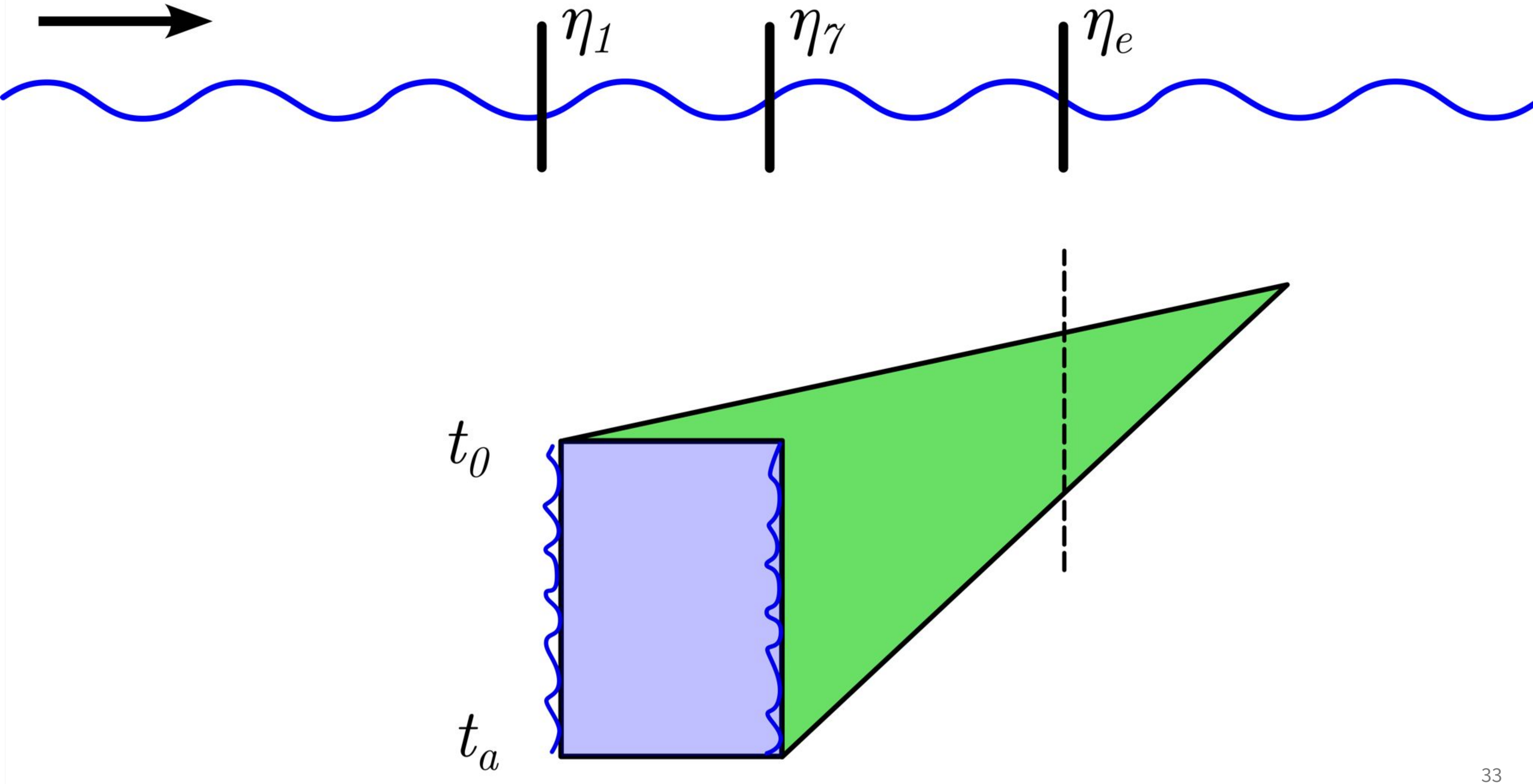
x, t → known from measurement
k, ω → preselected based on spectrum

$$C = \frac{1}{L}\sum_{l=1}^{L}(\tilde{\eta}_l - \eta_l)^2$$


η_1
η_e
t_0
t_{max}
t_{min}
t_a



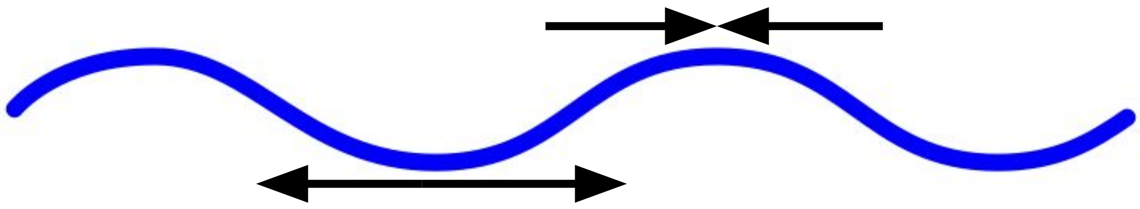
η_1
η_e
t_0
t_a


η_1
η_7
η_e
t_0
t_a

Trough-crest asymmetry (Nouguier)

Spatial Hilbert transform on LWT solution

$$\eta_{\mathrm{CWM}}(\boldsymbol{x} + \boldsymbol{D}(\boldsymbol{x}, t), t) = \eta_{\mathrm{LWT}}(\boldsymbol{x}, t)$$



Amplitude dispersion (Guérin)

Amplitude dispersion

$$\mathcal{U}_{s0} = \sum_{n=1}^{N} \left(a_n^2 + b_n^2\right) \omega_n k_n$$

$$\tilde{\omega_n} = \omega_n + k_n \mathcal{U}_{s0}/2$$

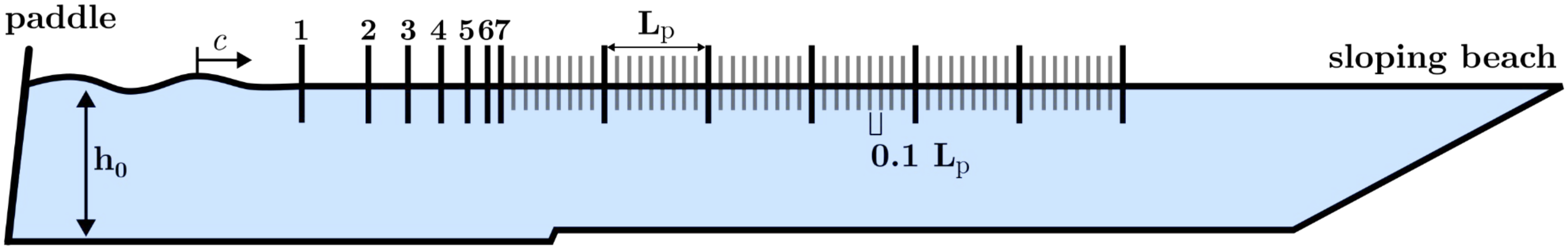
$$\tilde{\eta}(x,t) = \sum_{n=1}^{N} \left\{a_n \cos \Psi_n + b_n \sin \Psi_n\right\} ; \Psi_n = (k_n x - \tilde{\omega_n} t)$$

Nonlinear effects (efficient lagrangian models)

	Linear dispersion	Amplitude dispersion
Linear shape	Linear wave theory (LWT)	LWT + corrected dispersion relation (LWT-CDR)
Trough-crest asymmetry	Choppy wave model (CWM) (Nouguier, 2009)	Improved choppy wave model (ICWM) (Guérin, 2019)

Numerical Wave Tank (NWT)

- Physically realistic wave testing data with LiDAR like measurement spacing

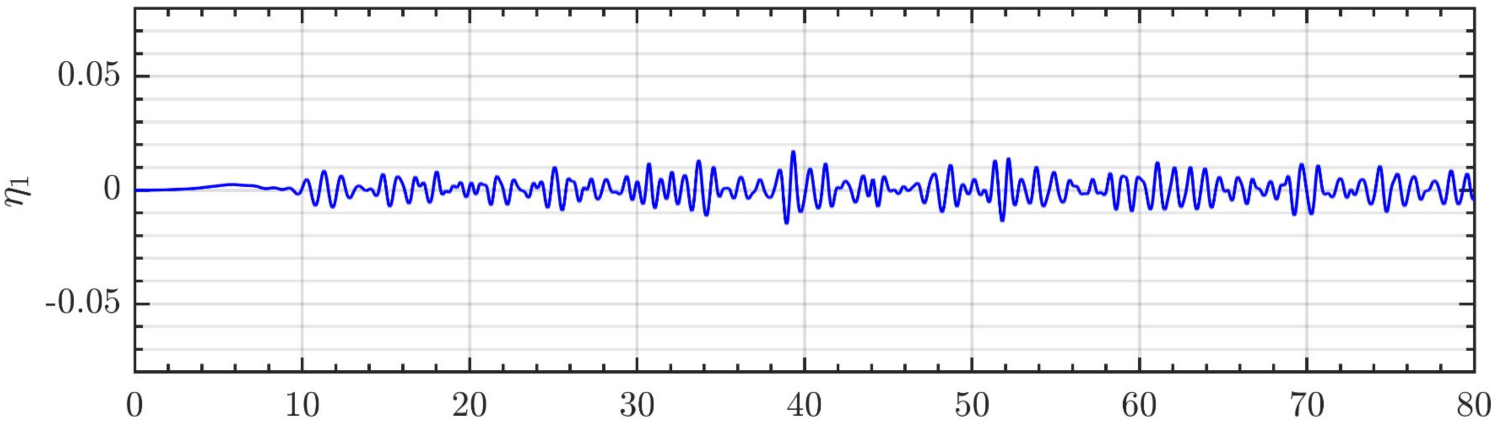


- Fully <u>nonlinear numerical wave tank</u> developed by Grilli and Subramanya, 1996; Grilli and Horrillo, 1997; Grilli et al. 2020 has been used to create synthetic wave data with which we can <u>validate our wave models</u>

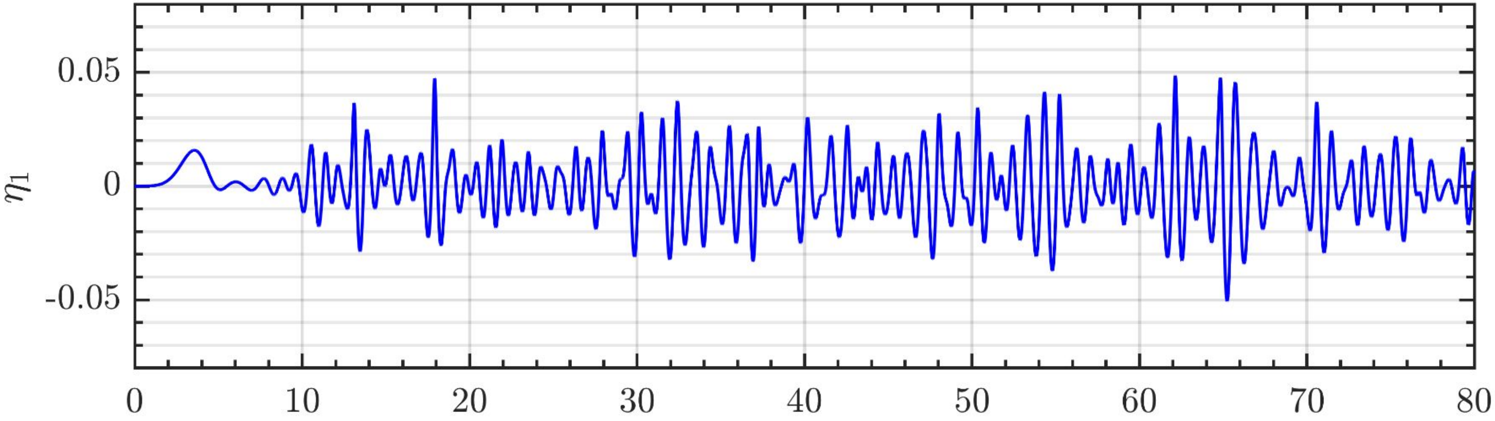
Numerical Experiment

case	Target H_s (m)	Target T_p (s)	$H_s/L_p(\%)$
A	0.020	1.0	1.281
B	0.040	1.0	2.562
C	0.060	1.0	3.844
D	0.080	1.0	5.125
E	0.100	1.0	6.406

A

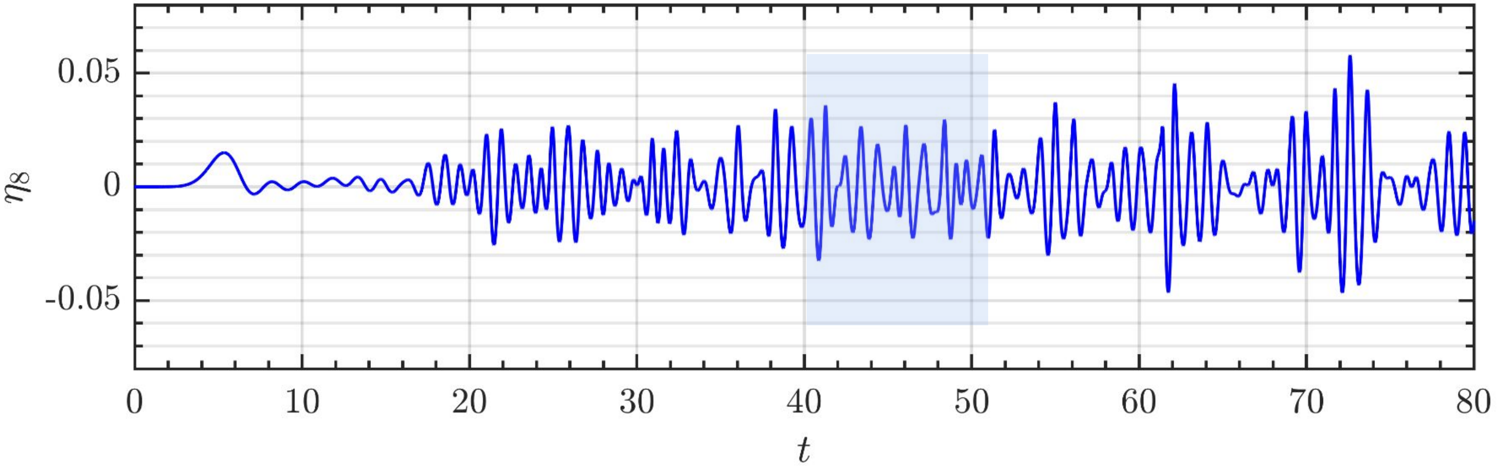


C



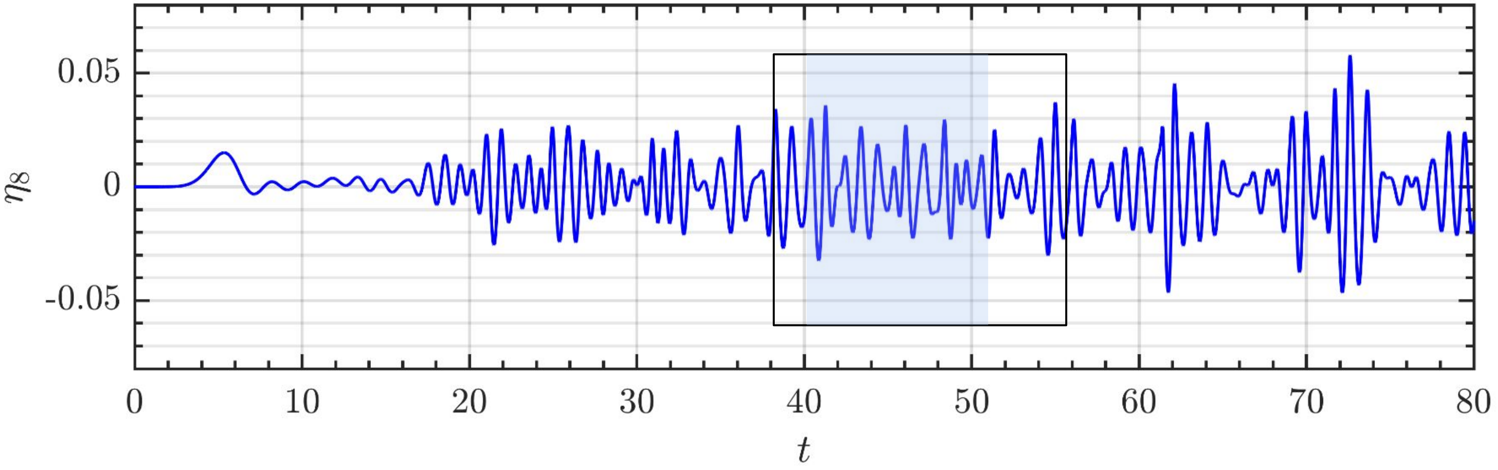
Post-process wave forecasting workflow

- Load saved file
- Evaluate spectrum for full time series
- Isolate data for model inversion

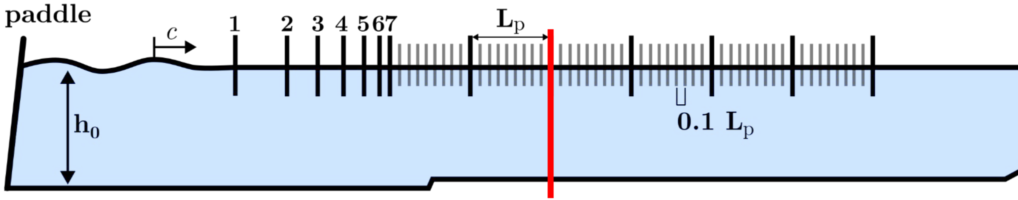


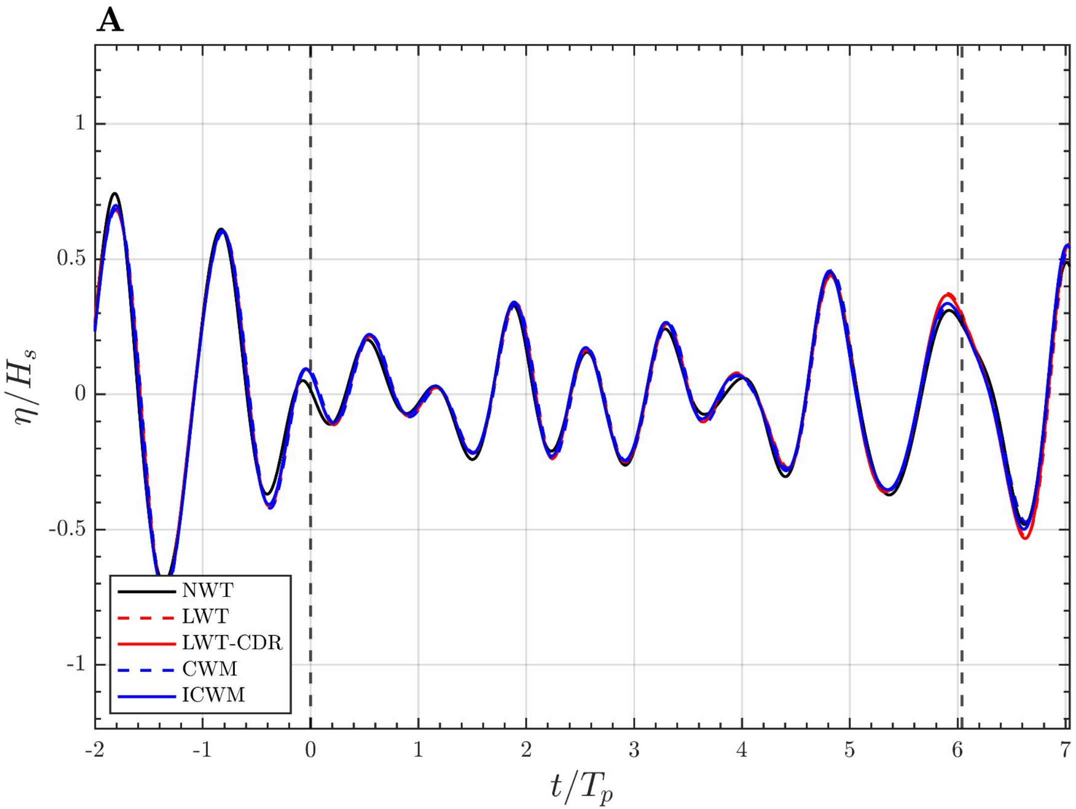
Post-process wave forecasting workflow

- Load saved file
- Evaluate spectrum for full time series
- Isolate data for model inversion
- **Evaluate model over new times, at new location**



A single realization





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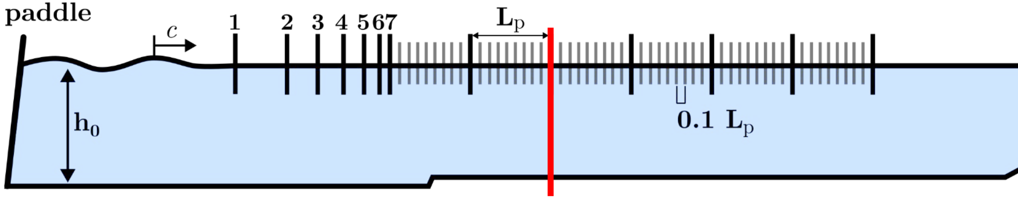

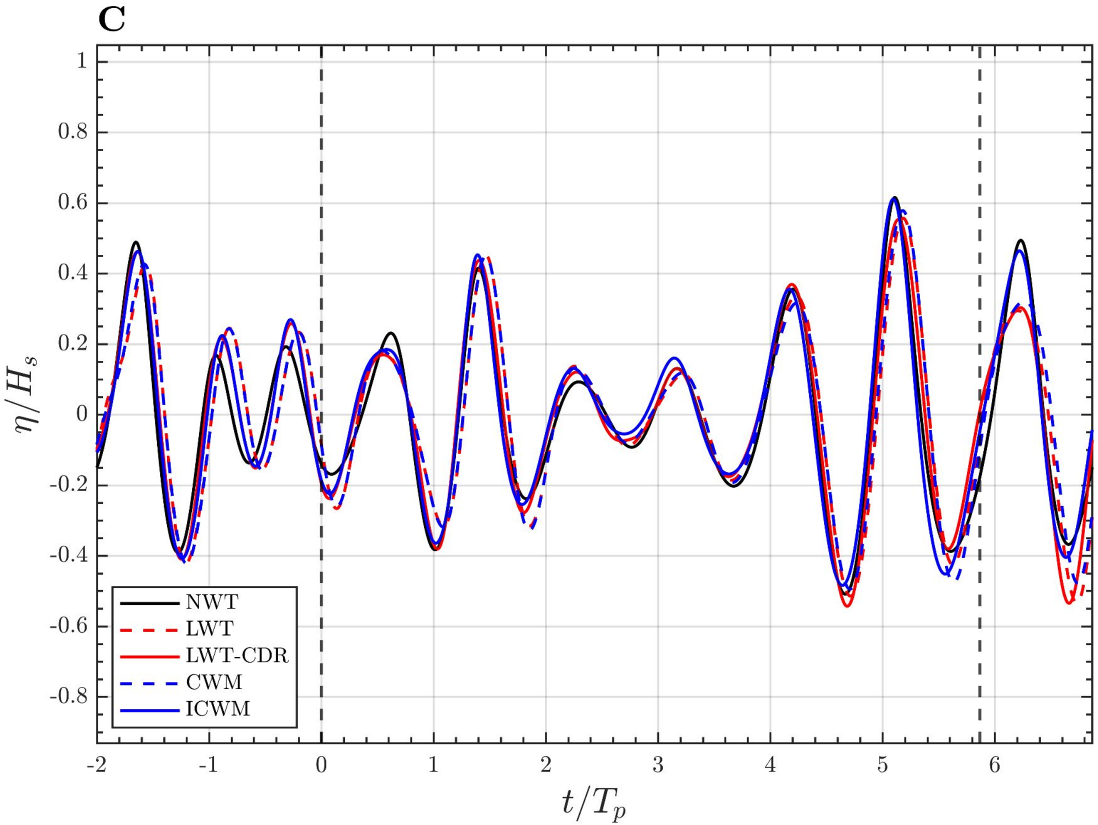

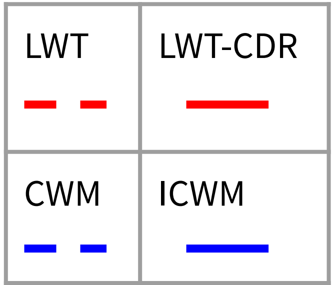

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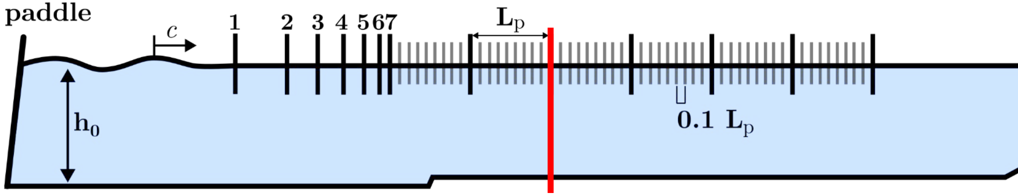
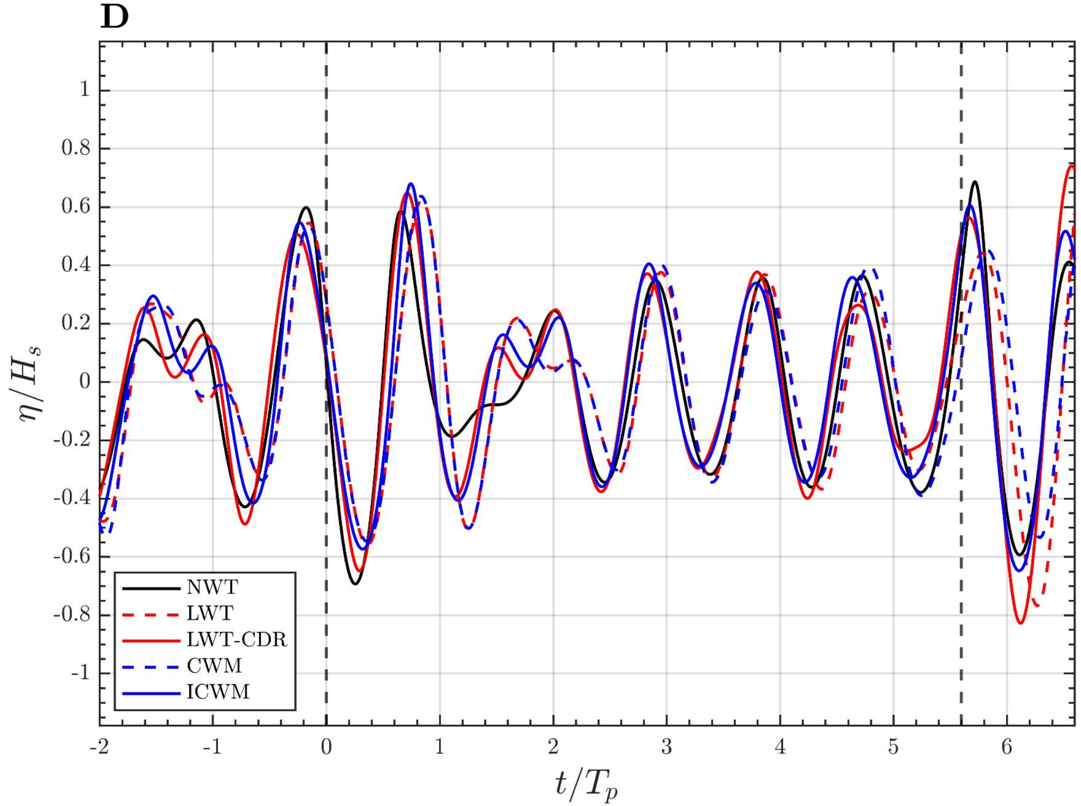




Error metrics: Elevation

$$\mathcal{E}\left(x_e, t_s\right) = \frac{1}{RH_s} \sum_{r=1}^{R} \left| \eta\left(x_e, t_s\right) - \tilde{\eta}\left(x_e, t_s\right) \right|_r$$

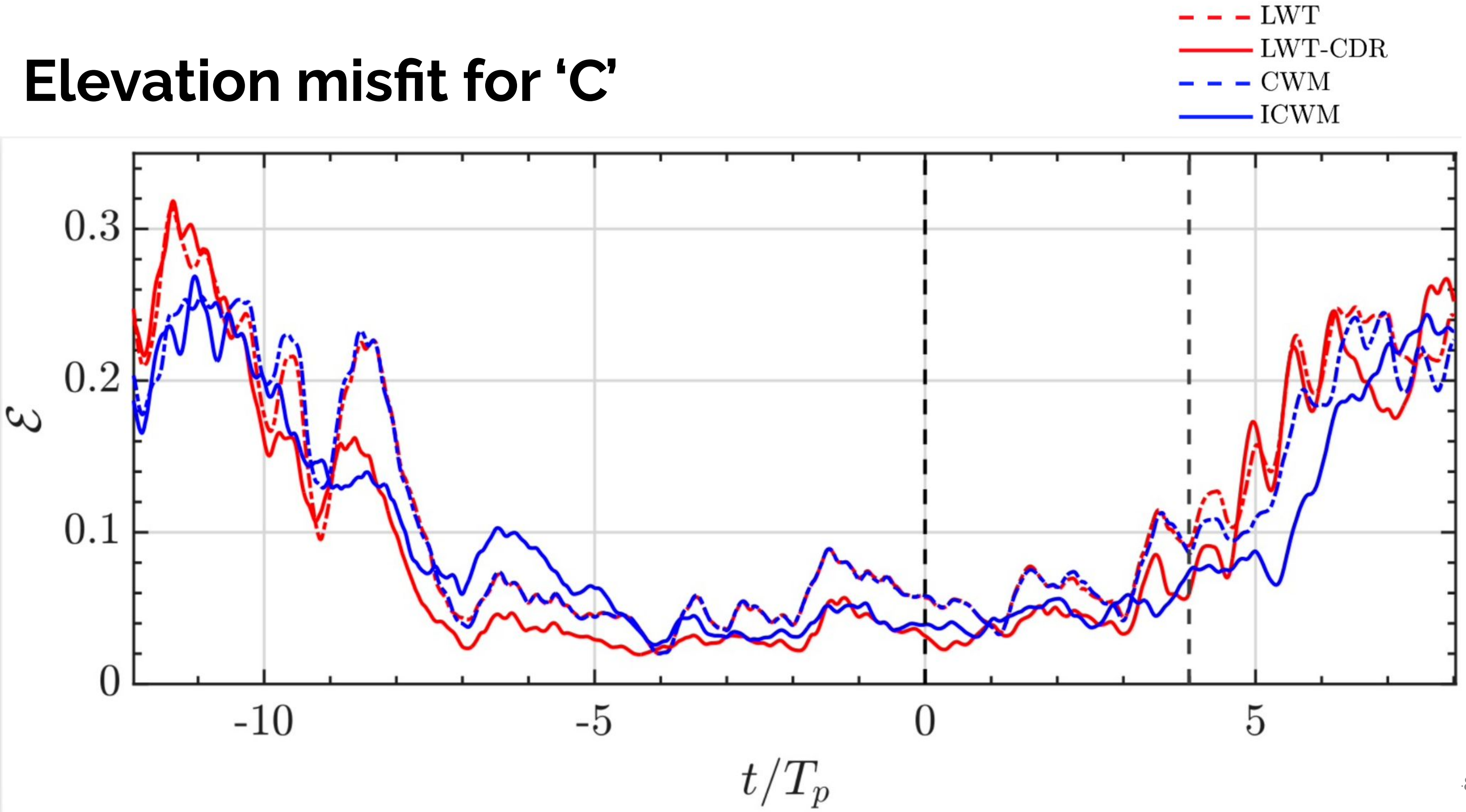
$$\mathcal{E}^F = \frac{1}{t_{\max}} \int_0^{t_{\max}} \mathcal{E}\left(x_e, t\right) dt$$

Error metrics: Phase

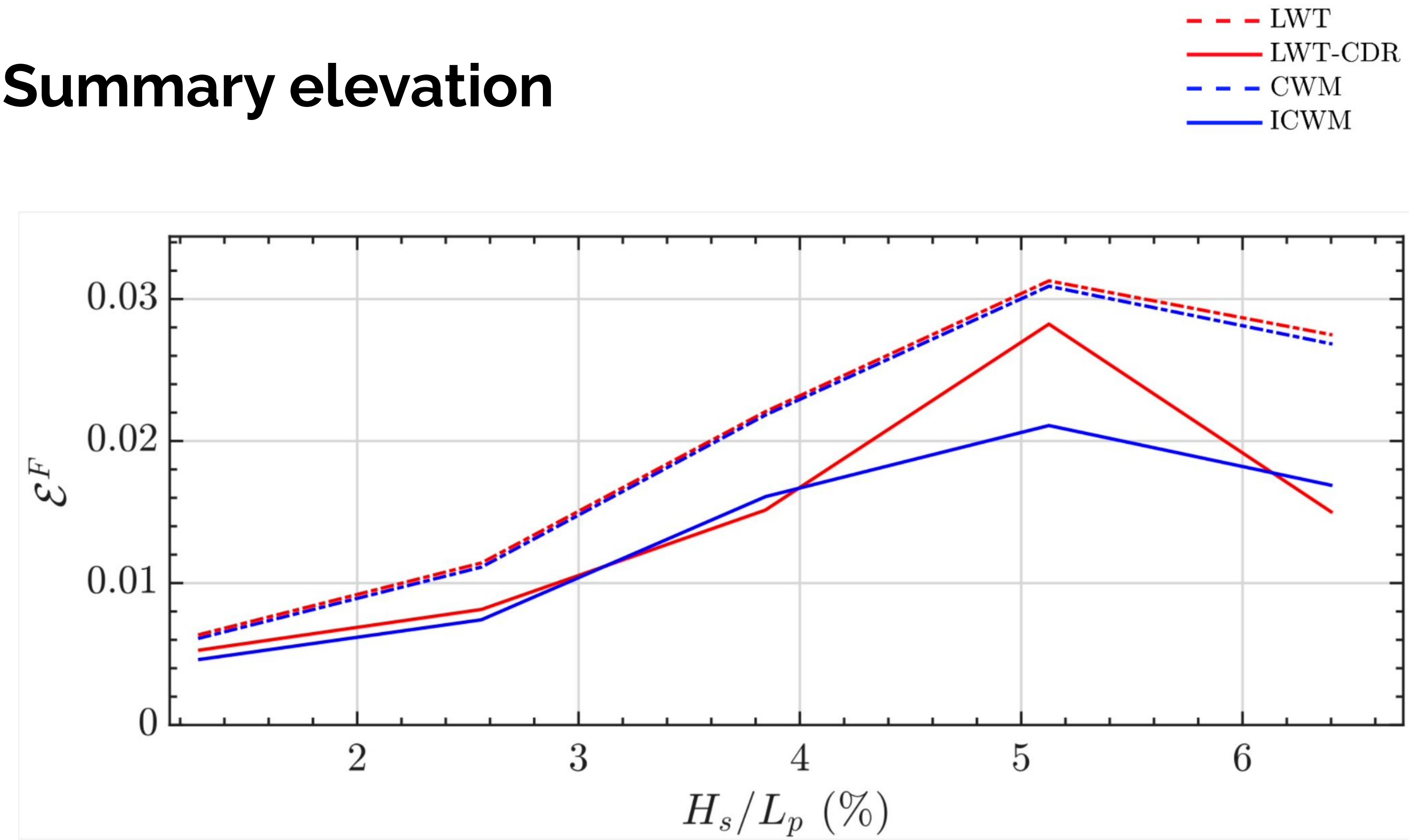
$$C(\tau) = \frac{1}{t_{\max}} \int_0^{t^{\max}} \tilde{\eta}\left(x_e, t\right) \eta_{L/NL}\left(x_e, t+\tau\right) \mathrm{d}t$$

$$\mathcal{E}^P = \left|\tau_{\max}\right| / T_p$$

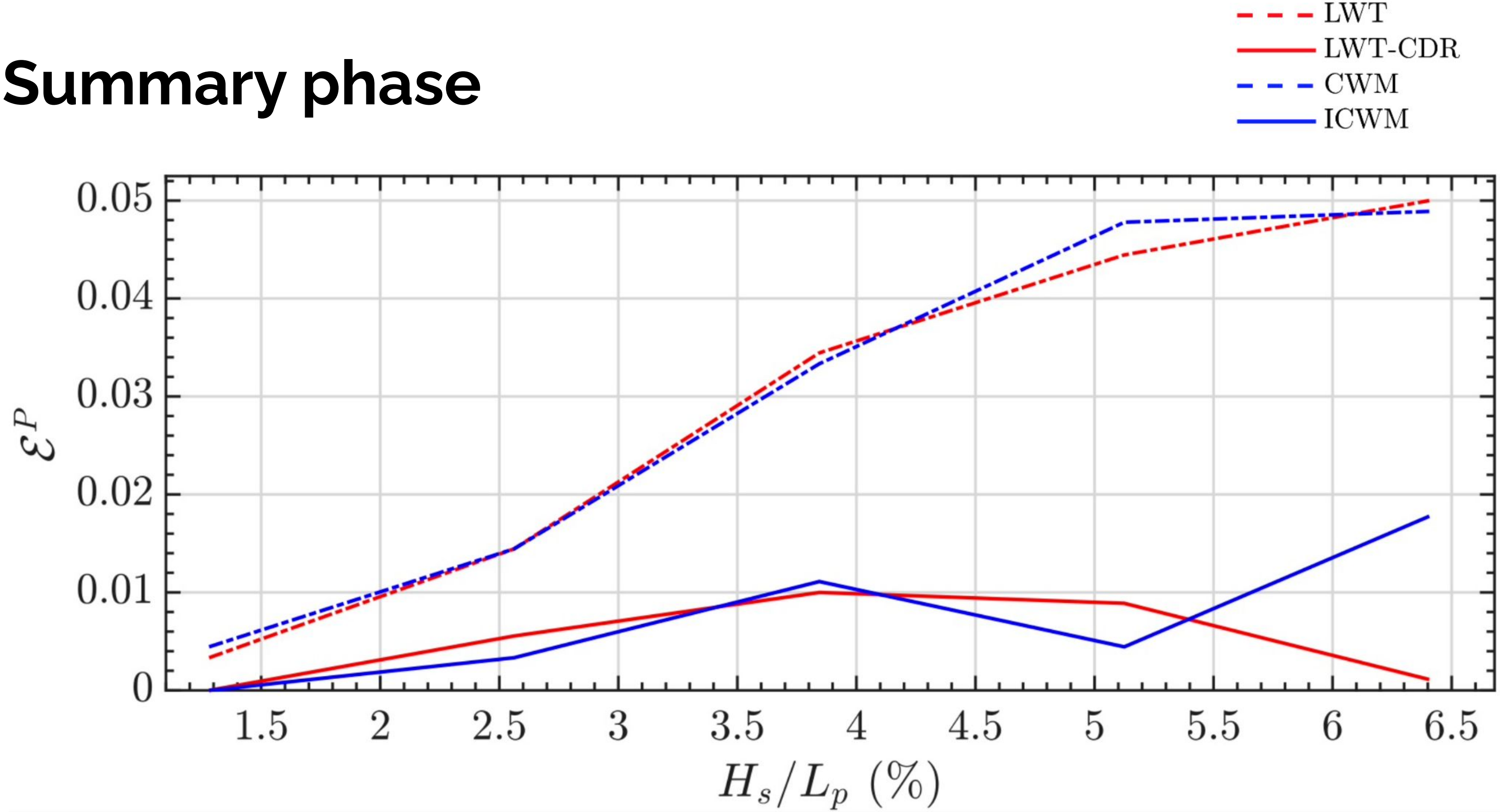
Elevation misfit for 'C'



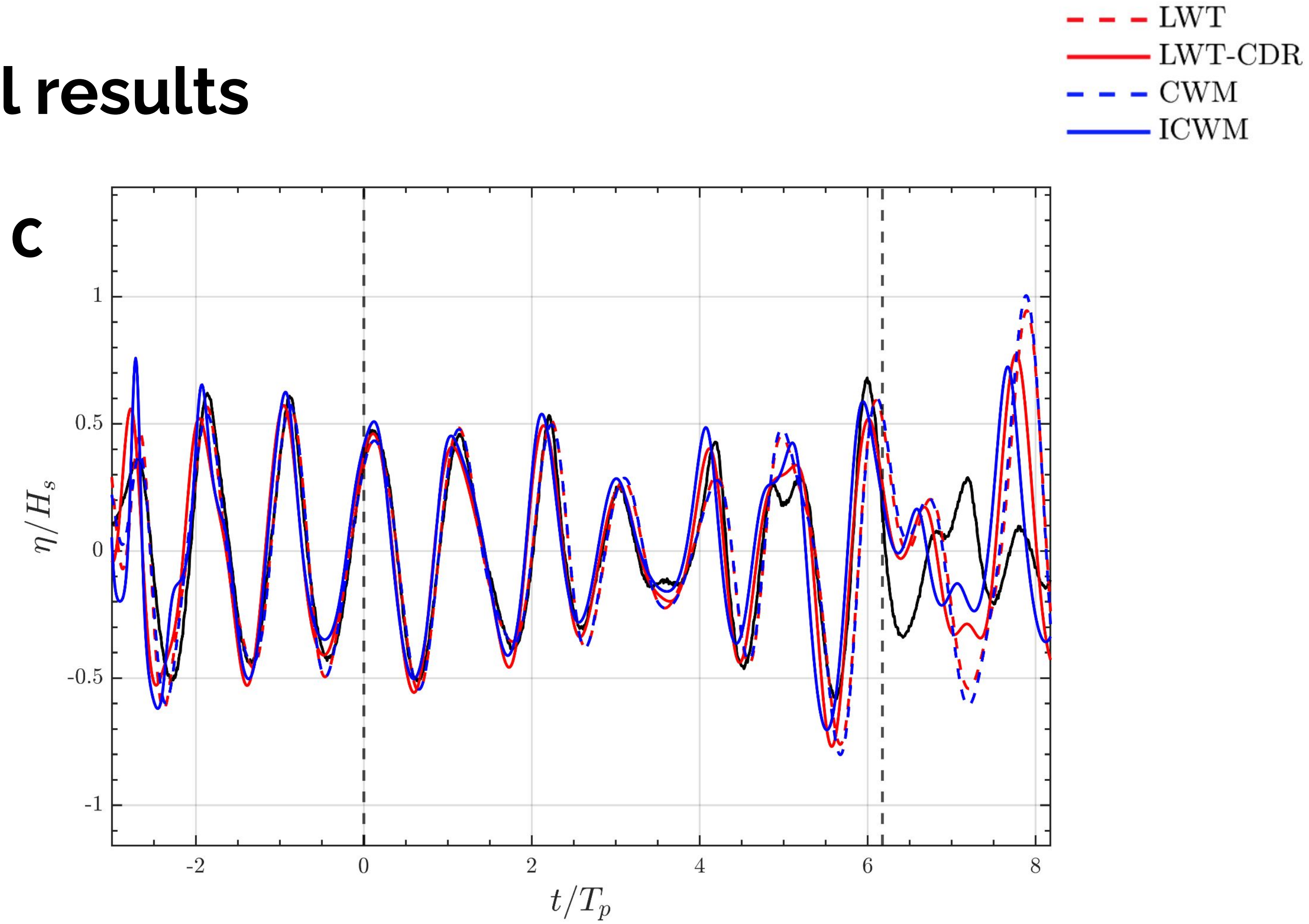
Summary elevation



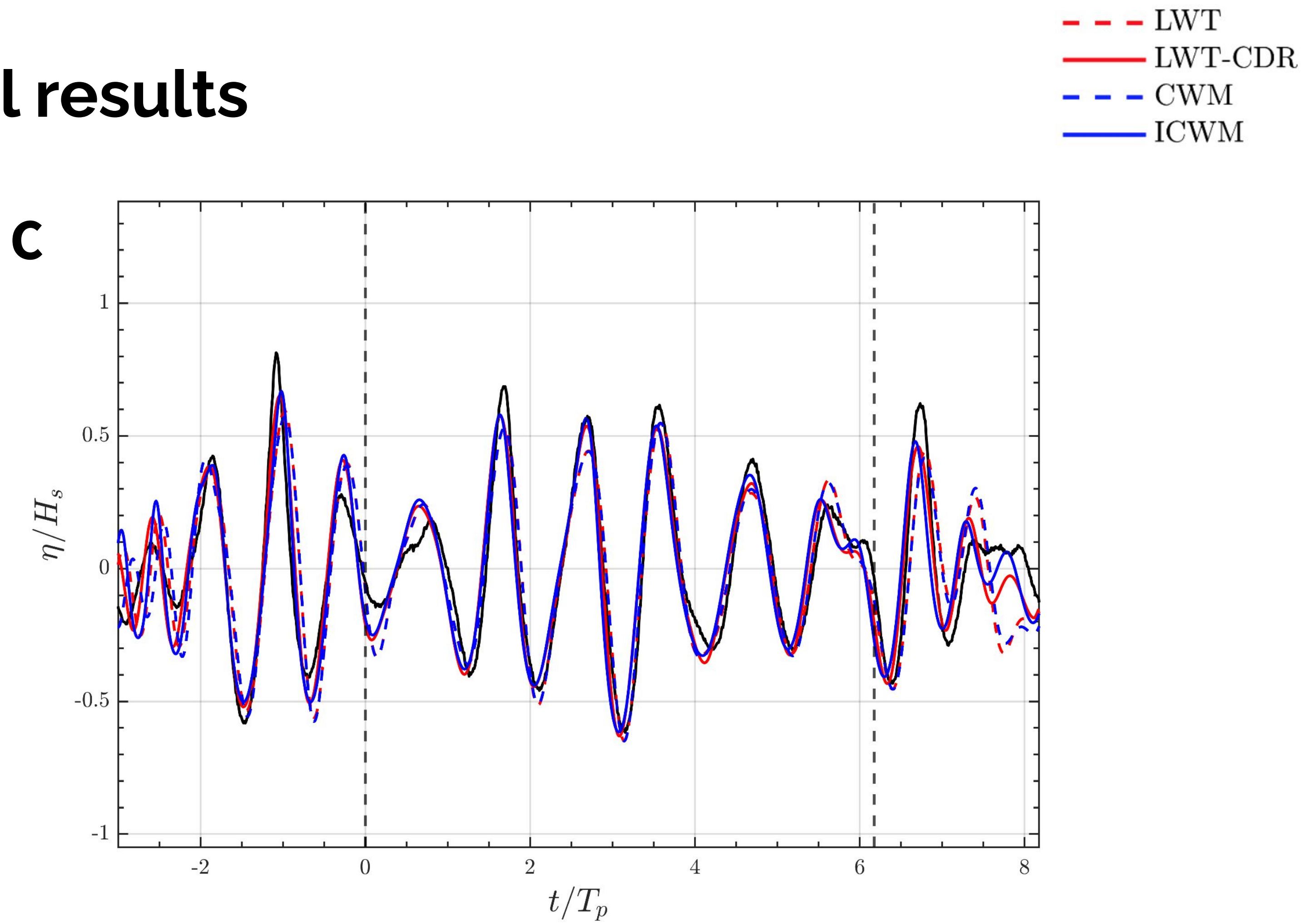
Summary phase



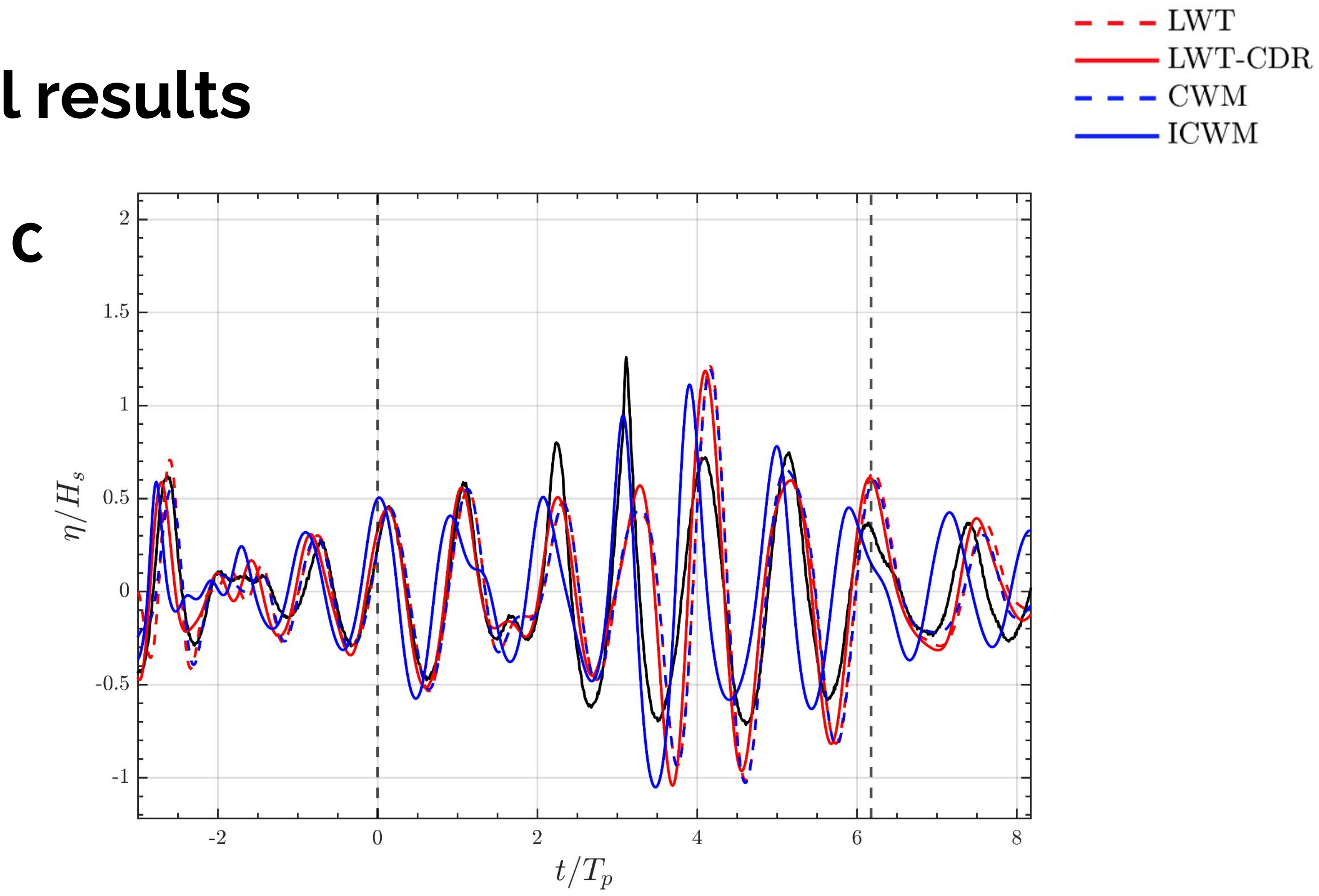
Physical results



Physical results



Physical results



Physical wave study

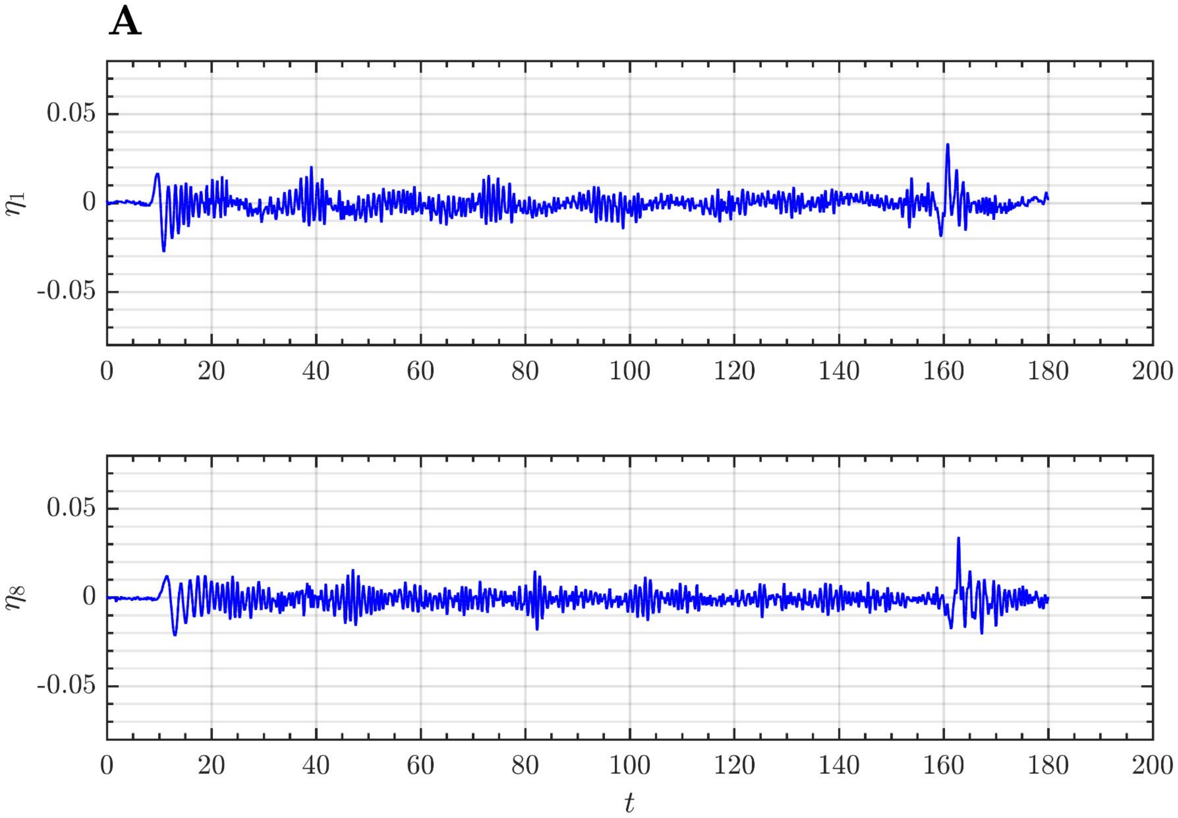
Figures example instances

Takeaways from physical study

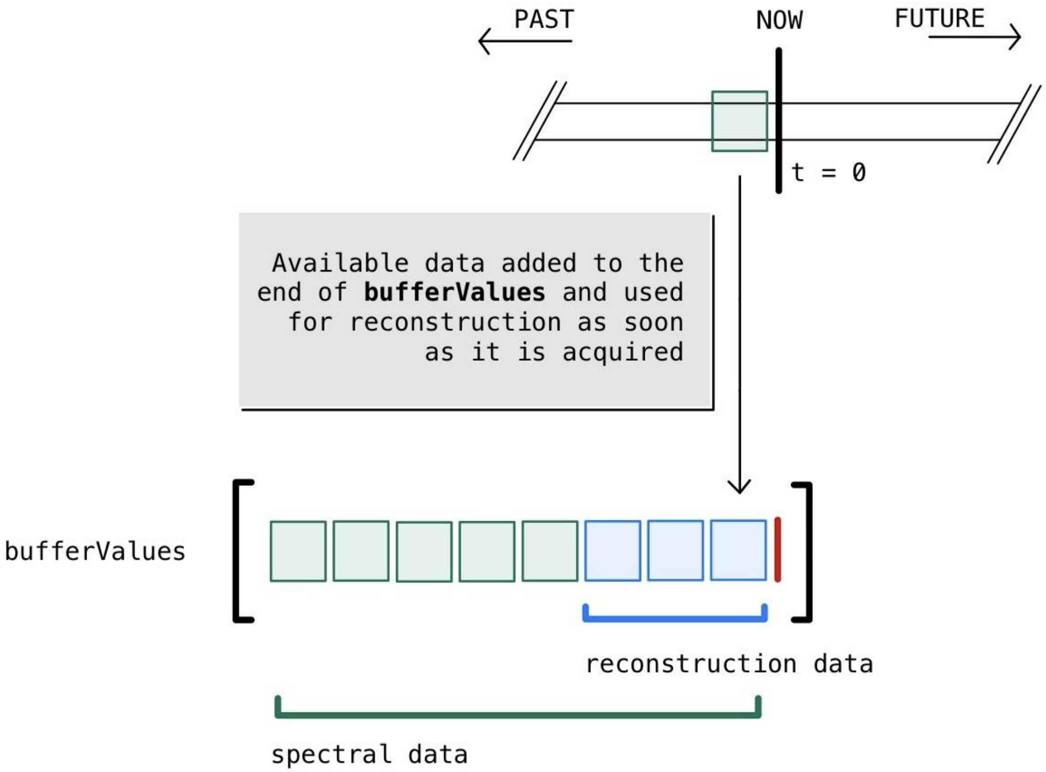
Show some cases that work well, mention that it occasionally fails, mention the reasons why and solutions to this problem that weren’t treated in this work

- 1D wave prediction model used here is affected by sloshing (2d modes), would need to be extended (gauges on both sides)
- Physics which we did not account for affecting the prediction process
- The importance of robustness should be considered if these improved models are to be deployed on a real turbine.

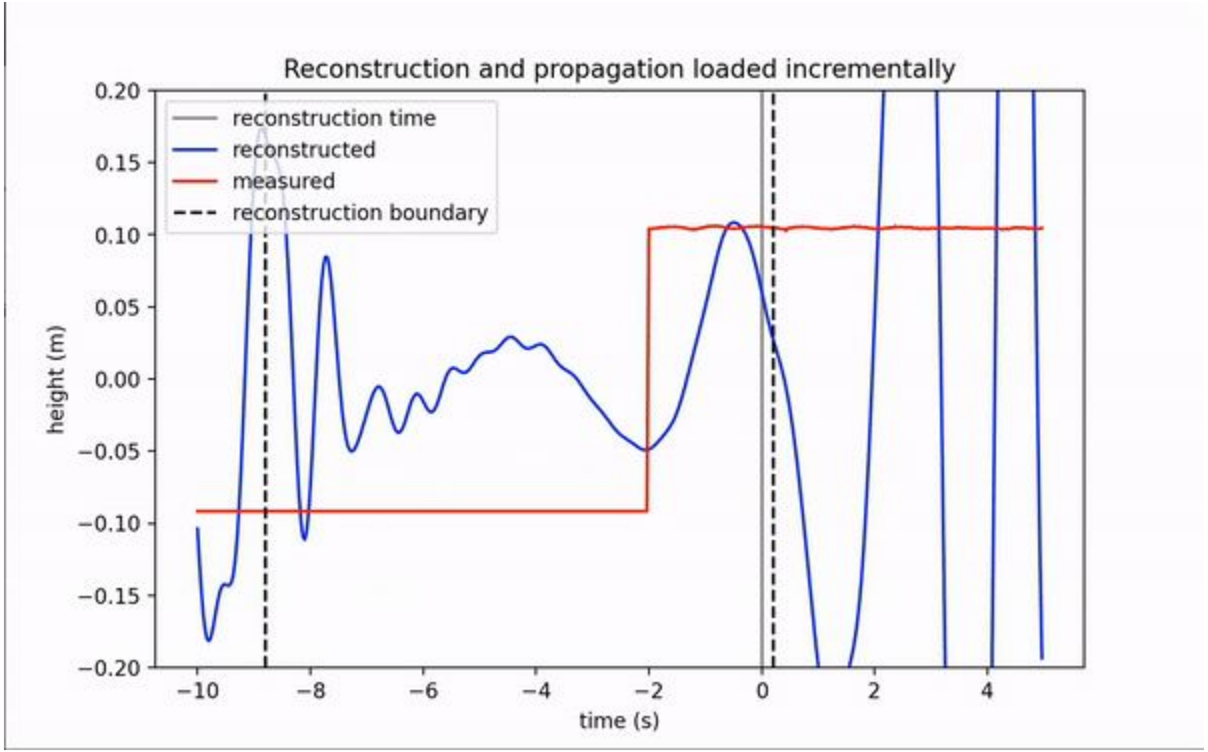
Seiching, other sources of noise



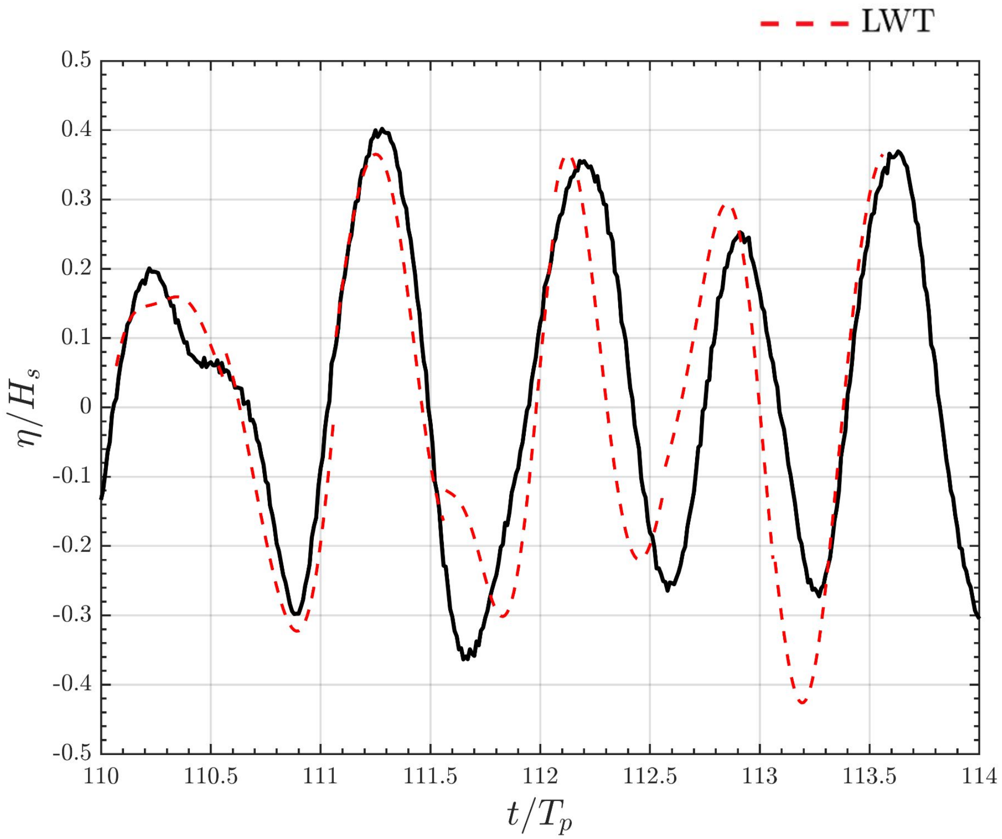
Real time wave forecasting workflow



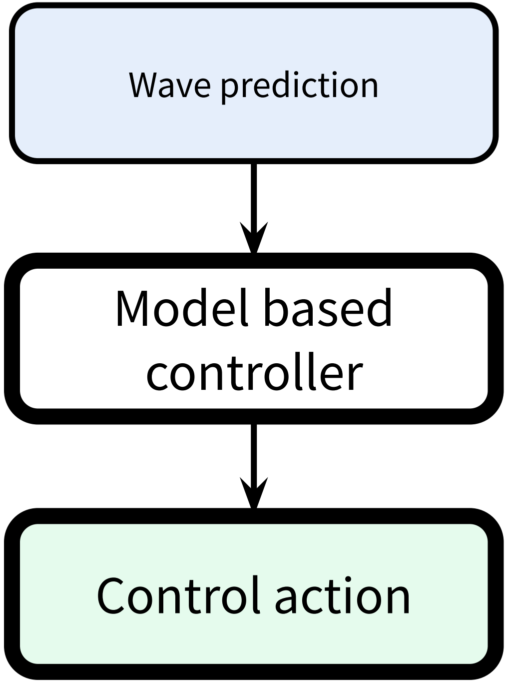
Series of real time wave predictions

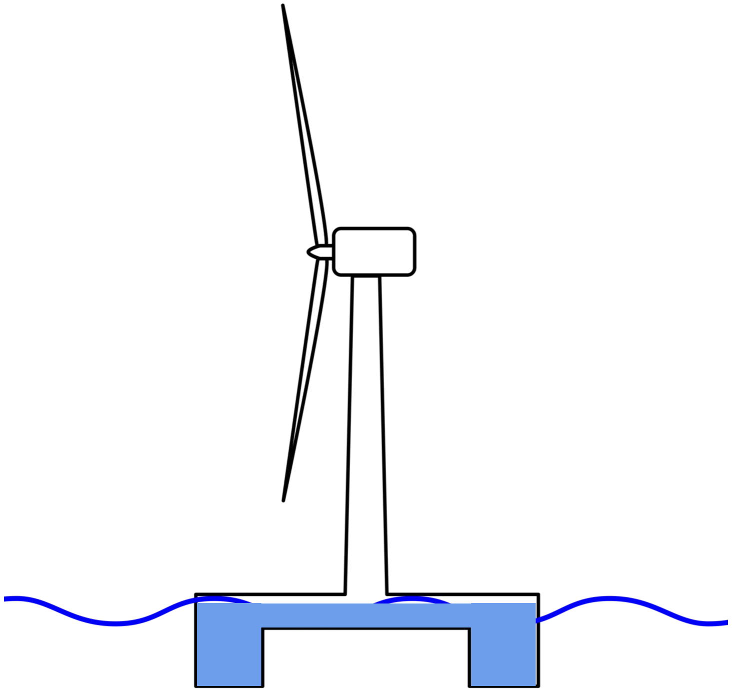


Real time predictions

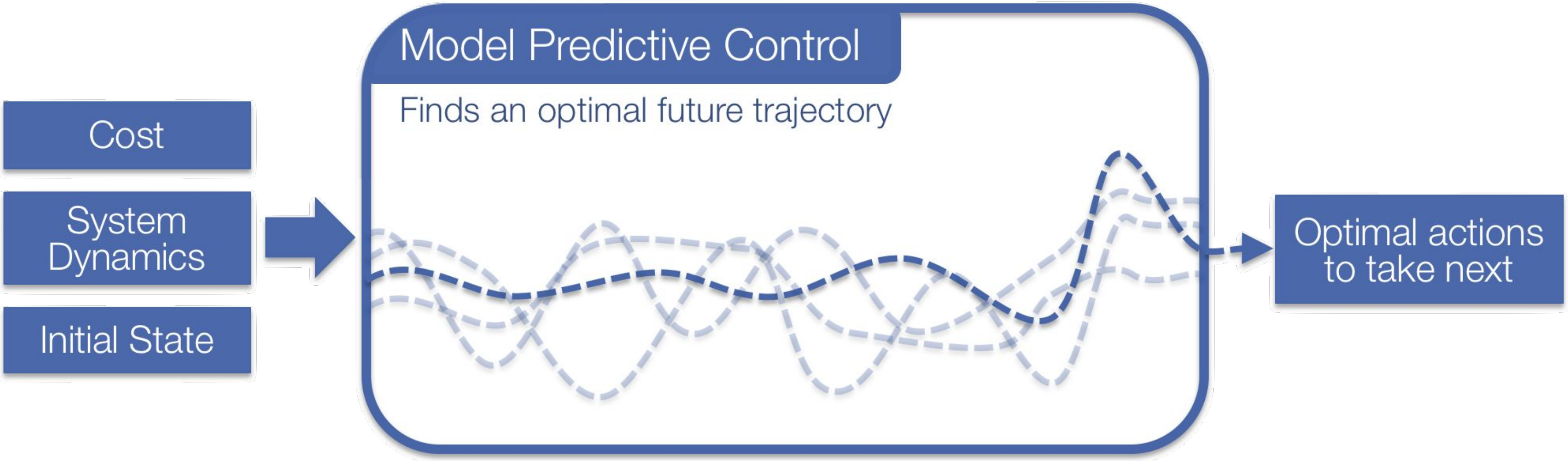


An improved control system



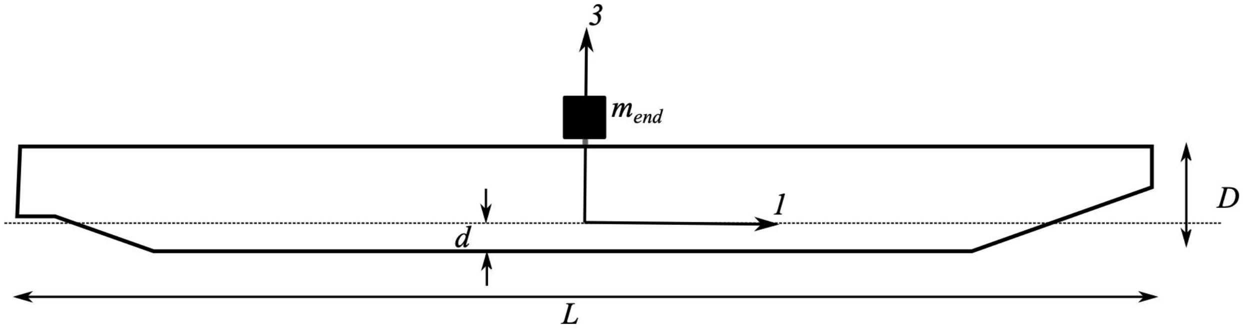


Model predictive control (MPC)

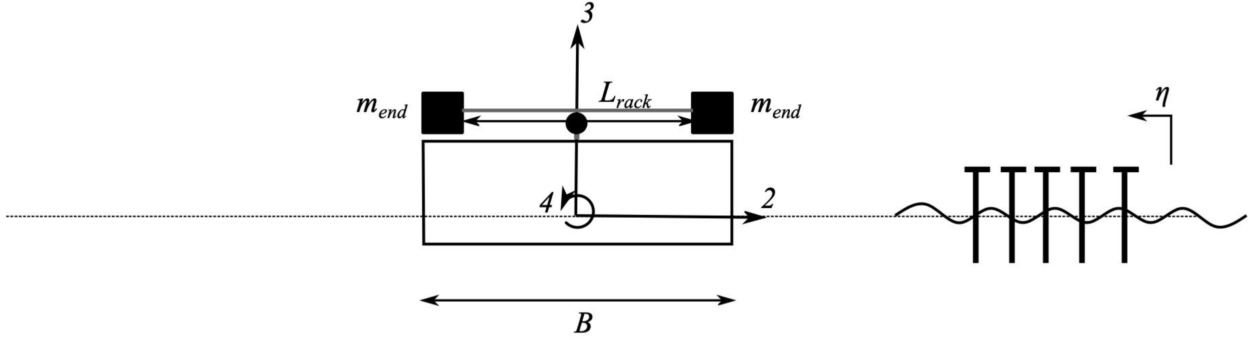


Amos, B., Rodriguez, I. D. J., Sacks, J., Boots, B., & Kolter, J. Z. (2019). *Differentiable MPC for End-to-end Planning and Control* (arXiv:1810.13400). arXiv. https://doi.org/10.48550/arXiv.1810.13400

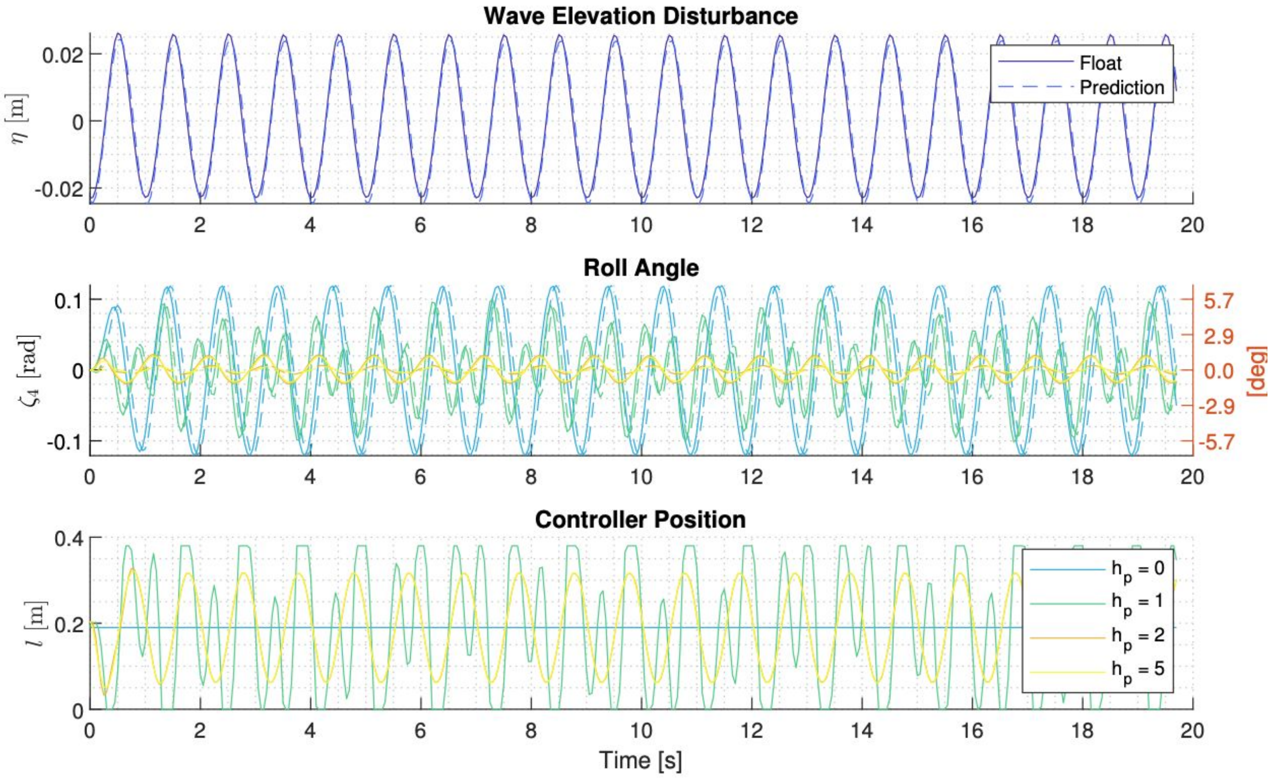
Steele et. al. (2023) - Barge Model



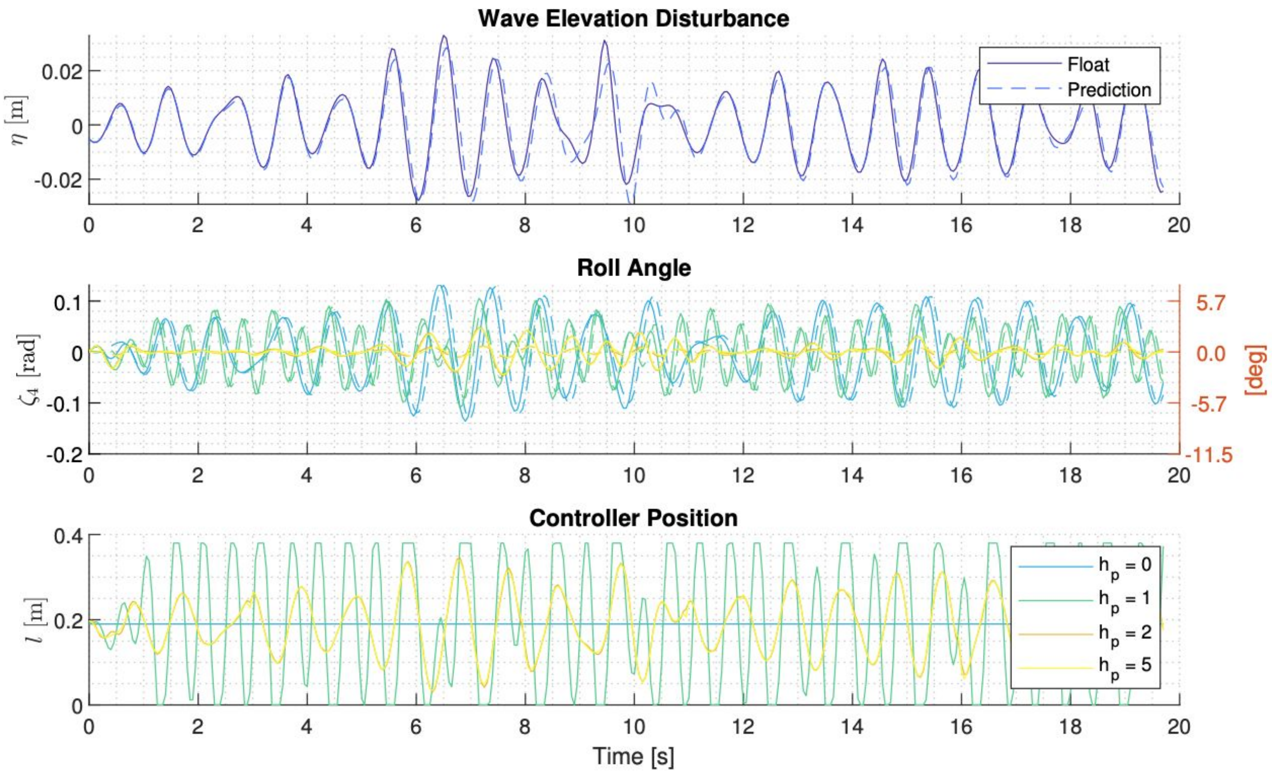
(a) Side view.



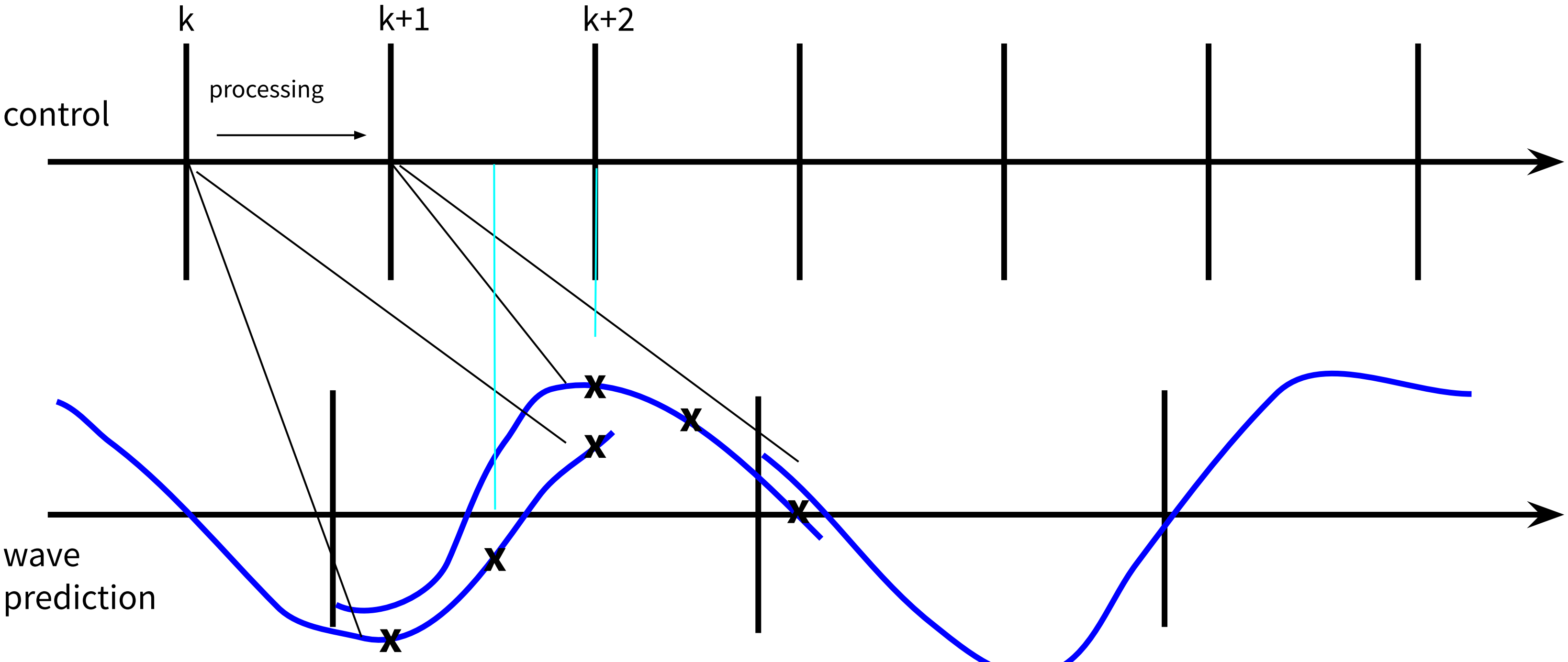
Steele et. al. (2023) - Numerical work



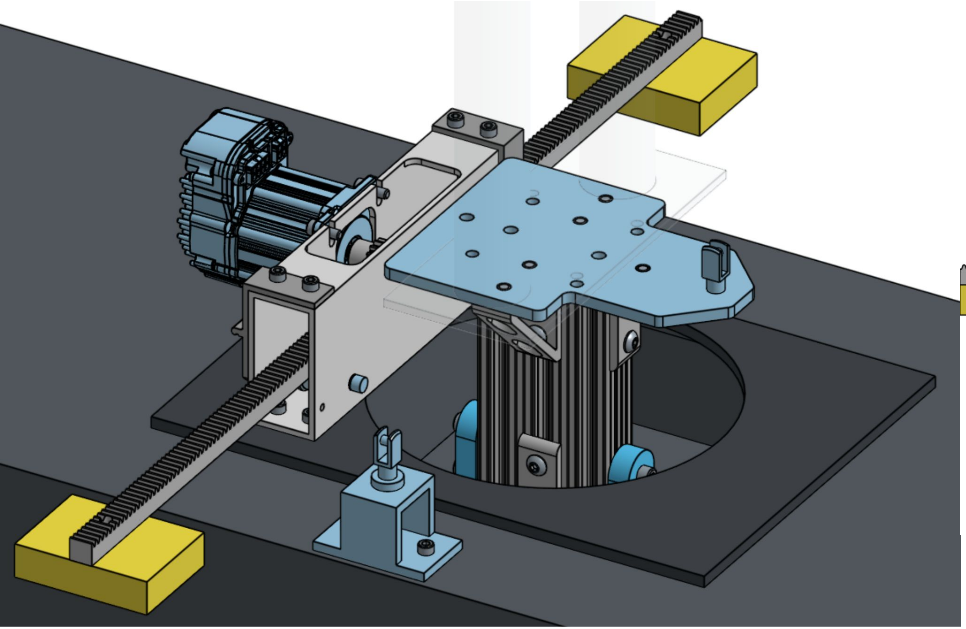
Steele et. al. (2023) - Numerical work, cont'd

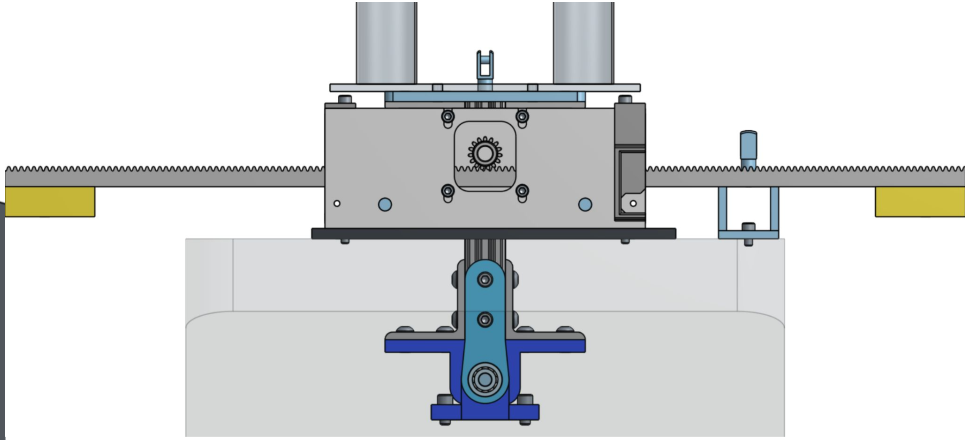


Real time synchronization

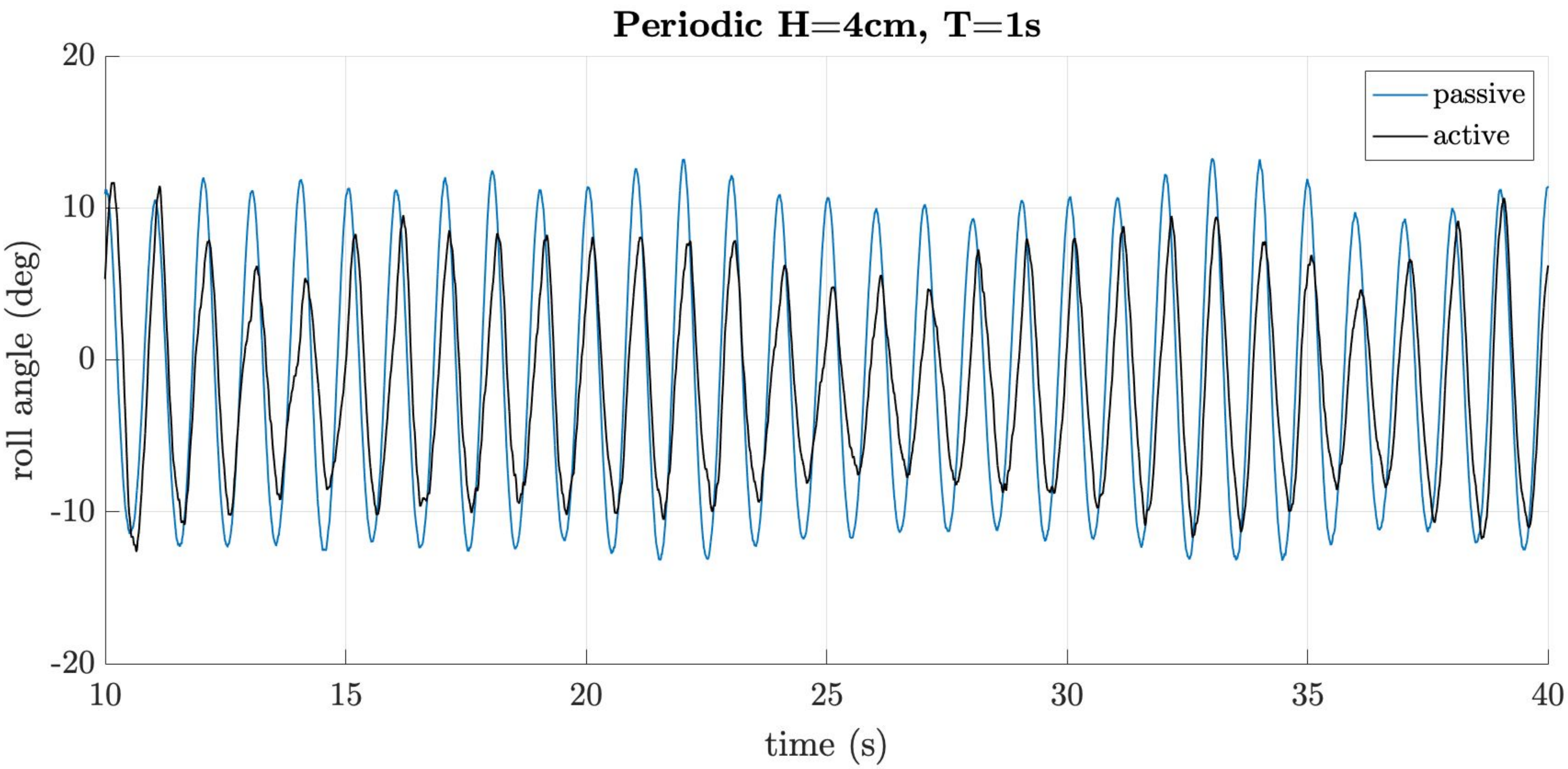


Experimental float mechanism

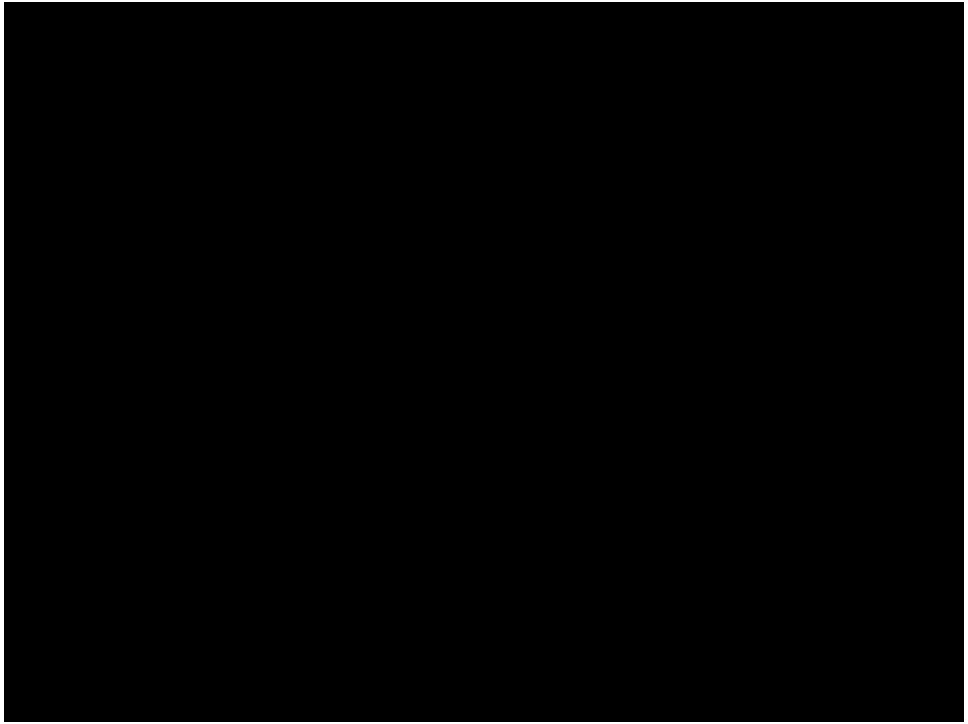




Preliminary results for roll stabilization



Example full experiment



Takeaways

- Shown the effectiveness of improved wave models at aligning wave phase
- Developed wave prediction algorithms for real time use
- Integrated into experimental control framework which can be continually improved
- Deployment to a real wind turbine has separate unanswered questions
  - Wave measurement?
  - Control action to complement blade pitch/ generator torque?
  - Coupled with even more complicated FOWT dynamics?

Personal takeaways

- Waves are awesome
- Experiments are hard
- Building complete systems is satisfying

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- Yuksel Alkarem (University of Maine)

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Full equations 1

$$\mathsf{A}^i_{mn} p_n = \mathsf{B}^i_m;$$

$$\mathsf{A}^i_{mn} = \sum_{\ell=1}^{L} k_n^{-3/2} \cos \Phi^{i'}_{n\ell} + \frac{\mu}{2} a^i_n k_n^{-1/2} P_{m\ell}(a^i_m, b^i_m),$$

$$\mathsf{A}^i_{m,N+n} = \sum_{\ell=1}^{L} k_n^{-3/2} \sin \Phi^{i'}_{n\ell} + \frac{\mu}{2} b^i_n k_n^{-1/2} P_{m\ell}(a^i_m, b^i_m),$$

$$\mathsf{A}^i_{N+m,n} = \sum_{\ell=1}^{L} k_n^{-3/2} \cos \Phi^{i'}_{n\ell} + \frac{\mu}{2} a^i_n k_n^{-1/2} Q_{m\ell}(a^i_m, b^i_m),$$

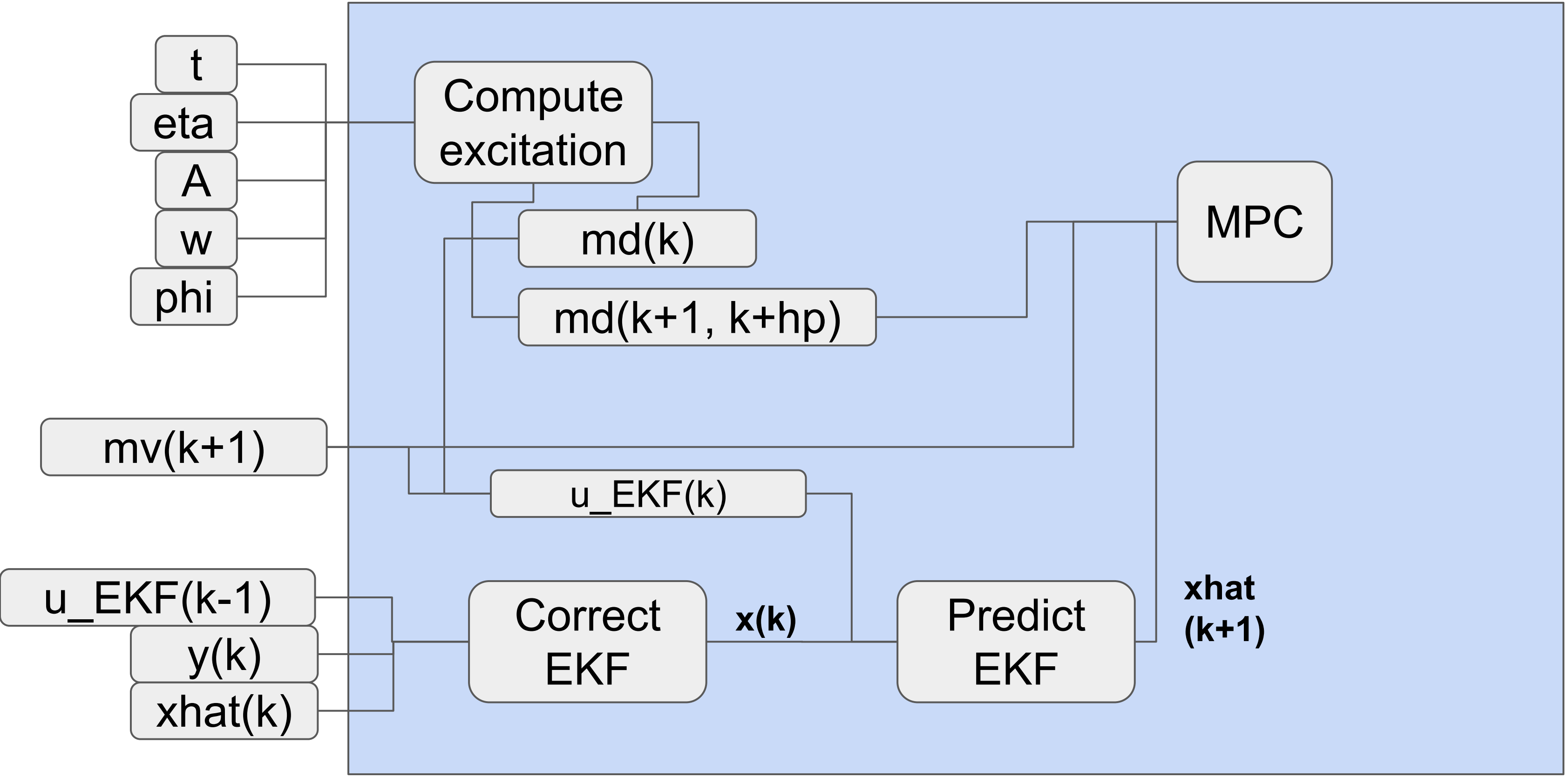
$$\mathsf{A}^i_{N+m,N+n} = \sum_{\ell=1}^{L} k_n^{-3/2} \sin \Phi^{i'}_{n\ell} + \frac{\mu}{2} b^i_n k_n^{-1/2} Q_{m\ell}(a_m I, b_m I),$$

$$\mathsf{B}^i_m = \sum_{\ell=1}^{L} \tilde{\eta}_\ell \, P_{m\ell}(a^i_m, b^i_m), \quad \mathsf{B}^i_{N+m} = \sum_{\ell=1}^{L} \tilde{\eta}_\ell \, Q_{m\ell}(a^i_m, b^i_m),$$

Full equations 2

$$
\begin{cases}
P_{m\ell} & = \cos\Phi'_{m\ell} - \lambda k_m^{-1/2} a_m \sin\Phi'_{m\ell} - b_m \cos\Phi'_{m\ell}\Bigg(\sin\Phi_{m\ell} \\
& \quad -\mu a_m \omega_m k_m^{-1/2} t_\ell k_m^{-1/2} a_m \cos\Phi_{m\ell} + b_m \sin\Phi_{m\ell} + 1 \Bigg) + \mu a_m k_m^{-1/2}, \\
Q_{m\ell} & = \sin\Phi'_{m\ell} - \lambda k_m^{-1/2} a_m \sin\Phi'_{m\ell} - b_m \cos\Phi'_{m\ell}\Bigg(-\cos\tilde{\Phi}_{m\ell} \\
& \quad -\mu b_m \omega_m k_m^{-1/2} t_\ell k_m^{-1/2} a_m \cos\Phi_{m\ell} + b_m \sin\Phi_{m\ell} + 1 \Bigg) + \mu b_m k_m^{-1/2}.
\end{cases}
\tag{3.11}
$$

Eq. 3.11 corresponds to ICWM when $\lambda = \mu = 1$; for CWM, $\lambda = 1$ and $\mu = 0$, and for LWT, both of these are zero. For CWM and ICWM, the iterative solution is initialized with the LWT solution for $i = 1$.


t
eta
A
w
phi
Compute excitation
md(k)
md(k+1, k+hp)
MPC
mv(k+1)
u_EKF(k)
u_EKF(k-1)
y(k)
xhat(k)
Correct EKF
x(k)
Predict EKF
xhat (k+1)