

Data-driven Modeling of Higher-Order Transfer Functions

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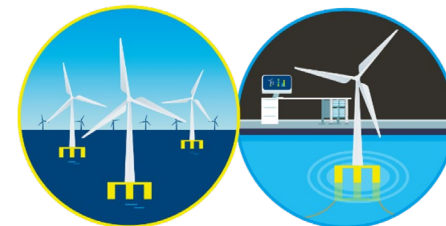
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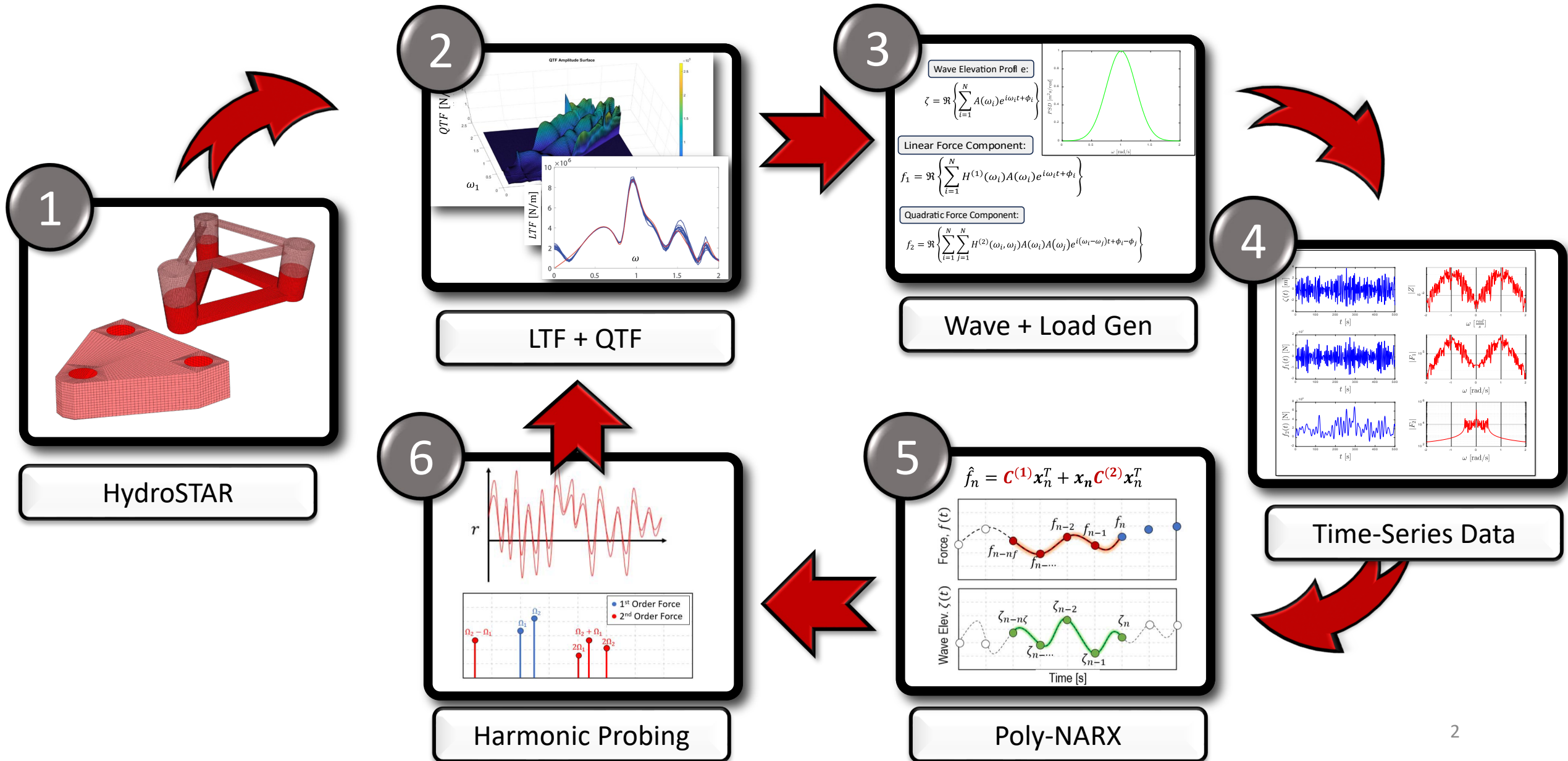


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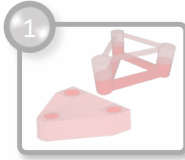


CYBERLAB KPN

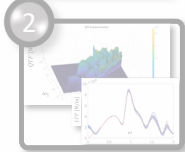
Validation Cycle



Validation Cycle



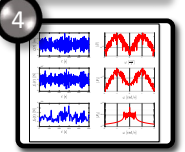
HydroSTAR



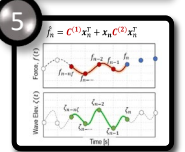
LTF + QTF



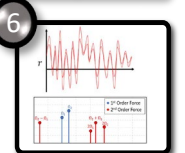
Wave + Load Gen



Time-Series Data



Poly-NARX



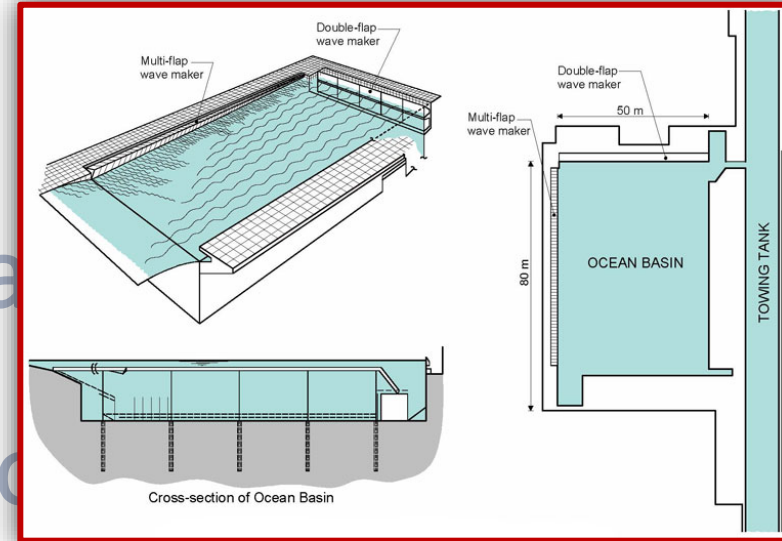
Harmonic Probing

HydroSTAR

Linear and Quadratic Transfer Functions

Synthetic Data Generation

Experimental

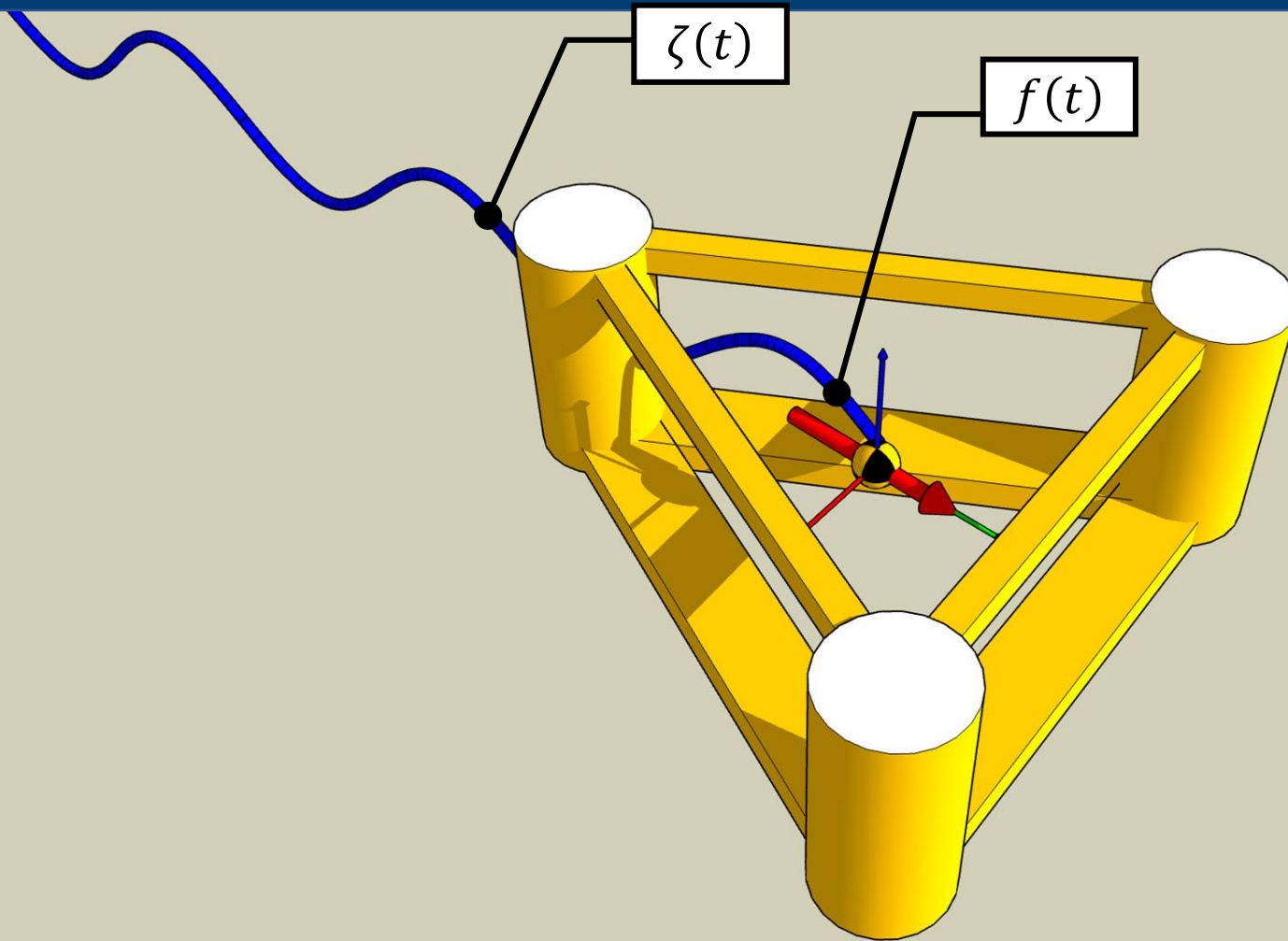


Time-Series Sets

Polynomial-NARX

Novel Harmonic Probing

3 Synthetic Data Generation



3 Synthetic Data Generation

Wave Elevation Profile:

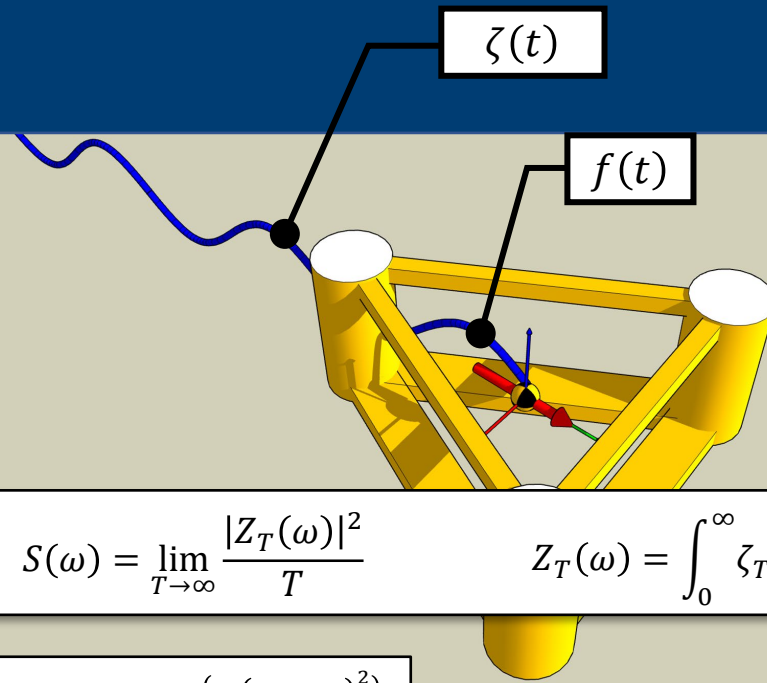
$$\zeta(t) = \Re \left\{ \sum_{i=1}^N A(\omega_i) e^{i\omega_i t + \phi_i} \right\} \quad A(\omega_i) = \sqrt{2S(\omega_i) d\omega}$$

Linear Force Component:

$$f_1(t) = \Re \left\{ \sum_{i=1}^N H^{(1)}(\omega_i) A(\omega_i) e^{i\omega_i t + \phi_i} \right\}$$

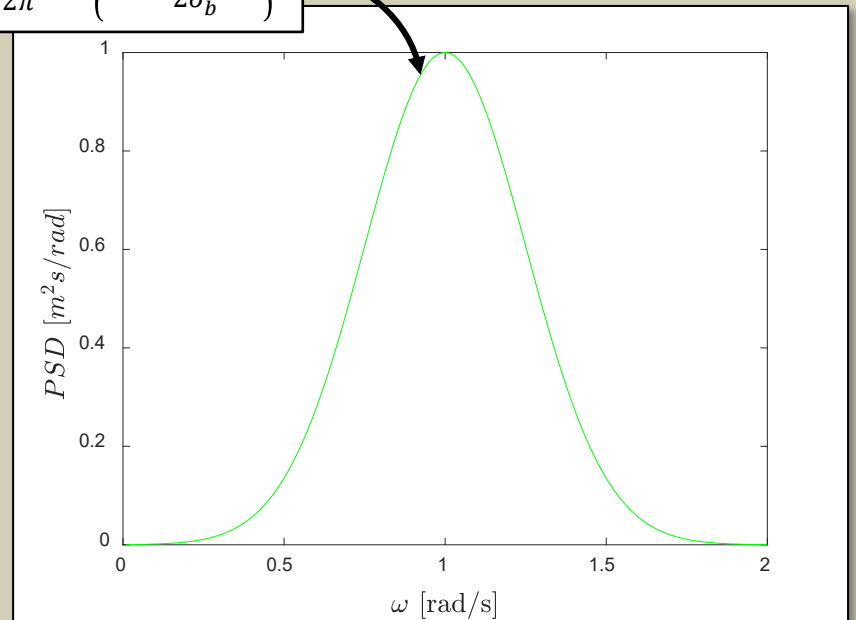
Quadratic Force Component:

$$f_2(t) = \Re \left\{ \sum_{i=1}^N \sum_{j=1}^N H^{(2)}(\omega_i, \omega_j) A(\omega_i) A(\omega_j) e^{i(\omega_i - \omega_j)t + \phi_i - \phi_j} \right\}$$



$$S(\omega) = \lim_{T \rightarrow \infty} \frac{|Z_T(\omega)|^2}{T} \quad Z_T(\omega) = \int_0^{\infty} \zeta_T(t) e^{-i\omega t} dt$$

$$S(\omega) = \frac{1}{\sigma_b \sqrt{2\pi}} \exp \left\{ -\frac{(\omega - \omega_\mu)^2}{2\sigma_b^2} \right\}$$



3 Synthetic Data Generation

Wave Elevation Profile:

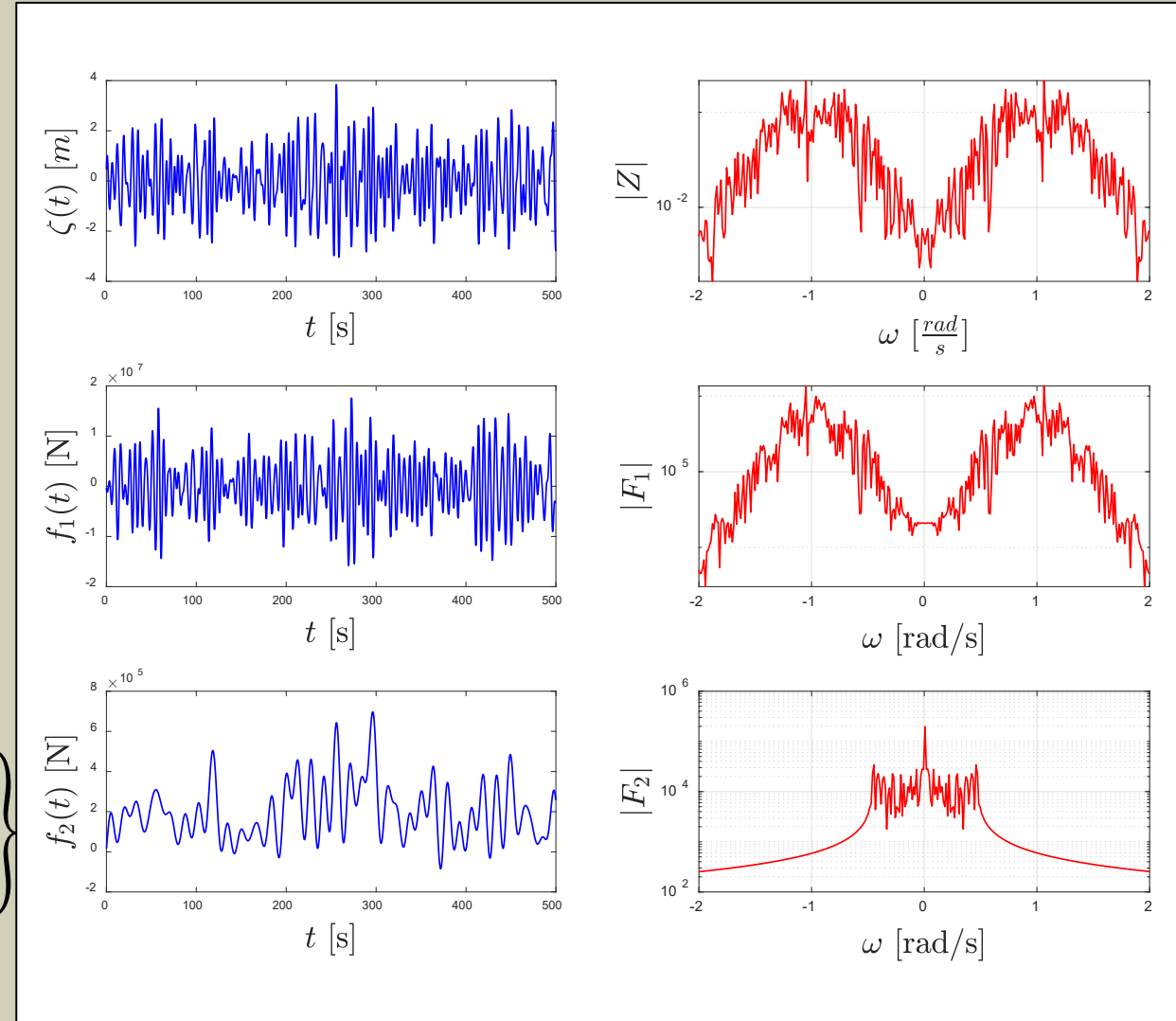
$$\zeta(t) = \Re \left\{ \sum_{i=1}^N A(\omega_i) e^{i\omega_i t + \phi_i} \right\} \quad A(\omega_i) = \sqrt{2S(\omega_i) d\omega}$$

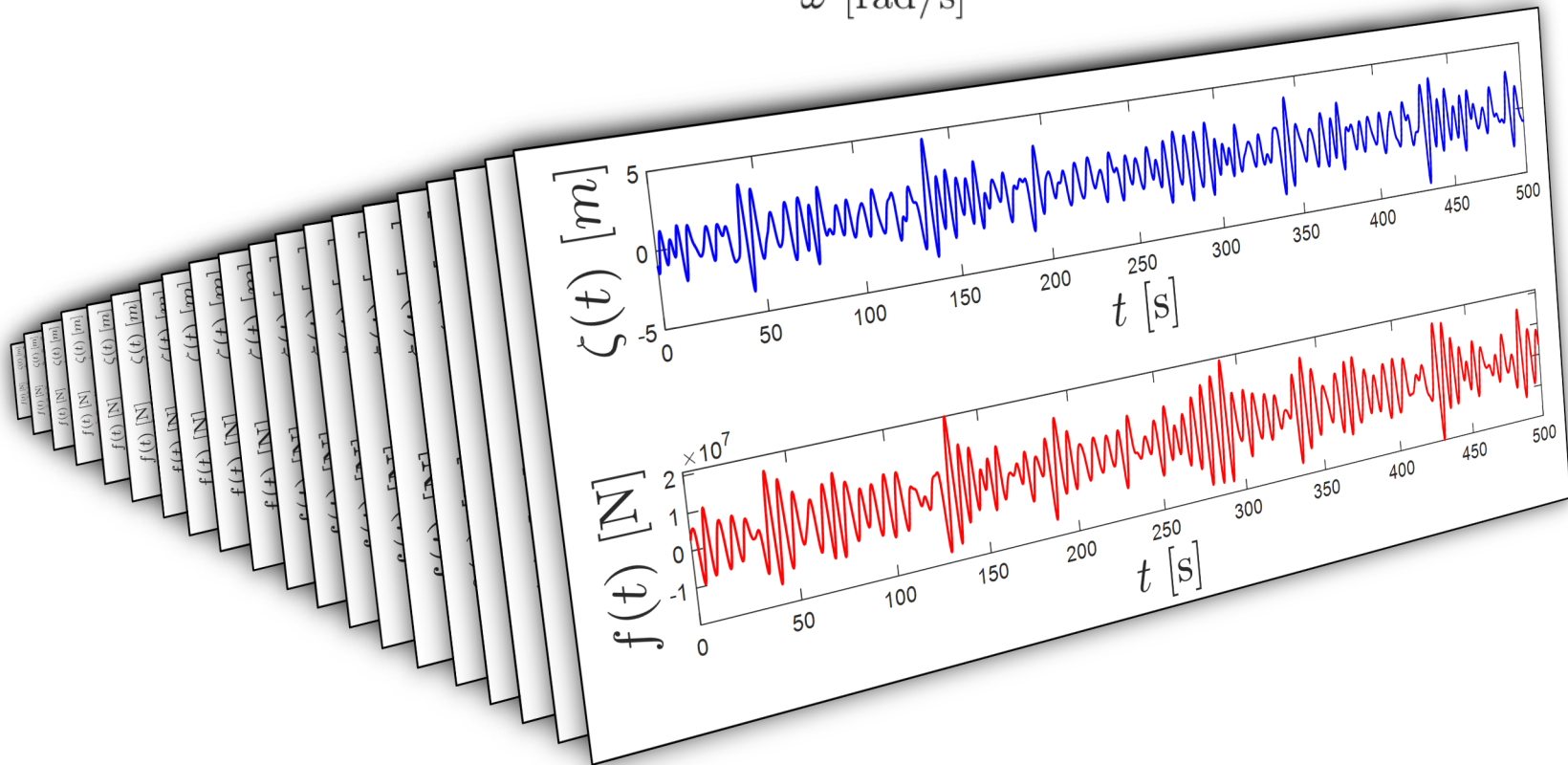
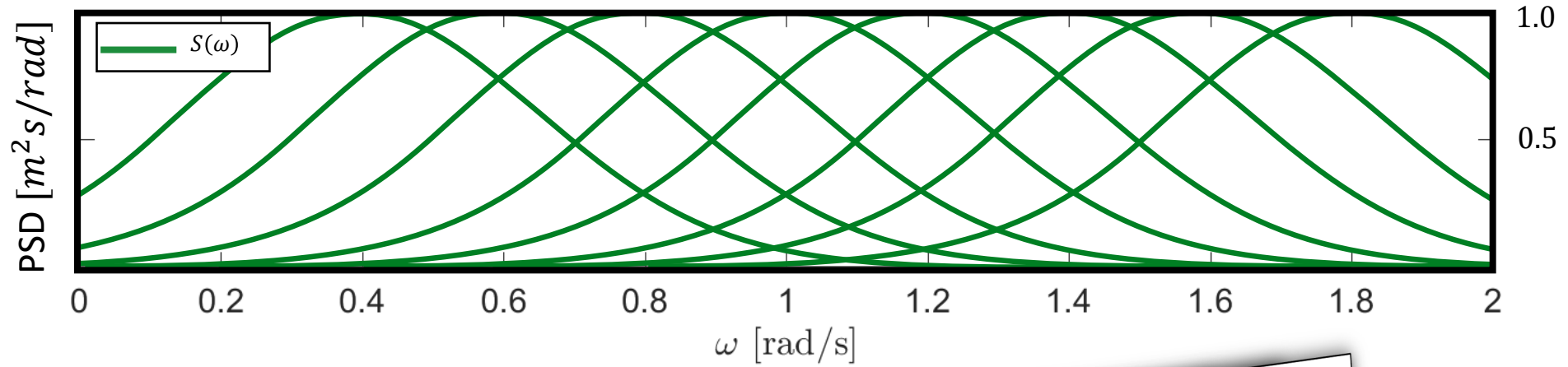
Linear Force Component:

$$f_1(t) = \Re \left\{ \sum_{i=1}^N H^{(1)}(\omega_i) A(\omega_i) e^{i\omega_i t + \phi_i} \right\}$$

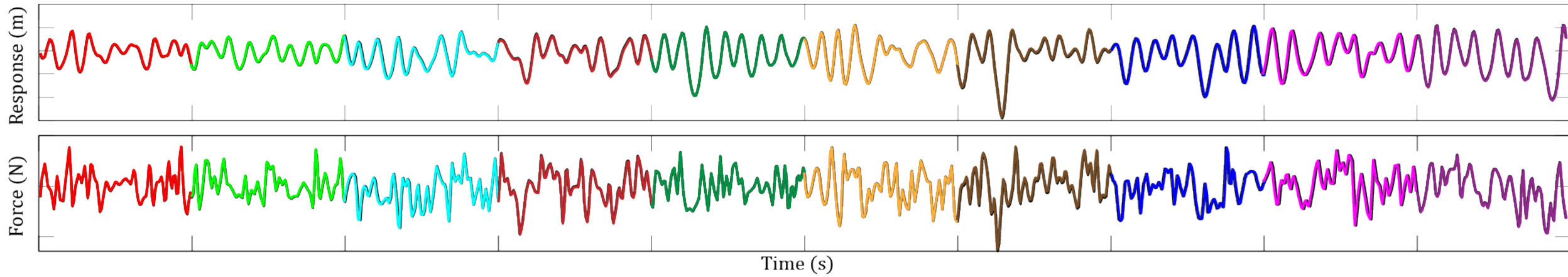
Quadratic Force Component:

$$f_2(t) = \Re \left\{ \sum_{i=1}^N \sum_{j=1}^N H^{(2)}(\omega_i, \omega_j) A(\omega_i) A(\omega_j) e^{i(\omega_i - \omega_j)t + \phi_i - \phi_j} \right\}$$

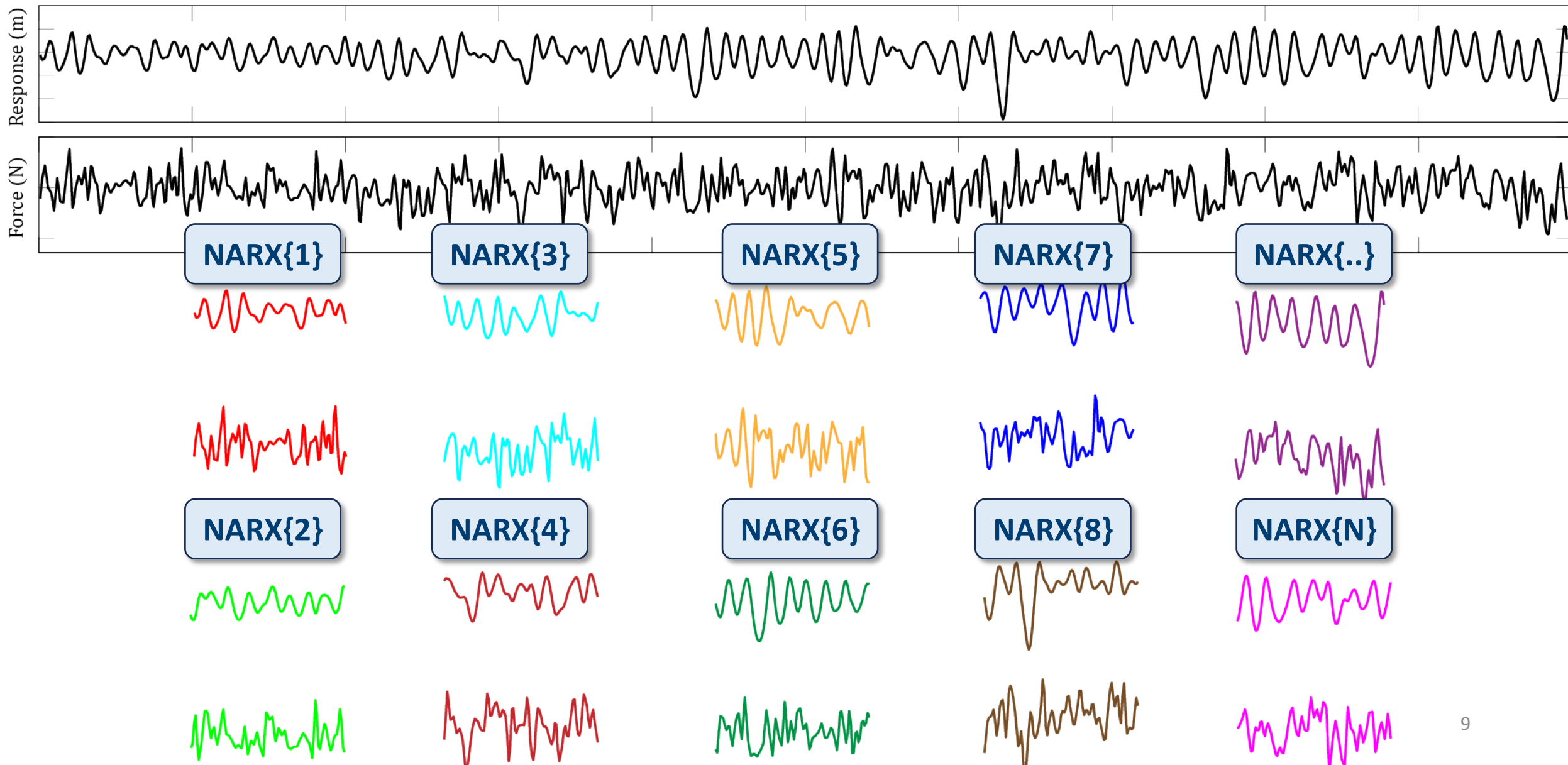




4 Time-Series Sets



4 Time-Series Sets

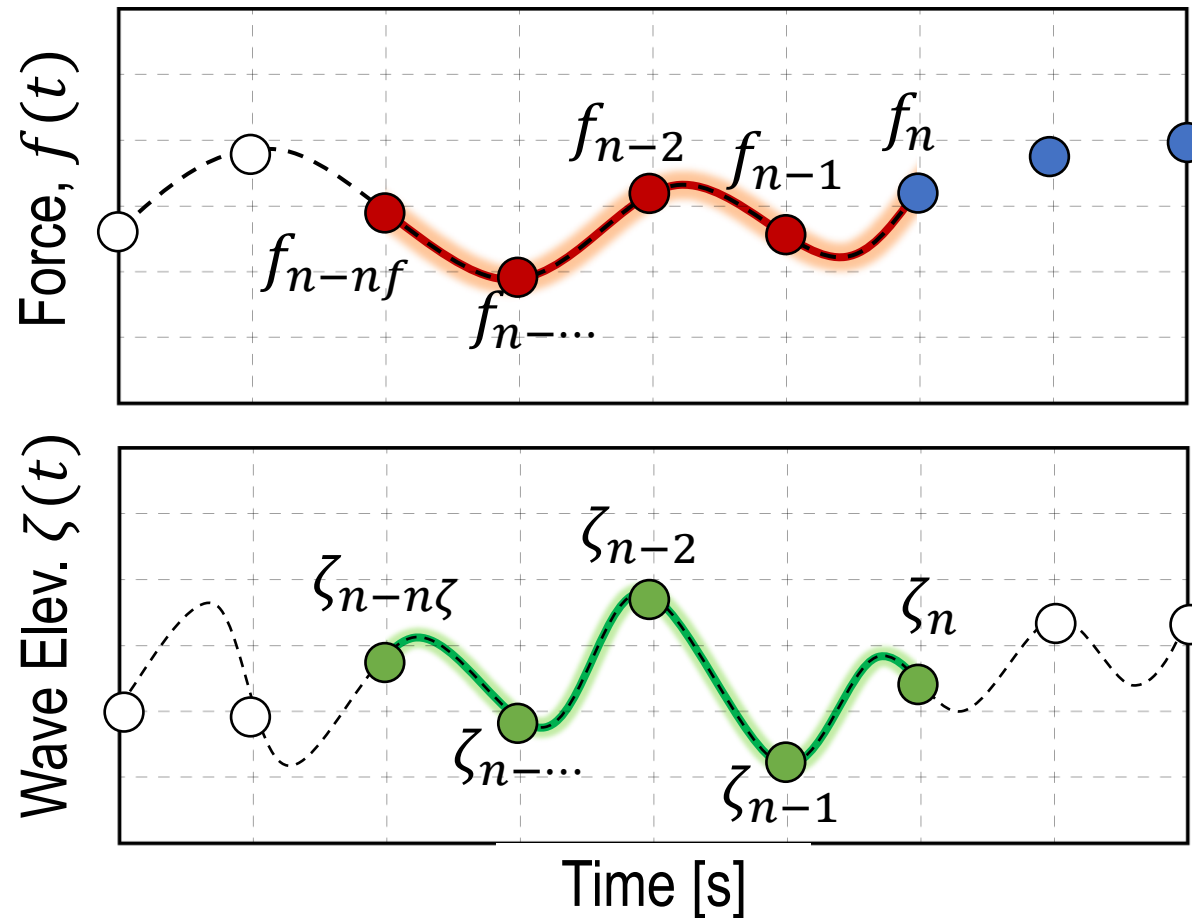


5 Polynomial-NARX

- Forecasting, data-driven, time-series model
- What it does:

$$f_n = \mathcal{F}(f_{n-1}, f_{n-2}, \dots, f_{n-n_f}, \zeta_n, \zeta_{n-1}, \dots, \zeta_{n-n_\zeta}) = \mathcal{F}(\mathbf{x}_n)$$

- Auto-regressive input
- Exogenous input
- Prediction

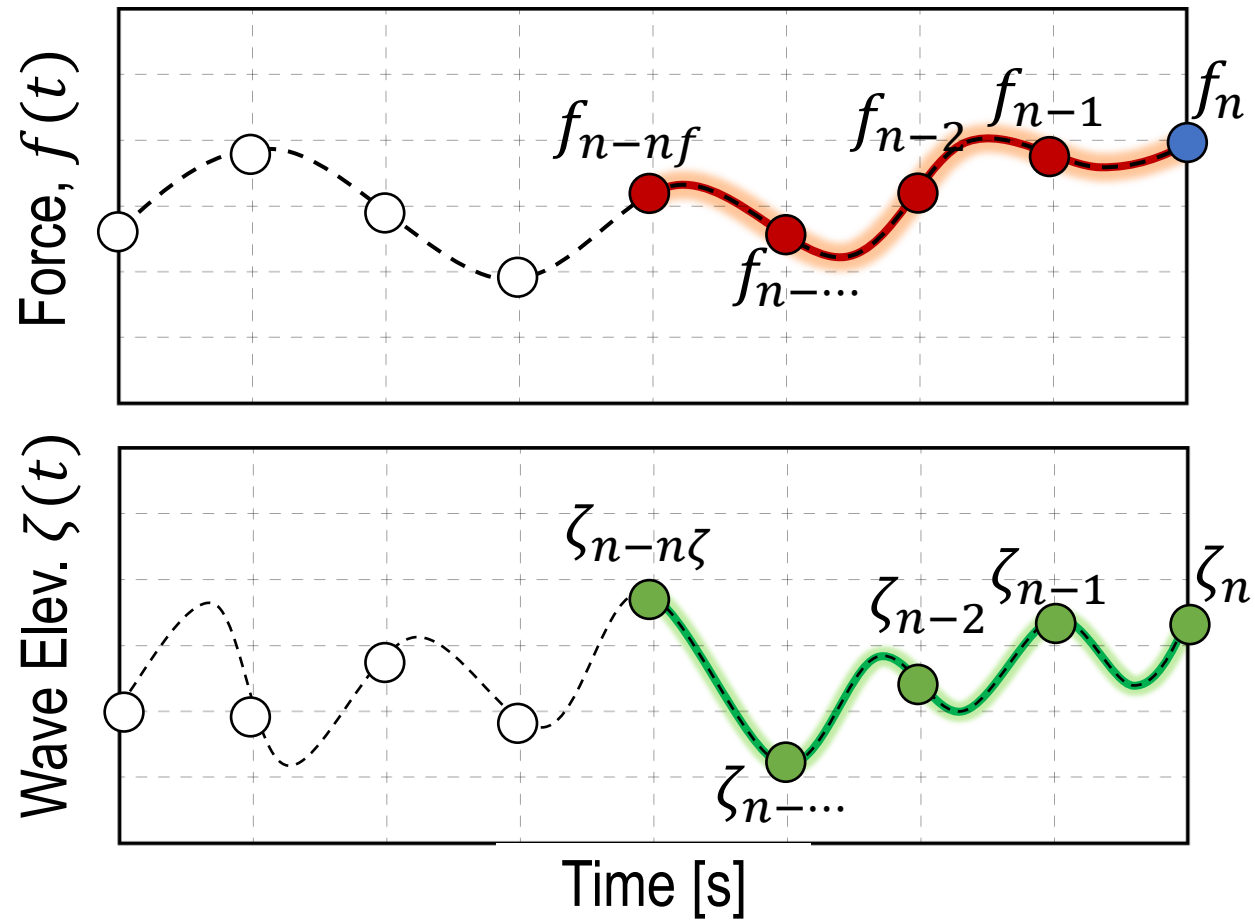


5 Polynomial-NARX

- Forecasting, data-driven, time-series model
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- Auto-regressive input
- Exogenous input
- Prediction



$$\mathbf{x}_n = \left[\begin{array}{c} \vdots \\ \vdots \\ \vdots \end{array} \right]^T$$

5 Polynomial-NARX

$$\hat{f}_n = \mathcal{F}(f_{n-1}, f_{n-2}, \dots, f_{n-n_f}, \zeta_n, \zeta_{n-1}, \dots, \zeta_{n-n_\zeta}) = \mathcal{F}(\mathbf{x}_n)$$

$$p = n_f + n_\zeta + 1$$

$$\hat{f}_n = \begin{bmatrix} c_1^{(1)} & c_2^{(1)} & c_3^{(1)} & c_4^{(1)} & \dots & c_p^{(1)} \end{bmatrix} \begin{bmatrix} f_{n-1} \\ f_{n-\dots} \\ f_{n-n_f} \\ \zeta_n \\ \zeta_{n-\dots} \\ \zeta_{n-n_\zeta} \end{bmatrix} + \begin{bmatrix} f_{n-1} \\ f_{n-\dots} \\ f_{n-n_f} \\ \zeta_n \\ \zeta_{n-\dots} \\ \zeta_{n-n_\zeta} \end{bmatrix}^T \begin{bmatrix} c_{11}^{(2)} & c_{12}^{(2)} & c_{13}^{(2)} & c_{14}^{(2)} & c_{1\dots}^{(2)} & c_{1p}^{(2)} \\ c_{21}^{(2)} & c_{22}^{(2)} & c_{23}^{(2)} & c_{24}^{(2)} & c_{2\dots}^{(2)} & c_{2p}^{(2)} \\ c_{31}^{(2)} & c_{32}^{(2)} & c_{33}^{(2)} & c_{34}^{(2)} & c_{3\dots}^{(2)} & c_{3p}^{(2)} \\ c_{41}^{(2)} & c_{42}^{(2)} & c_{43}^{(2)} & c_{44}^{(2)} & c_{4\dots}^{(2)} & c_{4p}^{(2)} \\ c_{\dots 1}^{(2)} & c_{\dots 2}^{(2)} & c_{\dots 3}^{(2)} & c_{\dots 4}^{(2)} & c_{\dots\dots}^{(2)} & c_{\dots p}^{(2)} \\ c_{p1}^{(2)} & c_{p2}^{(2)} & c_{p3}^{(2)} & c_{p4}^{(2)} & c_{p\dots}^{(2)} & c_{pp}^{(2)} \end{bmatrix} \begin{bmatrix} f_{n-1} \\ f_{n-\dots} \\ f_{n-n_f} \\ \zeta_n \\ \zeta_{n-\dots} \\ \zeta_{n-n_\zeta} \end{bmatrix}$$

$$\hat{f}_n = \mathbf{C}^{(1)} \mathbf{x}_n^T + \mathbf{x}_n \mathbf{C}^{(2)} \mathbf{x}_n^T$$

5 Polynomial-NARX

$$\hat{f}_n = \mathcal{F}(f_{n-1}, f_{n-2}, \dots, f_{n-n_f}, \zeta_n, \zeta_{n-1}, \dots, \zeta_{n-n_\zeta}) = \mathcal{F}(\mathbf{x}_n)$$

$$p = n_f + n_\zeta + 1$$

$$\hat{f}_n = \mathbf{c}^{(1)} \mathbf{x}_n^T + \mathbf{x}_n \mathbf{c}^{(2)} \mathbf{x}_n^T$$

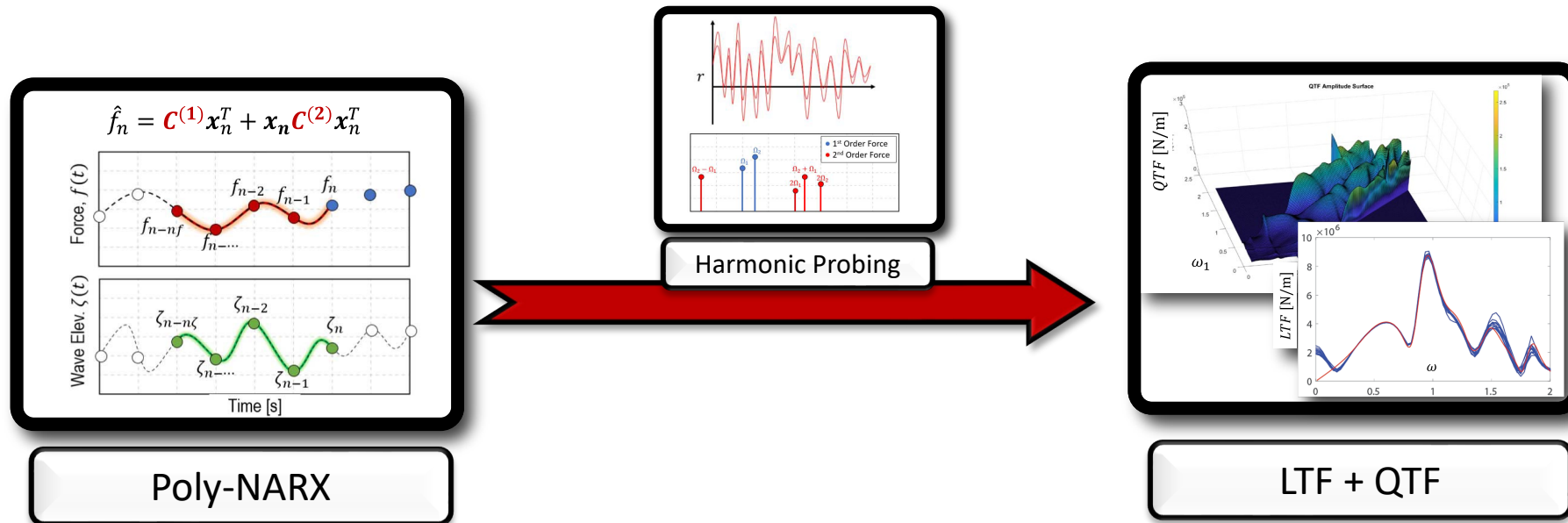
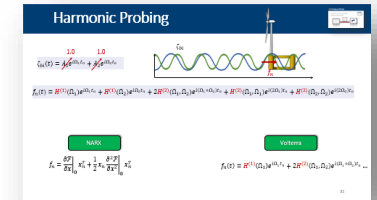
$$(\mathbf{c}^{(1)}, \mathbf{c}^{(2)}) = \arg \min_{\mathbf{c}^{(1)}, \mathbf{c}^{(2)}} \left\{ \frac{1}{2N} \sum_{i=1}^N (f_i - \hat{f}_i(\mathbf{c}^{(1)}, \mathbf{c}^{(2)}))^2 + \lambda \sum_{j=1}^p |c_j^{(1)}| + \lambda \sum_{k=1}^{p^2} |c_k^{(2)}| \right\}$$

λ : nonnegative parameter

5 Probing and Results

- Extracts Transfer Functions out of the learned coefficients.
- Improved the original method substantially.

[Link to probing explanation](#)



5 Probing and Results

NARX

$$f_n(t) = \mathbf{C}^{(1)} \mathbf{x}_n^T + \mathbf{x}_n \mathbf{C}^{(2)} \mathbf{x}_n^T$$

Volterra

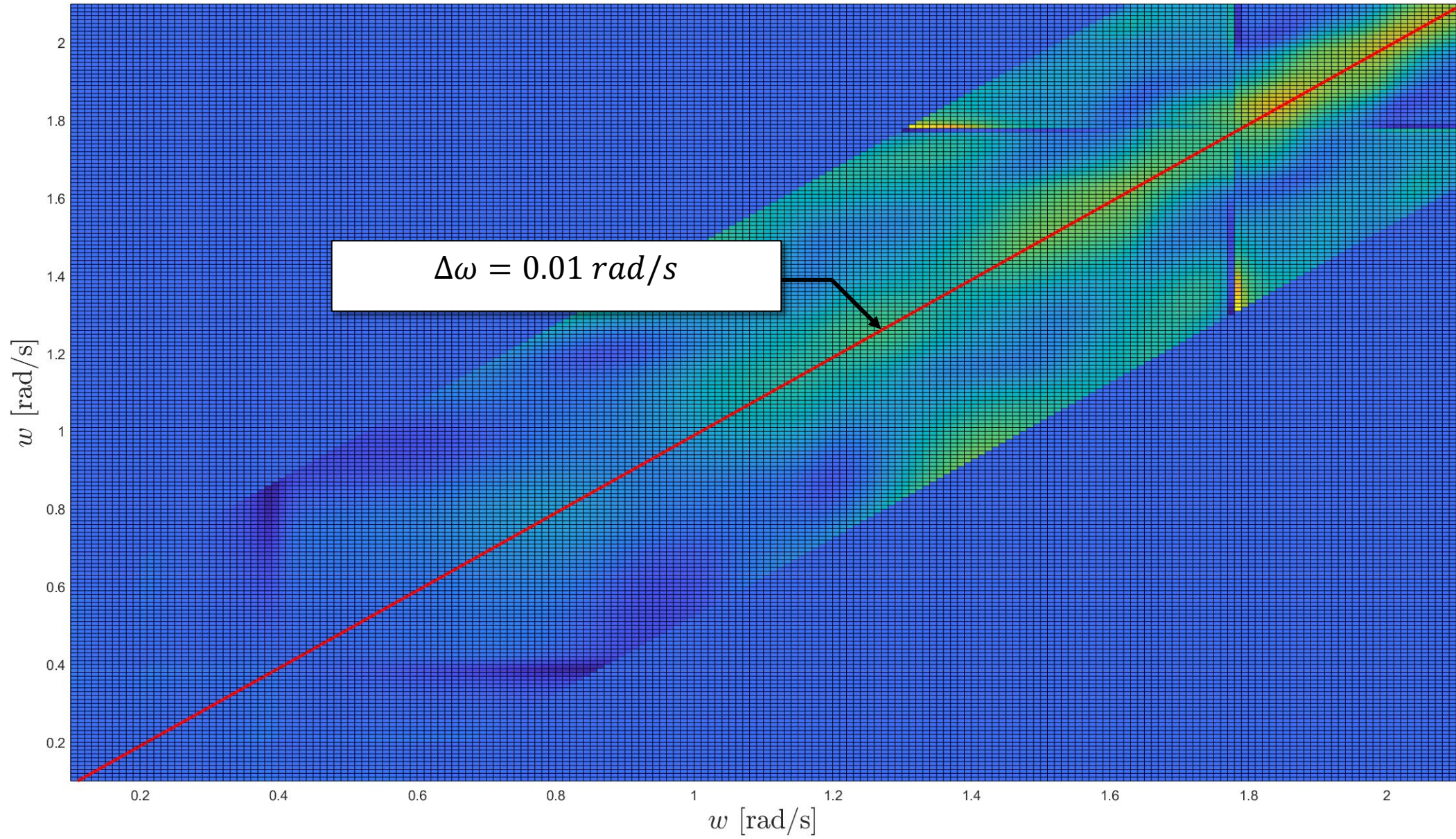
$$f_n(t) = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2) t_n} \dots$$

$$A e^{i\Omega_1 t_n} + B e^{2i\Omega_1 t_n} + C e^{i(\Omega_1 + \Omega_2) t_n} + D e^{i(2\Omega_1 + \Omega_2) t_n} + E e^{i\Omega_1 t_n} + F e^{i\Omega_2 t_n} = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2) t_n}$$

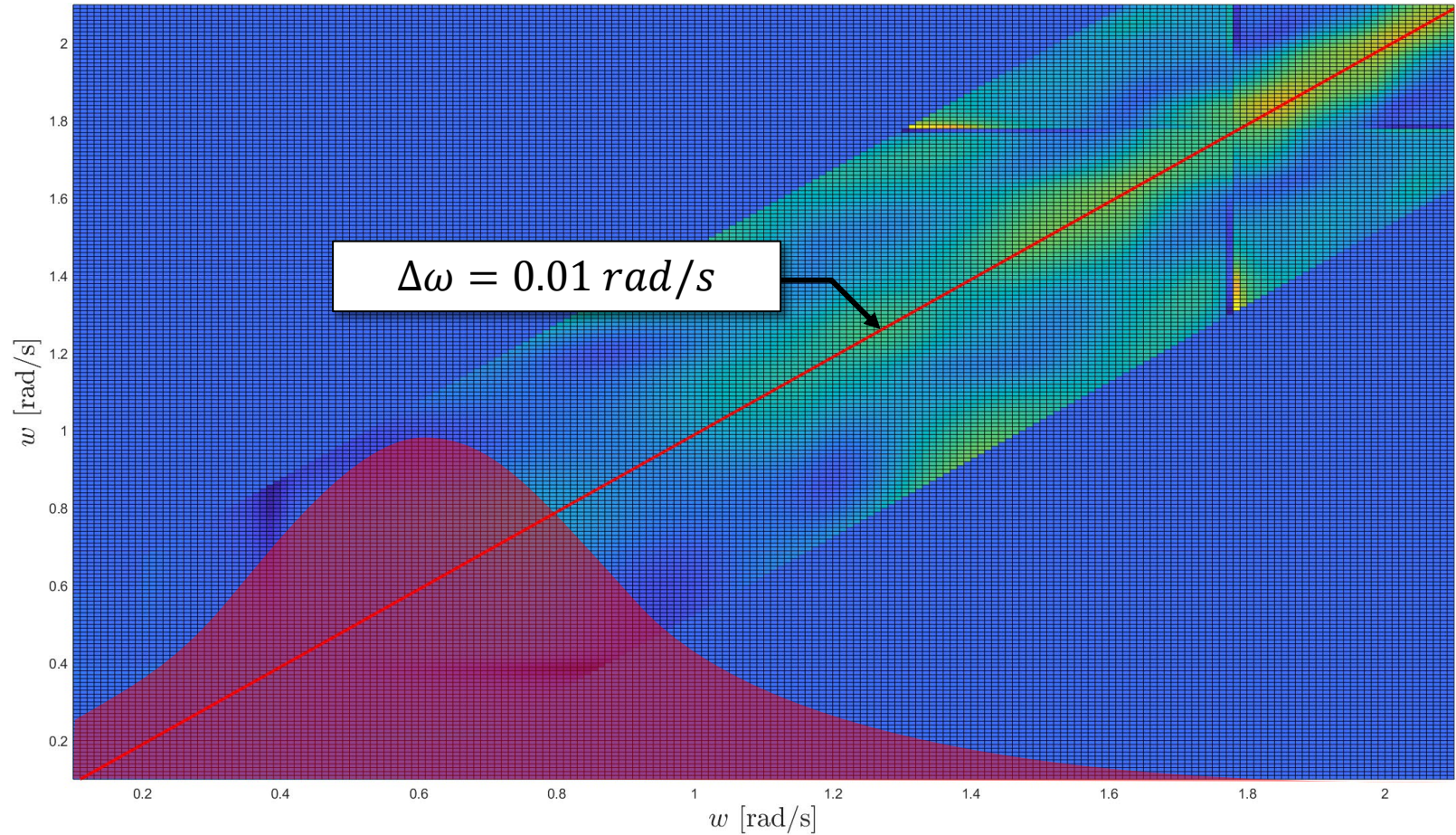
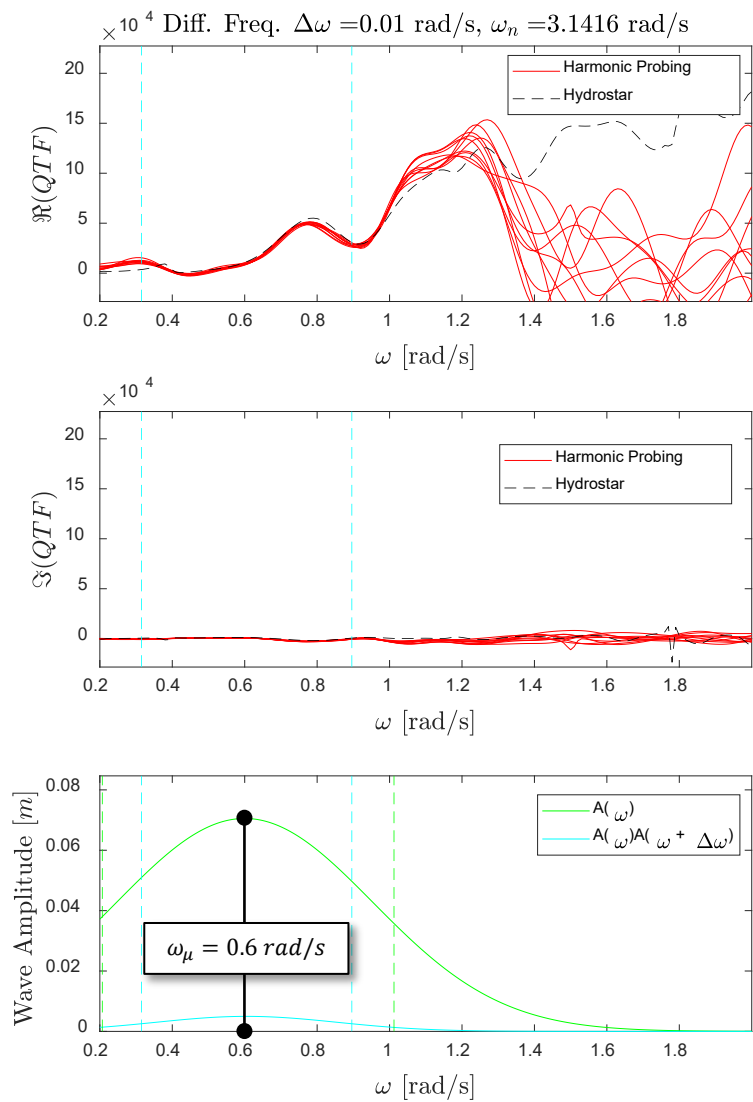
$$(A + E) e^{i\Omega_1 t_n} = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n}$$

$$A + E = H^{(1)}(\Omega_1)$$

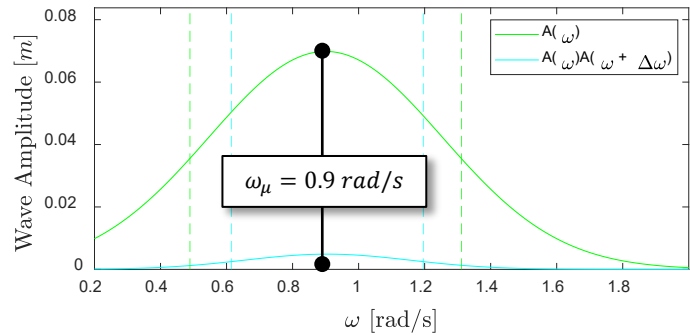
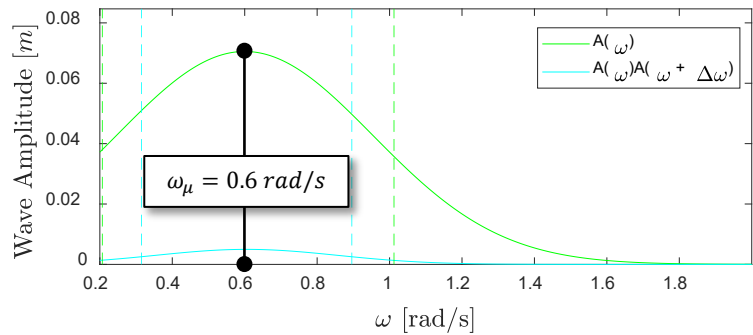
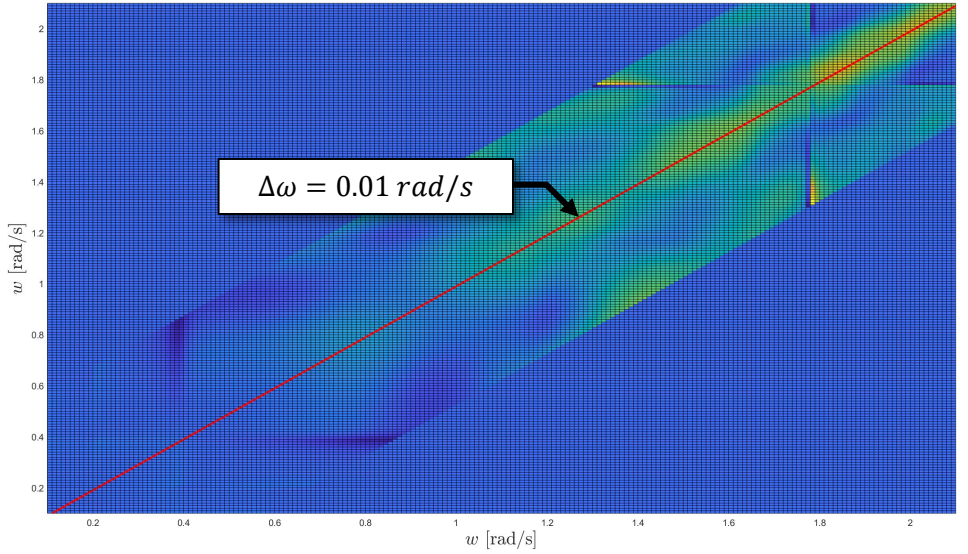
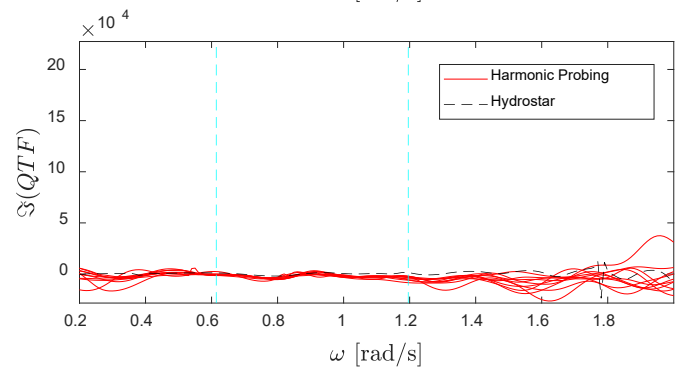
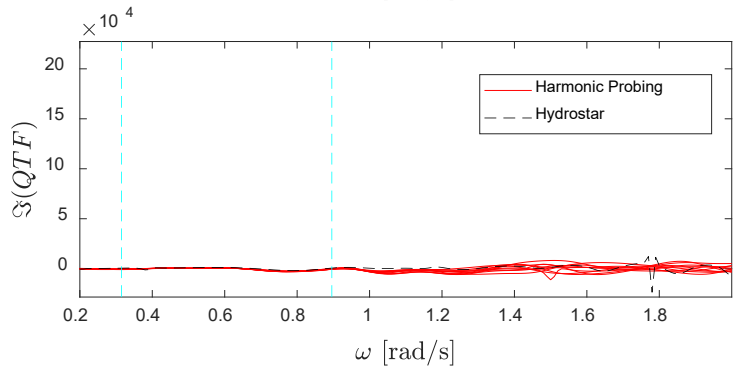
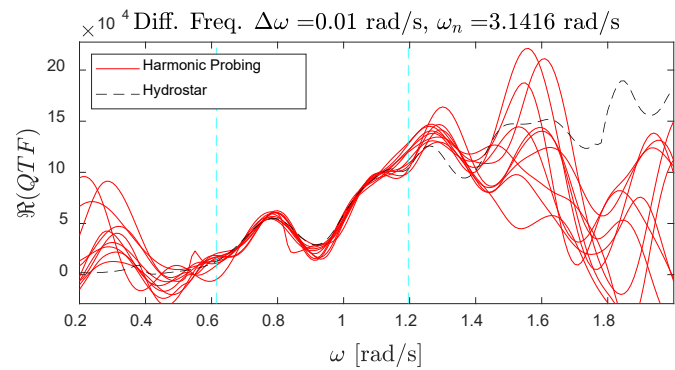
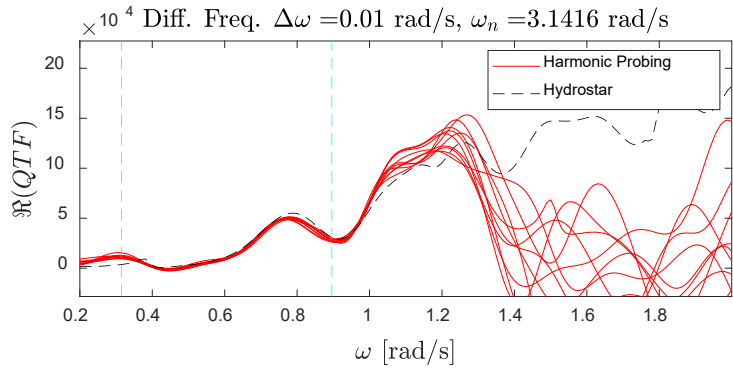
5 Probing and Results



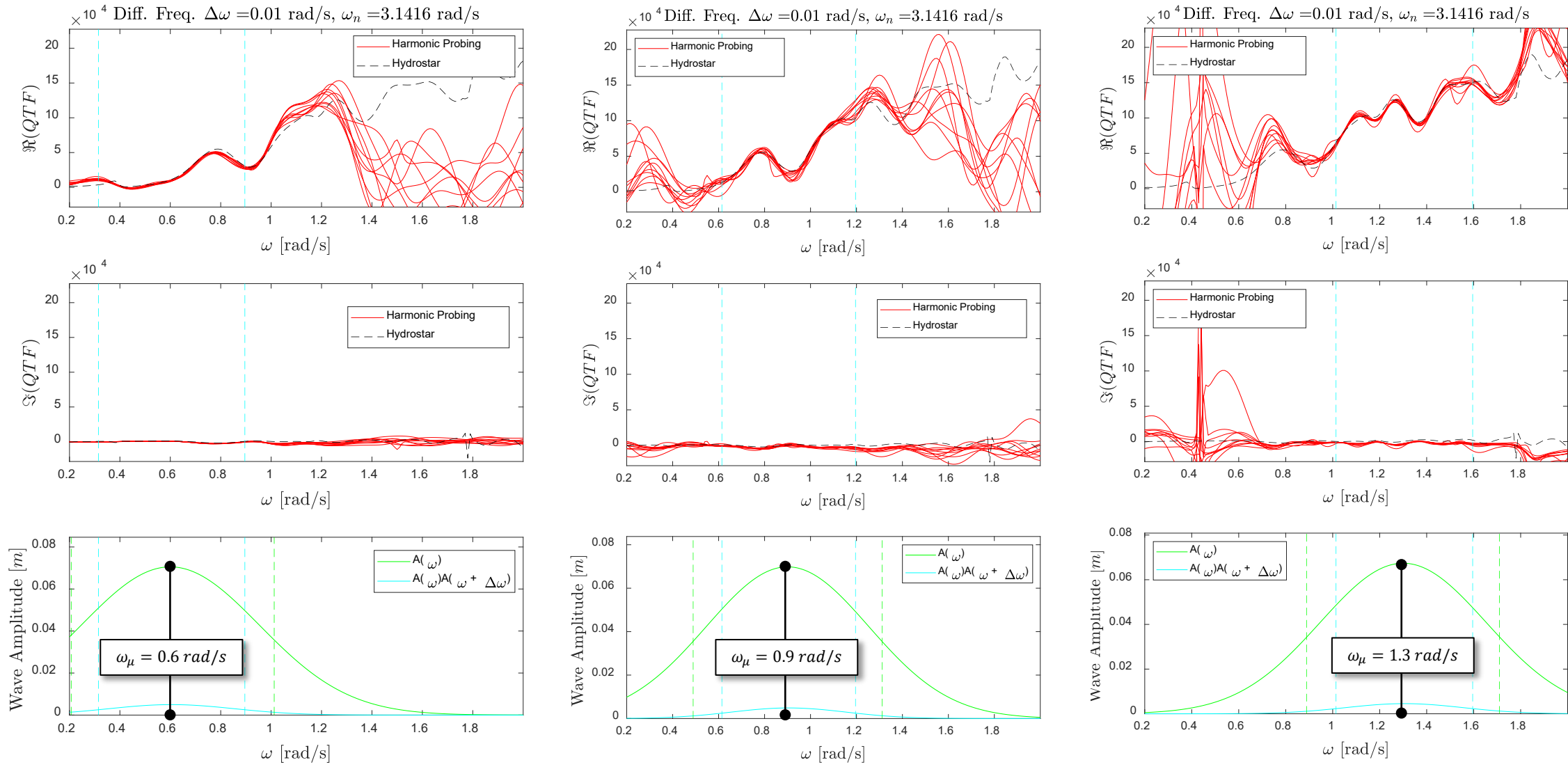
5 Probing and Results



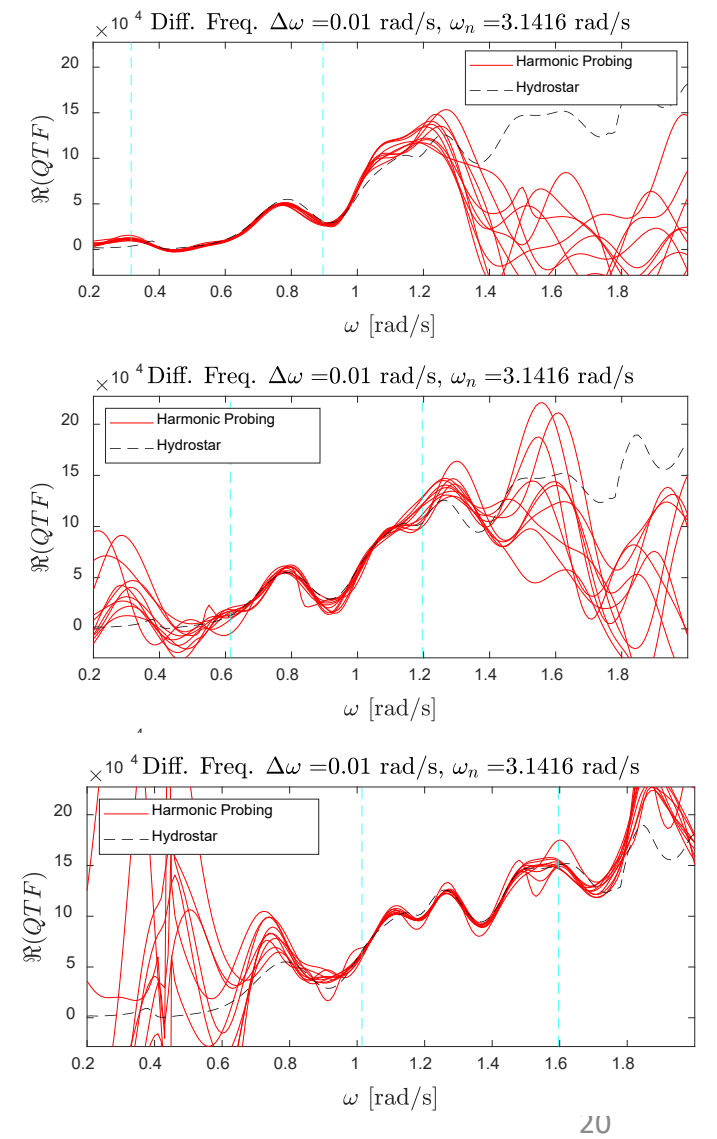
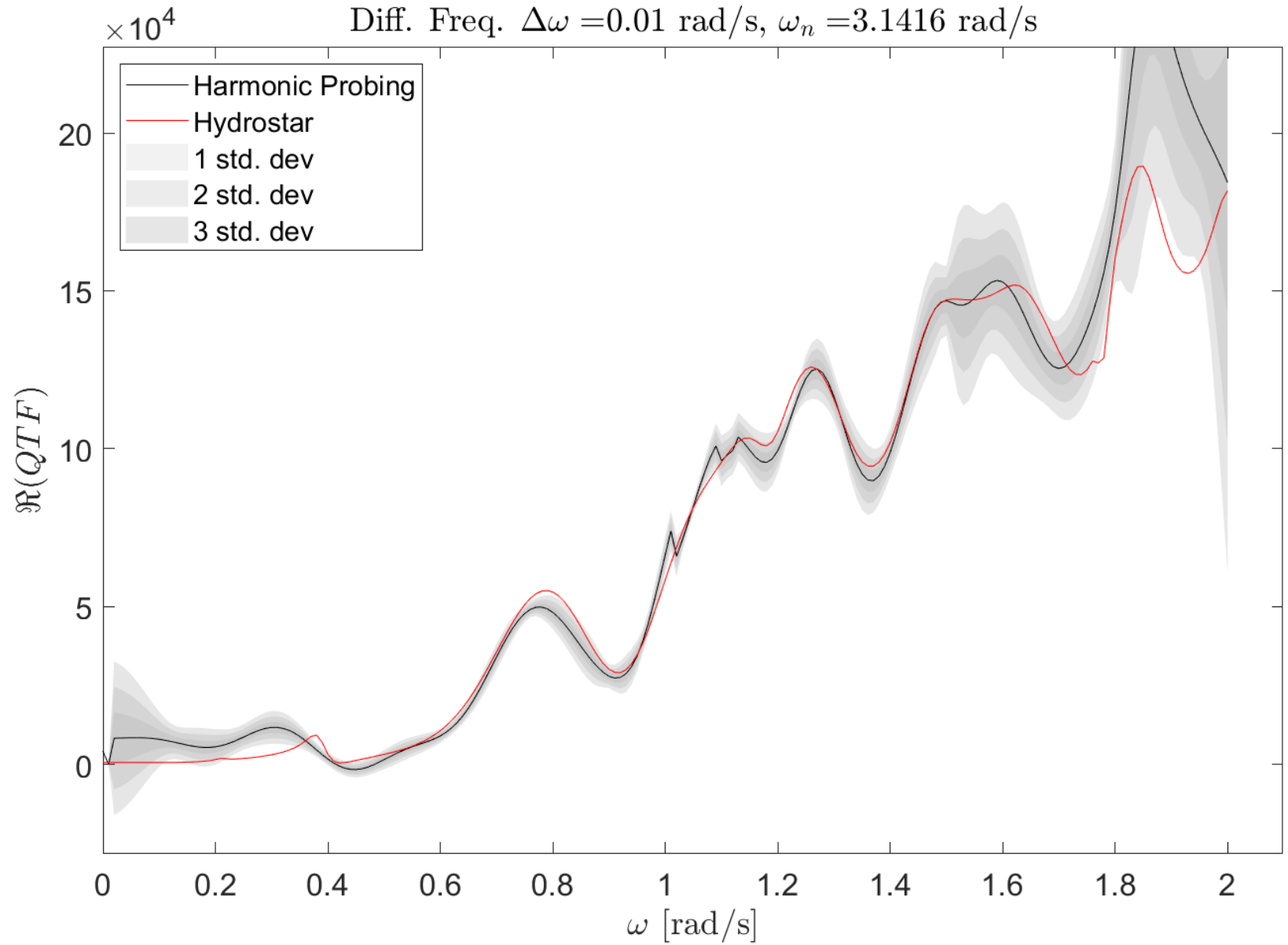
5 Probing and Results



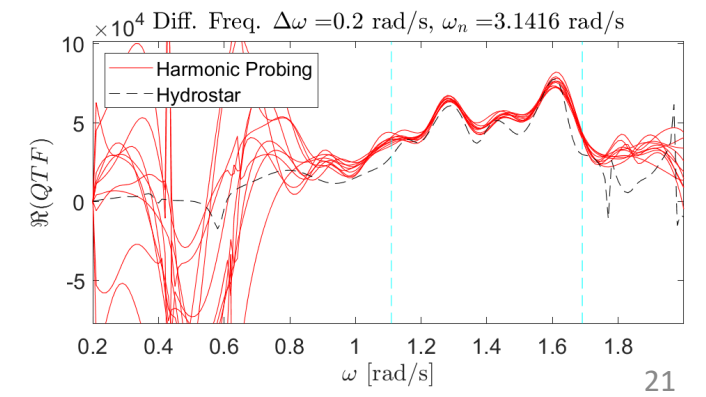
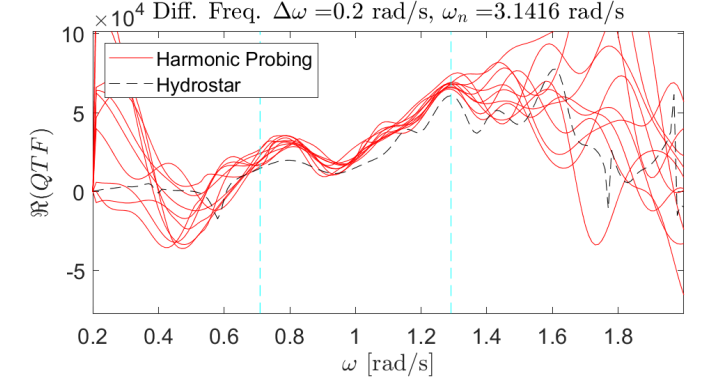
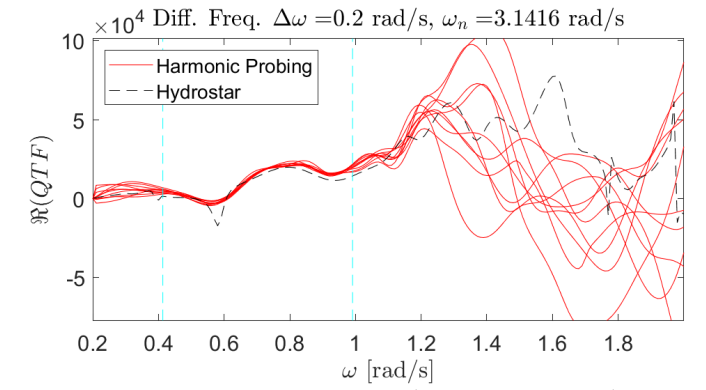
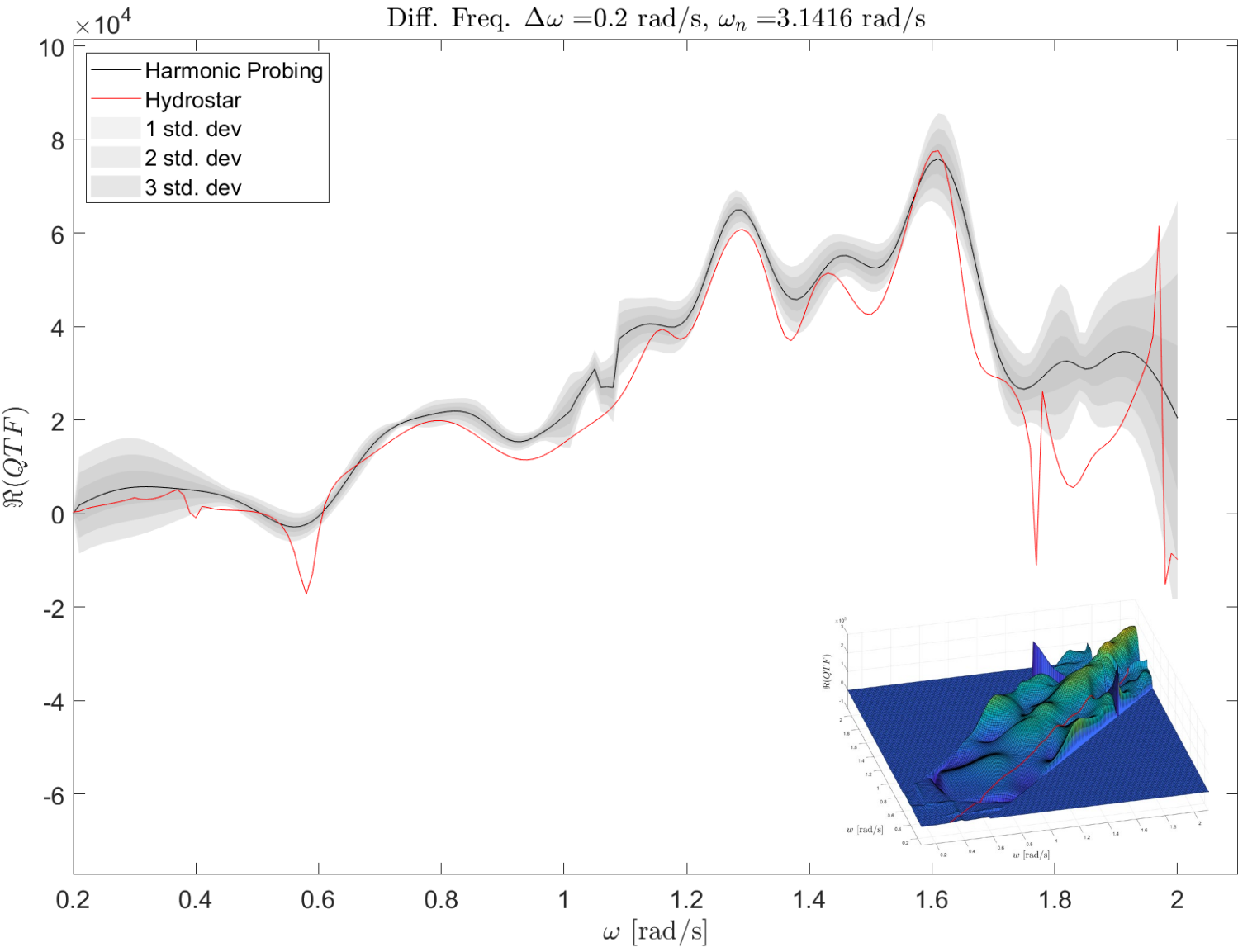
5 Probing and Results



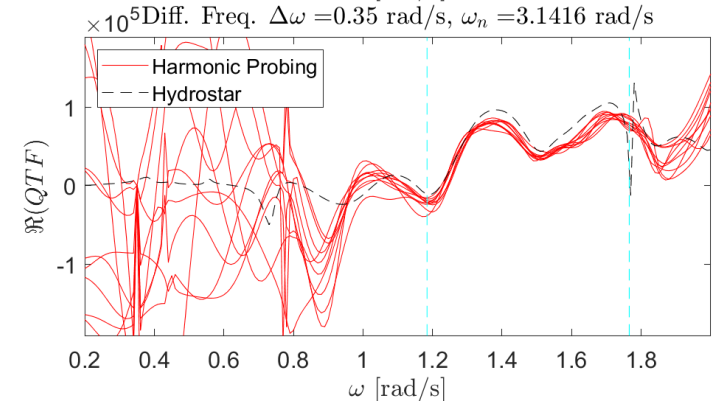
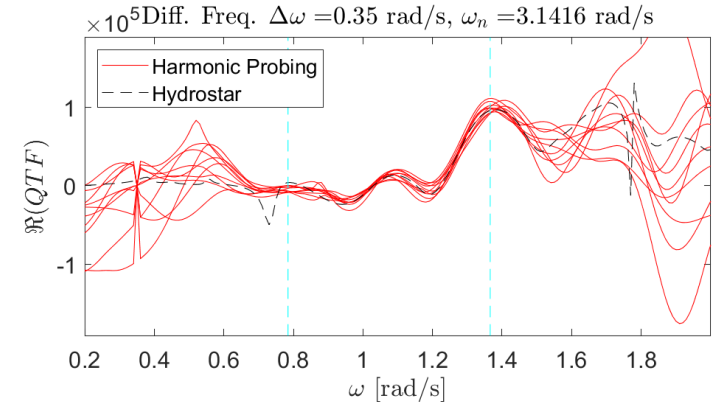
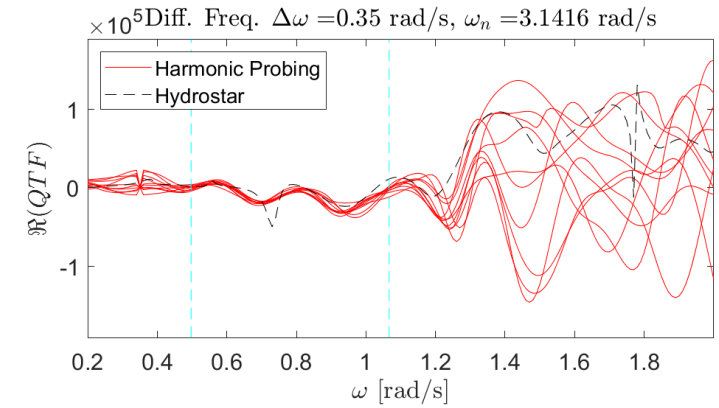
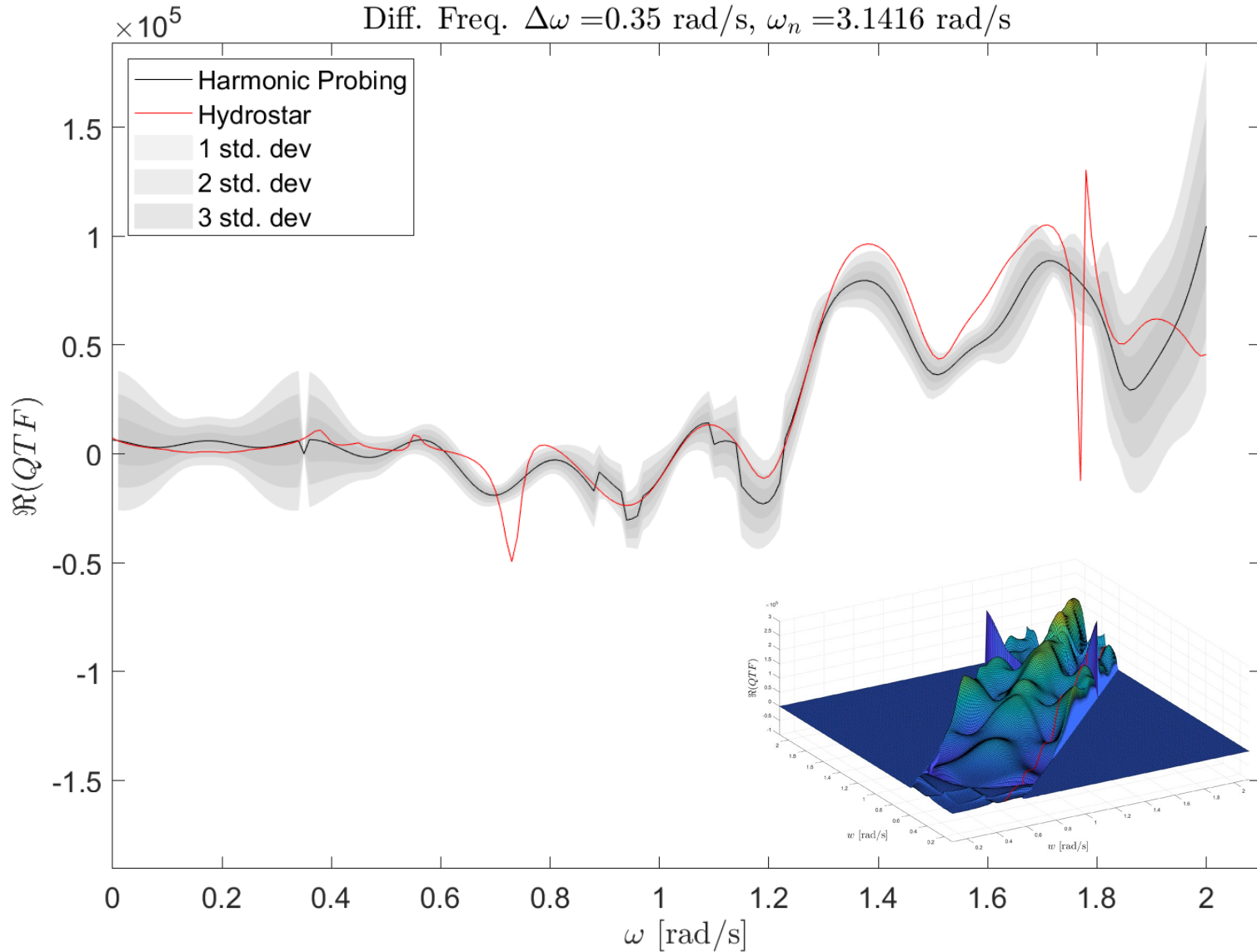
5 Probing and Results



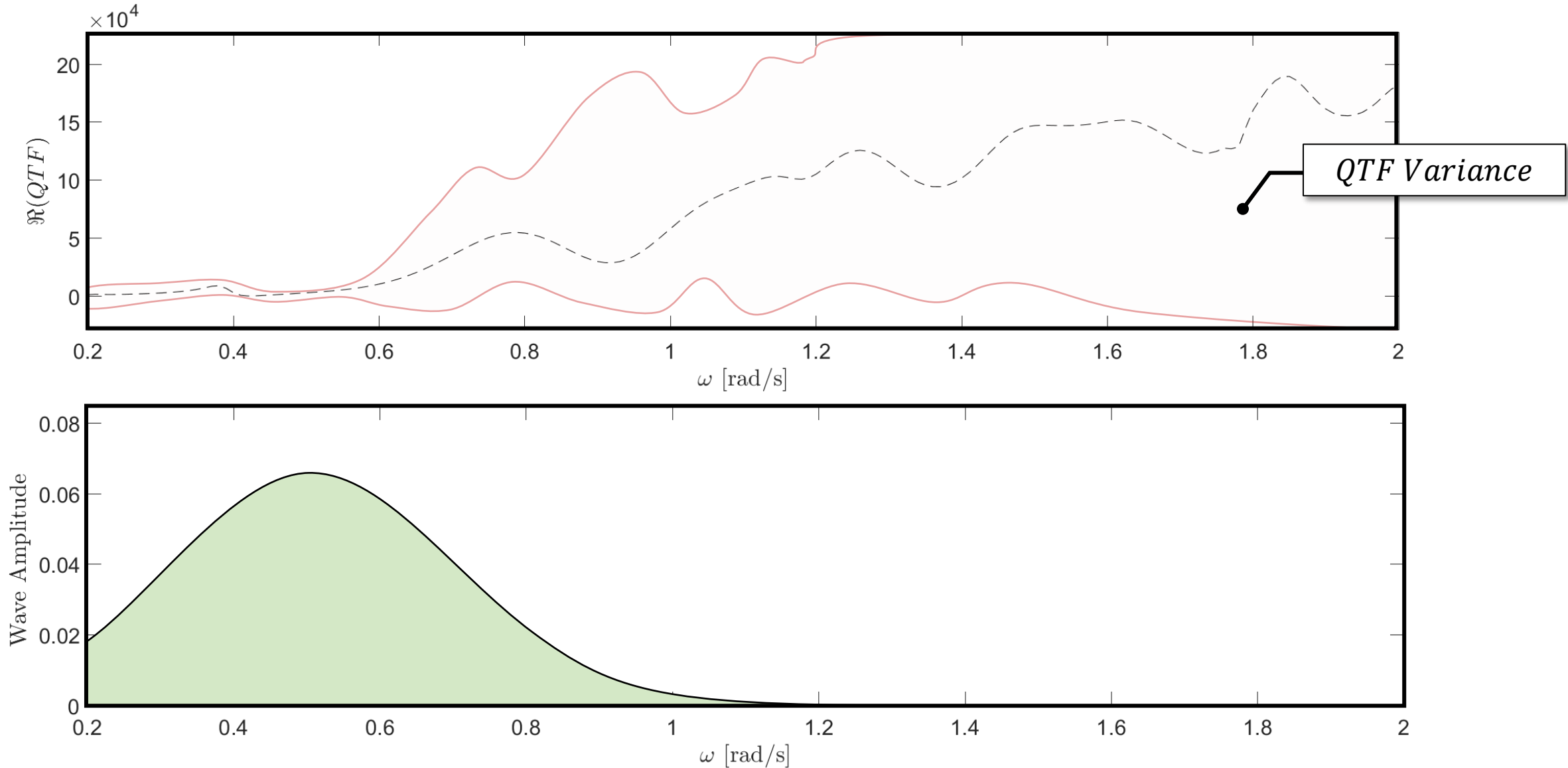
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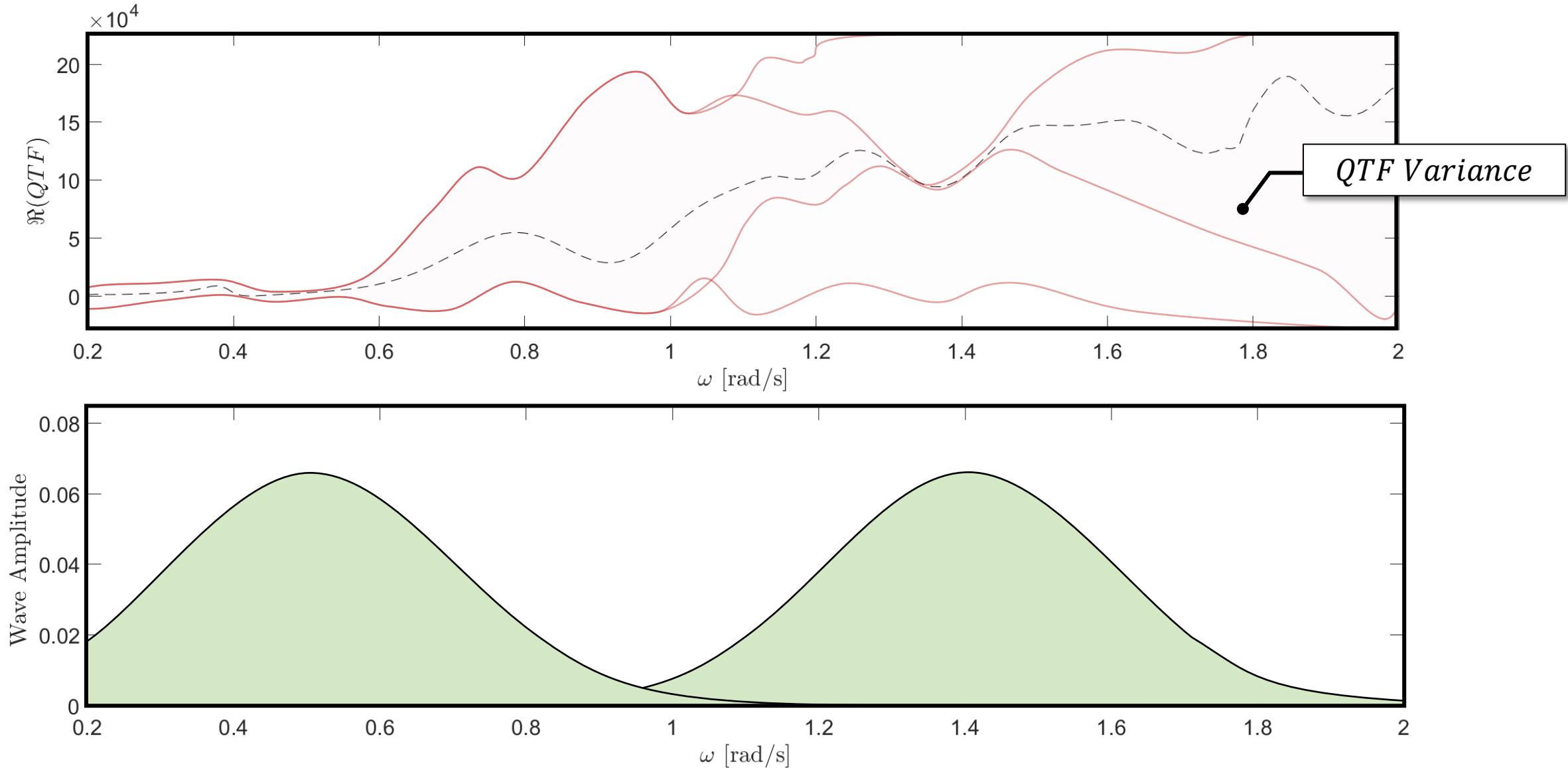
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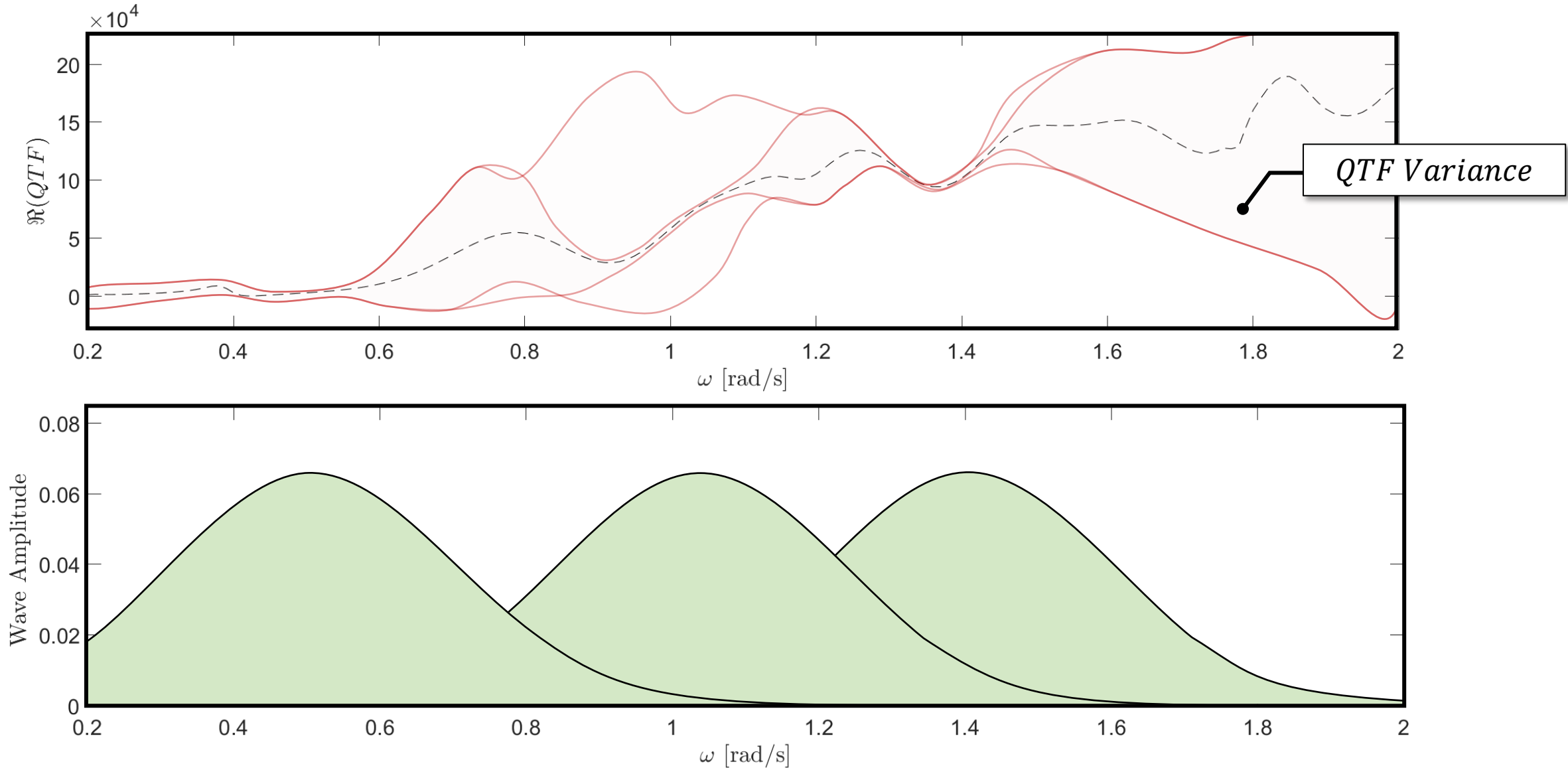
Optimal Experimental Design Perspective



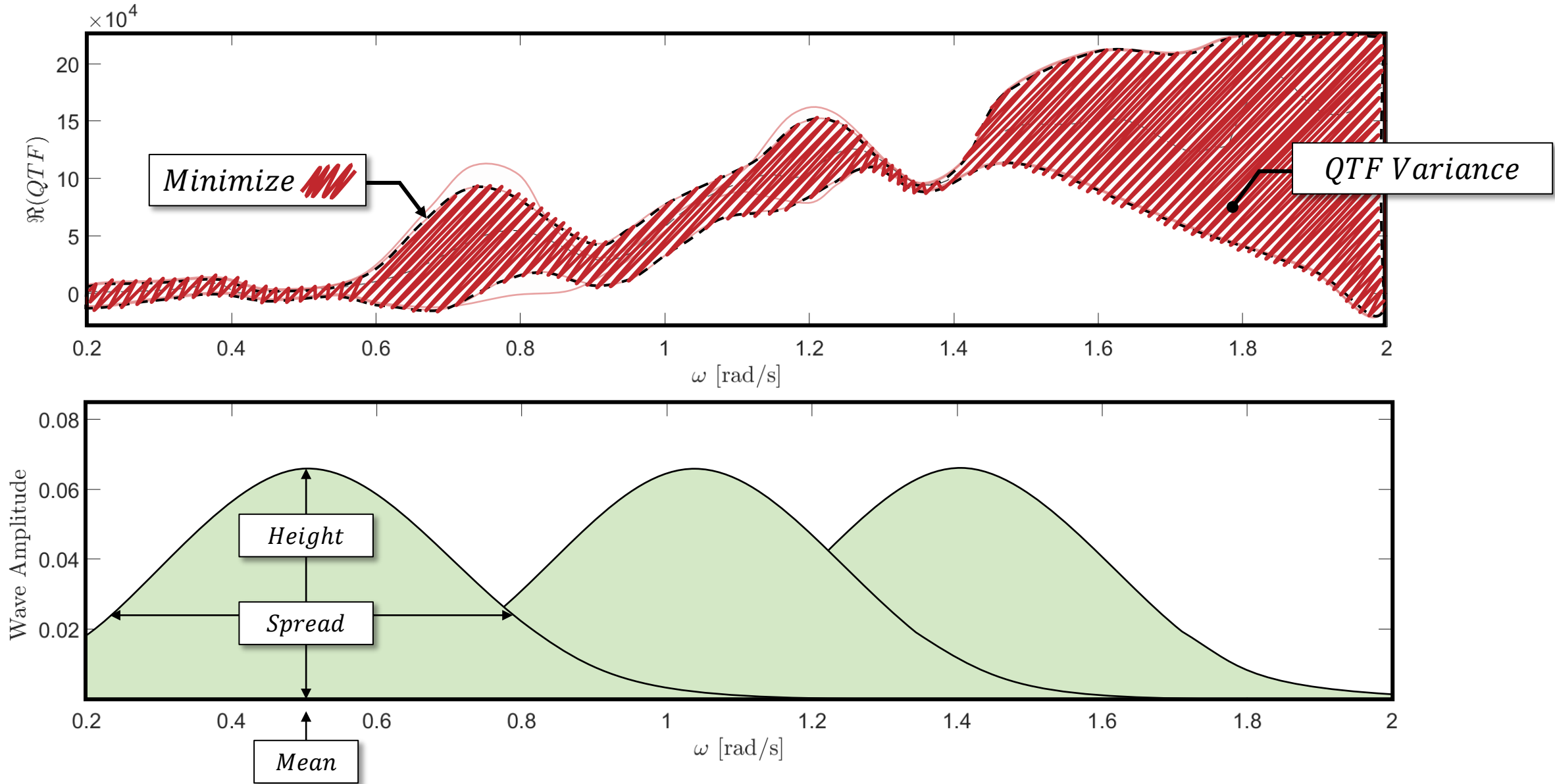
Optimal Experimental Design Perspective



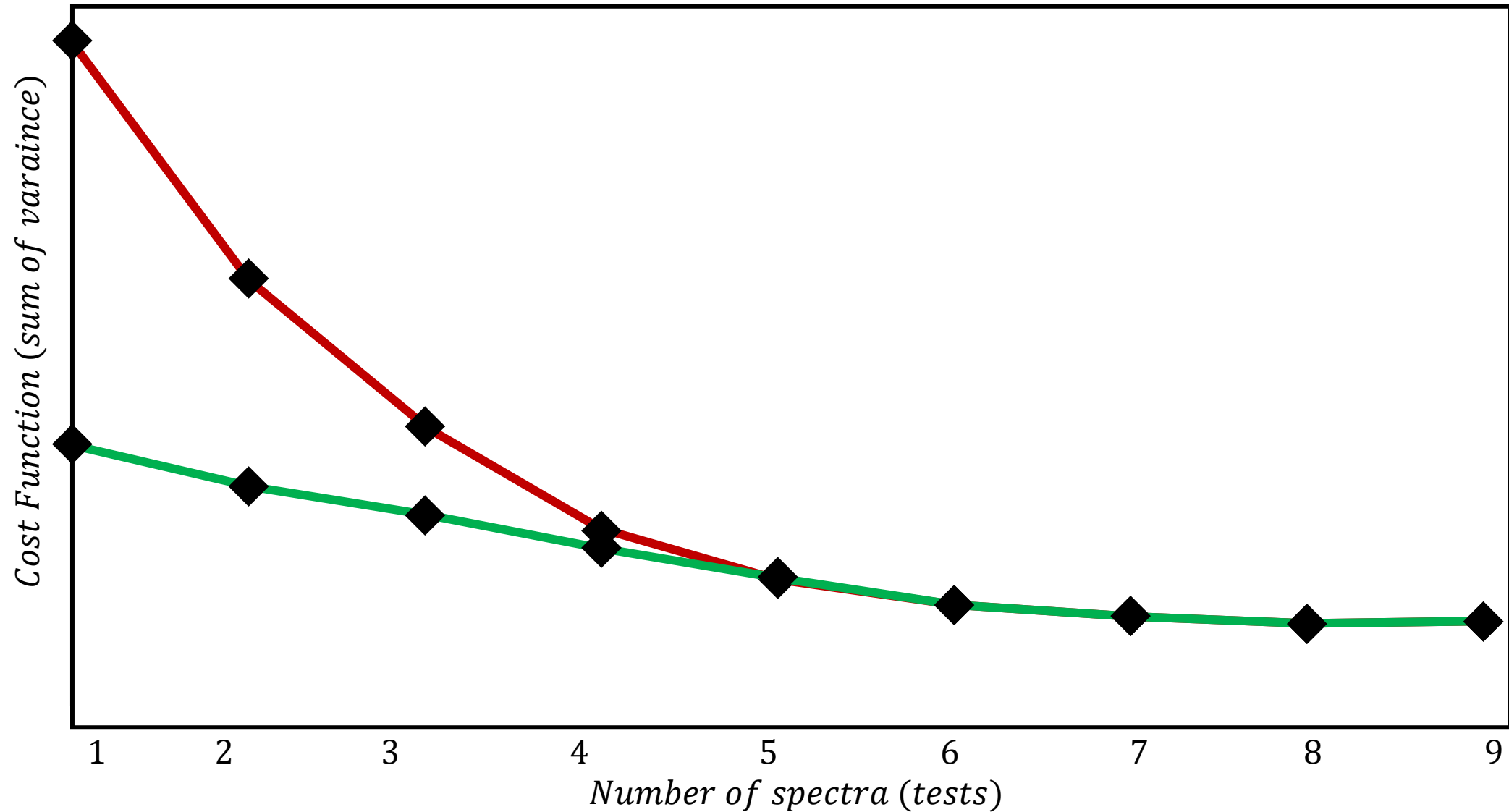
Optimal Experimental Design Perspective



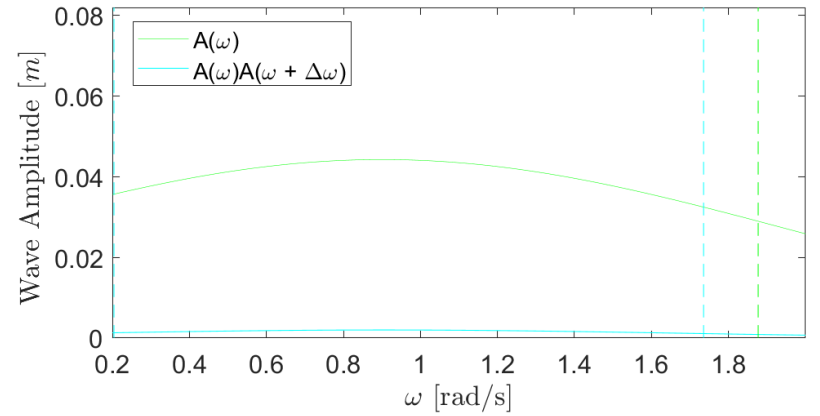
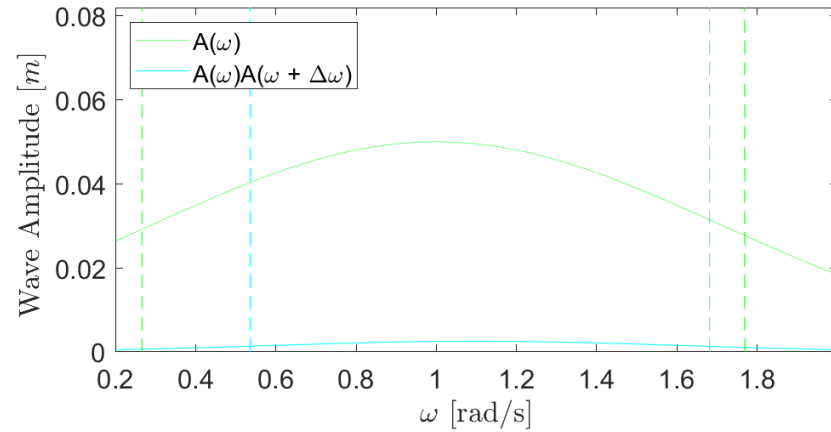
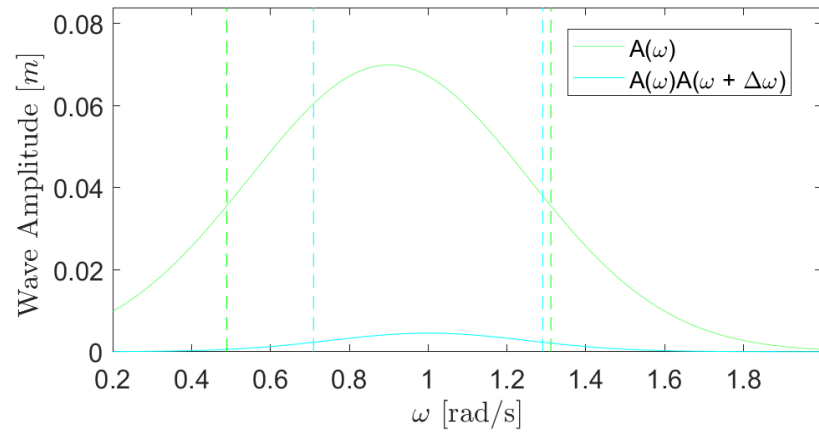
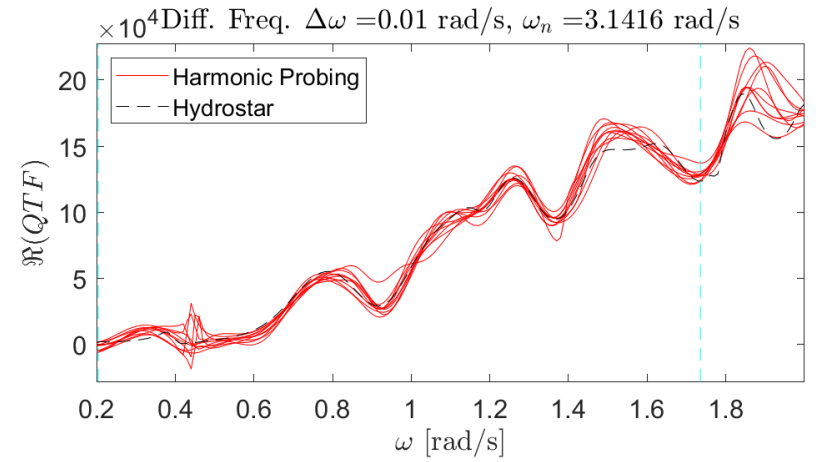
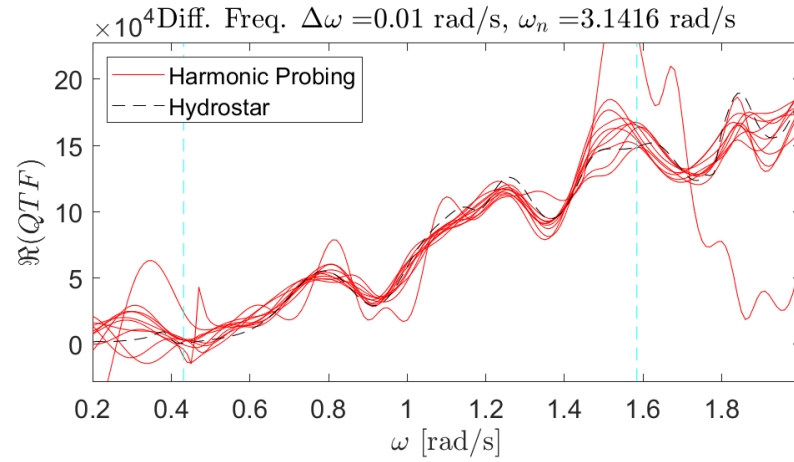
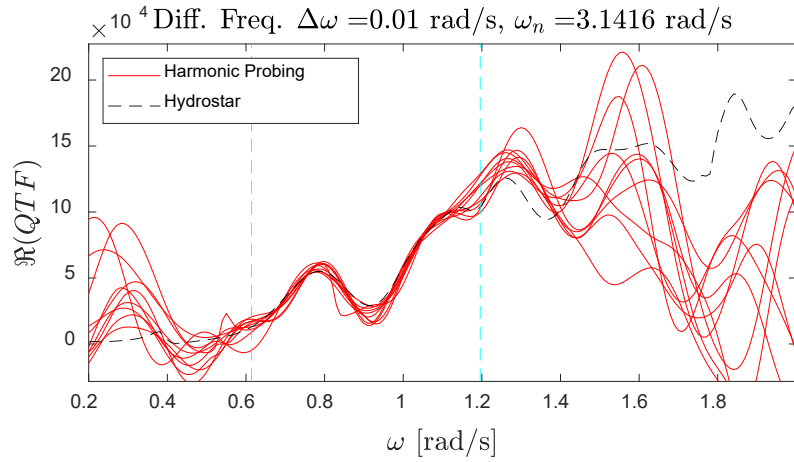
Optimal Experimental Design Perspective



Optimal Experimental Design Perspective



Optimal Experimental Design Perspective



$\mu = 0.90$ r/s

$\sigma = 0.25$ r/s

$\mu = 1.00$ r/s

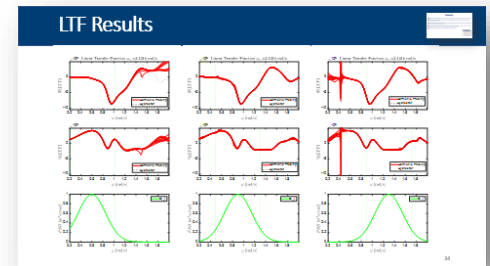
$\sigma = 0.50$ r/s

$\mu = 0.90$ r/s

$\sigma = 0.75$ r/s

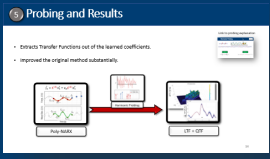
Summary

- ✓ Validated harmonic probing algorithm for both LTF and QTF estimations using synthetic data (Windmoor Hydrostar model).
- ✓ It is observed that the dispersion of LTF and QTF estimates is smaller where the spectral energy of the wave elevation profile (WEP) is concentrated.
- ✓ Identify different portion of LTF and QTF independently using WEPs characterized by Gaussian spectral energy distributions with different mean and standard deviation.
- ✓ A procedure for merging LTF and QTF estimates obtained for different WEP is proposed; the procedure allows for obtaining LTF and QTF estimates for the entire frequency range of interest with good accuracy.
- ✓ Optimization of number, mean, and standard deviation of each WEP spectrum

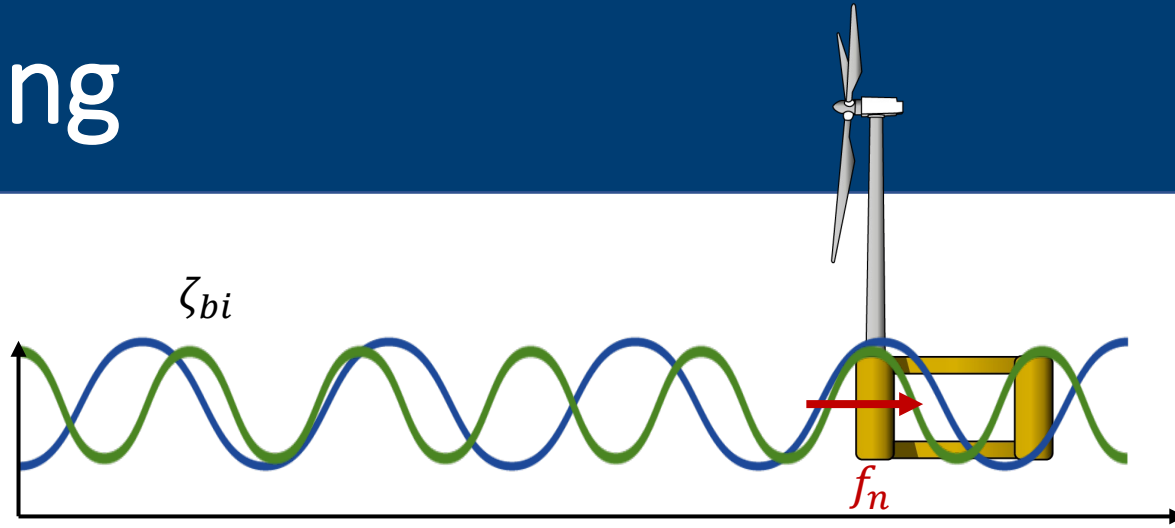


Appendix A

Harmonic Probing



$$\zeta_{bi}(t) = \overset{1.0}{A_1} e^{i\Omega_1 t_n} + \overset{1.0}{A_2} e^{i\Omega_2 t_n}$$



$$f_n(t) = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + H^{(1)}(\Omega_2) e^{i\Omega_2 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2) t_n} + H^{(2)}(\Omega_1, \Omega_1) e^{i(2\Omega_1) t_n} + H^{(2)}(\Omega_2, \Omega_2) e^{i(2\Omega_2) t_n}$$

NARX

Volterra

$$f_n = \frac{\partial \mathcal{F}}{\partial \mathbf{x}} \Big|_0 \mathbf{x}_n^T + \frac{1}{2} \mathbf{x}_n \frac{\partial^2 \mathcal{F}}{\partial \mathbf{x}^2} \Big|_0 \mathbf{x}_n^T$$

$$f_n(t) = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2) t_n} \dots$$

Harmonic Probing

NARX

$$f_n = \left. \frac{\partial \mathcal{F}}{\partial \mathbf{x}} \right|_0 \mathbf{x}_n^T + \frac{1}{2} \mathbf{x}_n \left. \frac{\partial^2 \mathcal{F}}{\partial \mathbf{x}^2} \right|_0 \mathbf{x}_n^T$$

$$\mathbf{x}_n = (f_{n-1}, f_{n-2}, \dots, f_{n-n_f}, \zeta_n, \zeta_{n-1}, \dots, \zeta_{n-n_\zeta})$$

Volterra

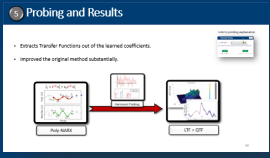
$$f_n(t) = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2)t_n} \dots$$

- Present n : $[e^{i\Omega_1 t_n}]$
 Past $n-1$: $[e^{i\Omega_1 t_n}] e^{-i\Omega_1 \Delta t}$
 Past $n-2$: $[e^{i\Omega_1 t_n}] e^{-2i\Omega_1 \Delta t}$
 \vdots

$$\mathbf{x}_n = \begin{bmatrix} f_{n-1} \\ f_{n-2} \\ \zeta_n \\ \zeta_{n-1} \end{bmatrix}^T = \begin{bmatrix} [H^{(1)}(\Omega_1) e^{i\Omega_1} + H^{(1)}(\Omega_2) e^{i\Omega_2} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2)} + \dots] e^{t_n - \Delta t} \\ [H^{(1)}(\Omega_1) e^{i\Omega_1} + H^{(1)}(\Omega_2) e^{i\Omega_2} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2)} + \dots] e^{t_n - 2\Delta t} \\ e^{i\Omega_1 t_n} + e^{i\Omega_2 t_n} \\ e^{i\Omega_1(t_{n-1})} + e^{i\Omega_2(t_n - \Delta t)} \end{bmatrix}^T$$

$$\left. \frac{\partial \mathcal{F}}{\partial \mathbf{x}} \right|_0 \mathbf{x}_n^T + \frac{1}{2} \mathbf{x}_n \left. \frac{\partial^2 \mathcal{F}}{\partial \mathbf{x}^2} \right|_0 \mathbf{x}_n^T = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2)t_n}$$

Harmonic Probing



$$\left. \frac{\partial \mathcal{F}}{\partial \mathbf{x}} \right|_0 \mathbf{x}_n^T + \frac{1}{2} \mathbf{x}_n^T \left. \frac{\partial^2 \mathcal{F}}{\partial \mathbf{x}^2} \right|_0 \mathbf{x}_n = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2) t_n}$$

$$A e^{i\Omega_1 t_n} + B e^{2i\Omega_1 t_n} + C e^{i(\Omega_1 + \Omega_2) t_n} + D e^{i(2\Omega_1 + \Omega_2) t_n} + E e^{i\Omega_1 t_n} + F e^{i\Omega_2 t_n} = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n} + 2H^{(2)}(\Omega_1, \Omega_2) e^{i(\Omega_1 + \Omega_2) t_n}$$

$$(A + E) e^{i\Omega_1 t_n} = H^{(1)}(\Omega_1) e^{i\Omega_1 t_n}$$

$$A + E = H^{(1)}(\Omega_1)$$

LTF Results

Summary

- ✓ Efficient harmonic probing algorithm for LTF and STFT estimation using frequency-based (DFT) methods
- ✓ A. proposed that the degree of ST and STFT estimation is under a specific range of the wave number
- ✓ Linear LTF estimation
- ✓ Accurate different order of ST and STFT independently using WVD (Wavelet-based Fourier transform)
- ✓ L. proposed for reducing ST and STFT estimation obtained for different STFT parameters for obtaining a search frequency by the STFT frequency range of interest
- ✓ Distribution of number, size, and loaded elements of each STFT operation

