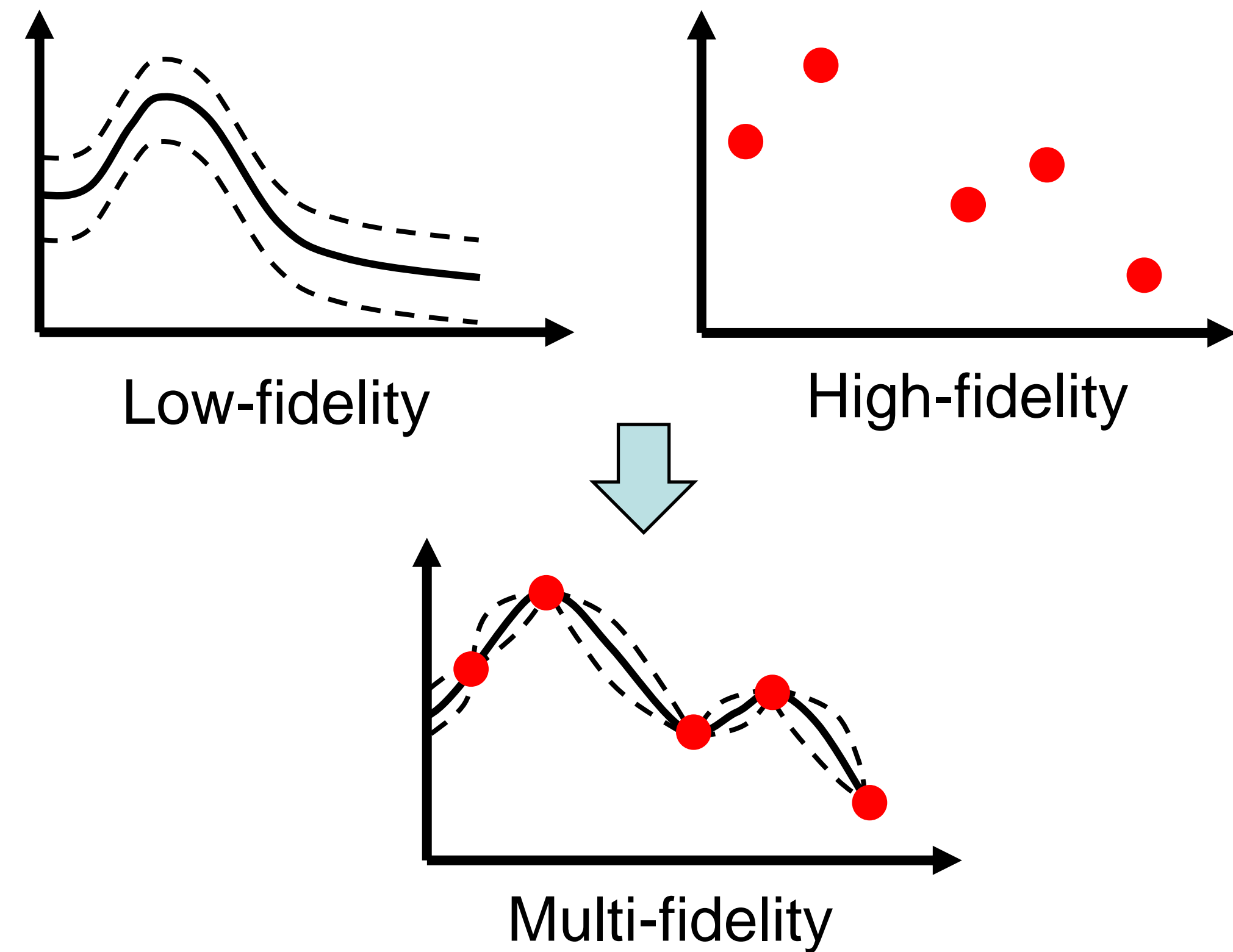


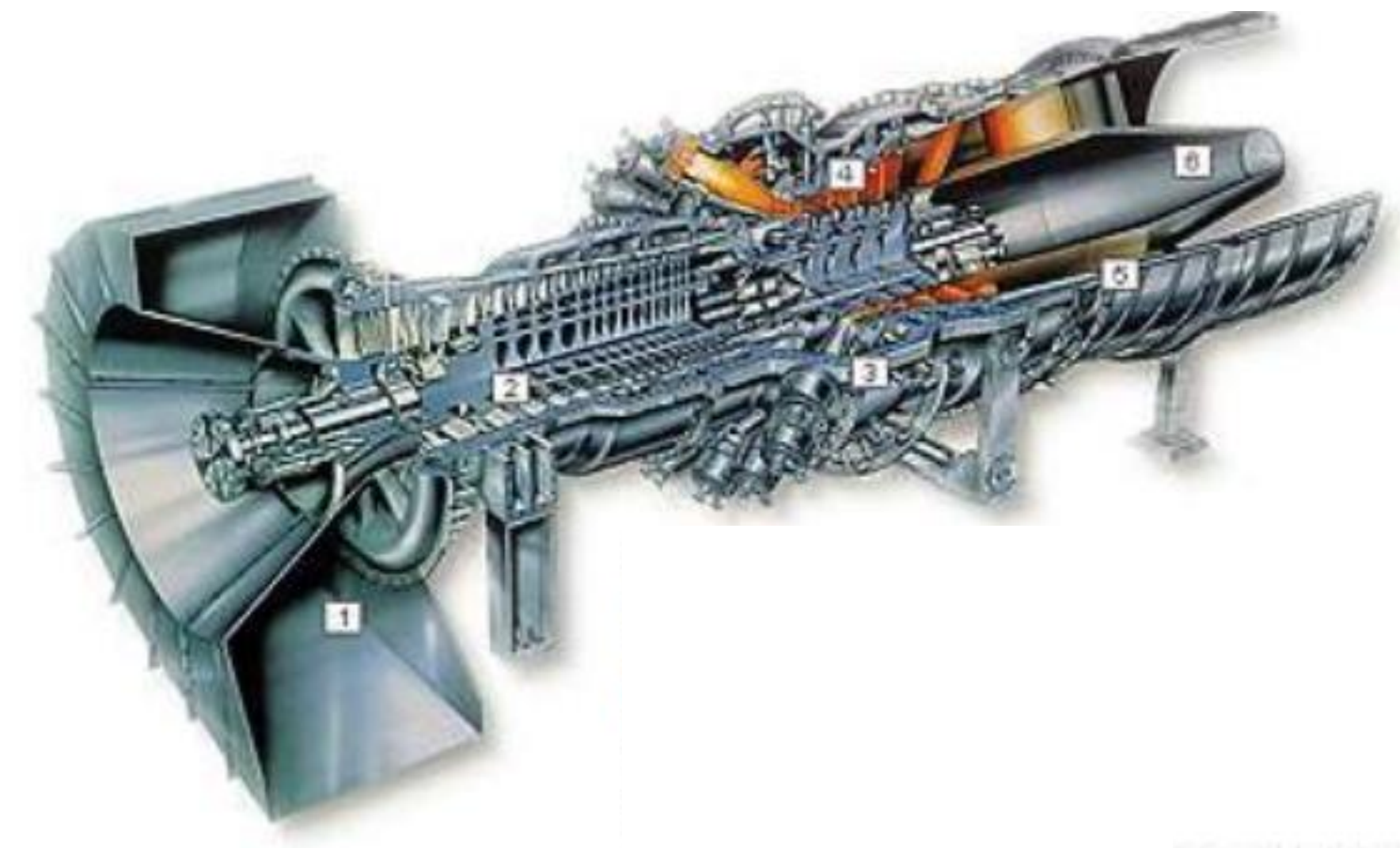
Robust Flame Frequency Response Identification via a Multi-Fidelity Approach

S. Guo, C. F. Silva, W. Polifke

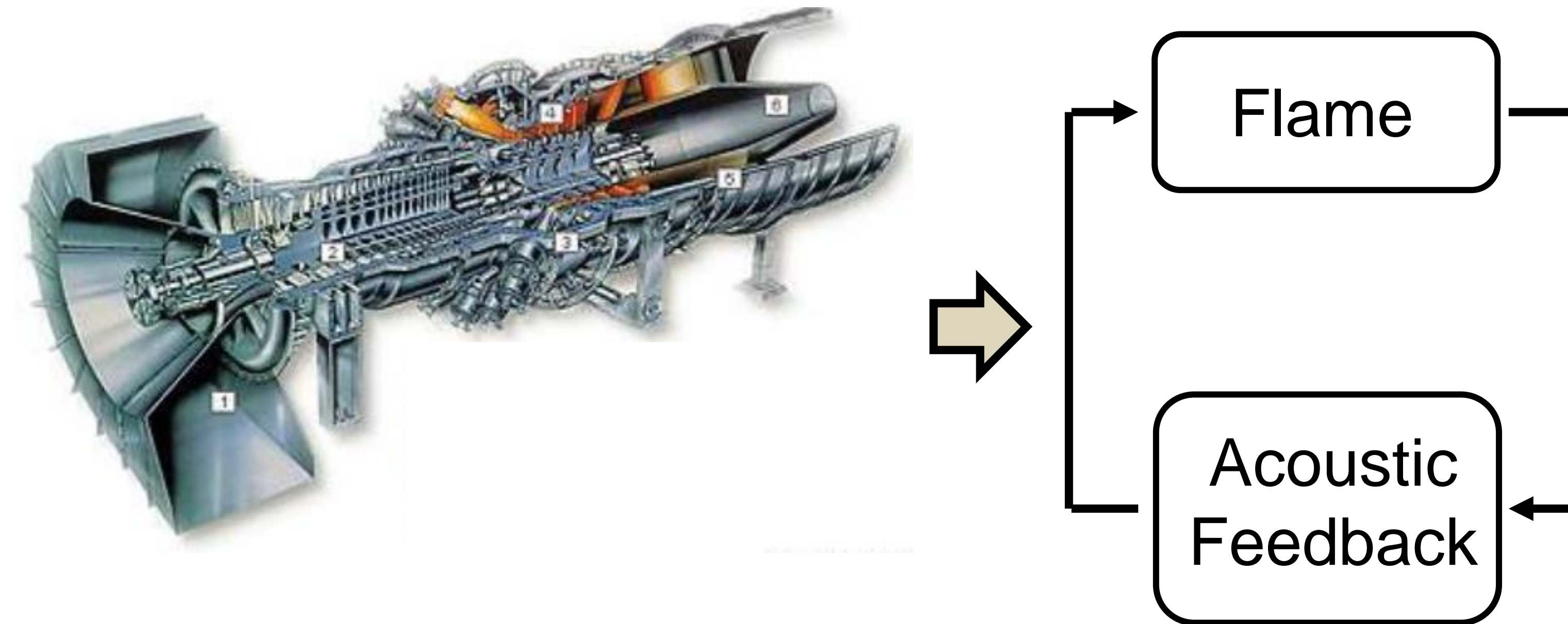
CM⁴P, Porto, Portugal, 2019



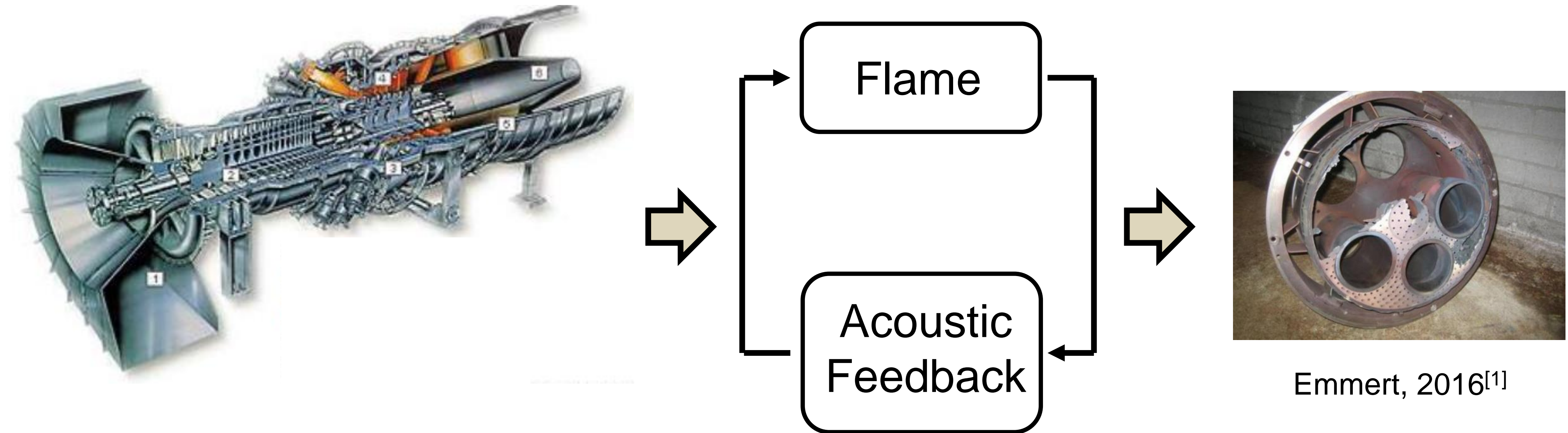
Combustion instability threatens the stable operation of a gas turbine



Combustion instability threatens the stable operation of a gas turbine

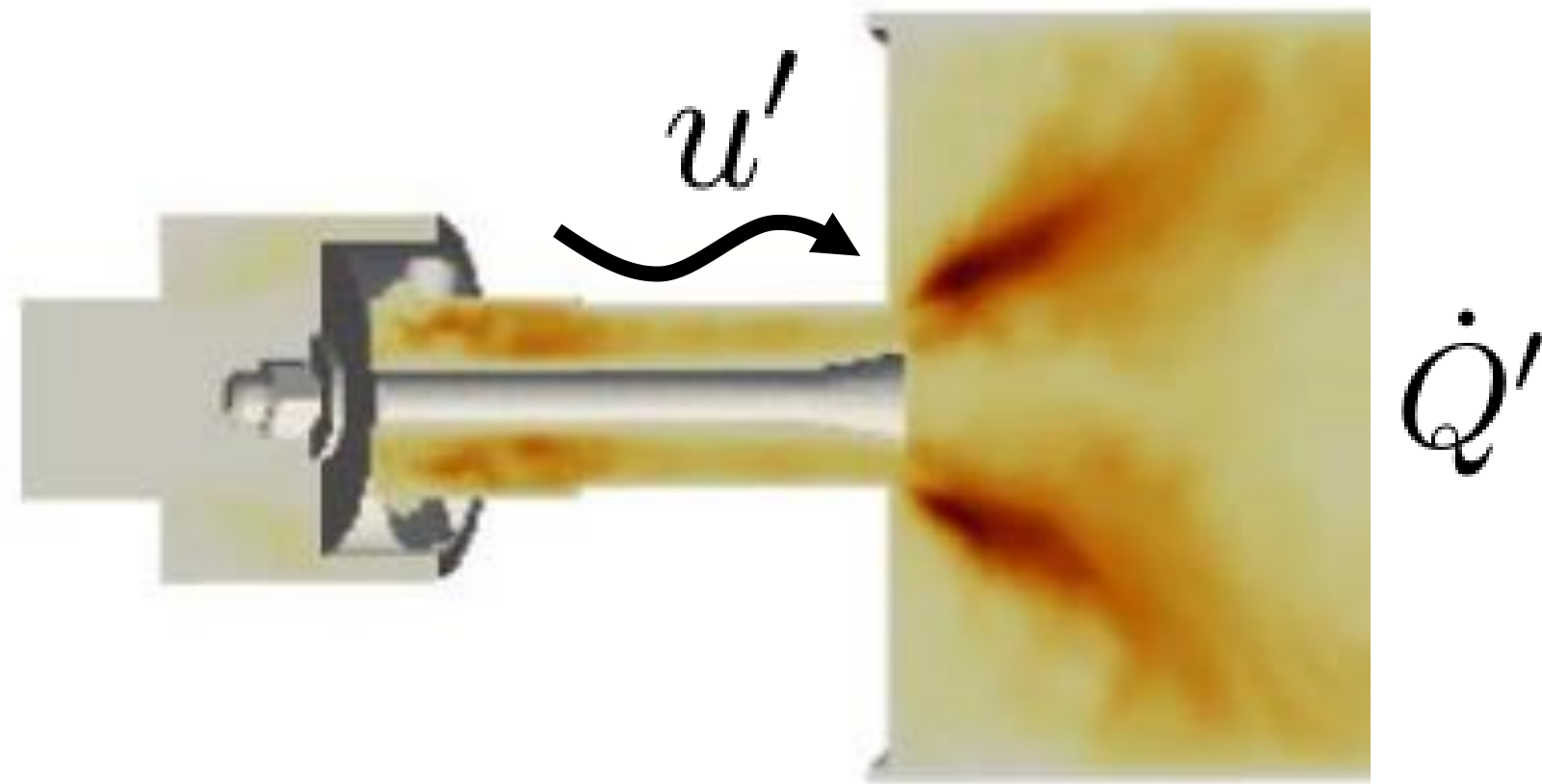


Combustion instability threatens the stable operation of a gas turbine



[1] T. Emmert. State Space Modeling of Thermoacoustic System with Application to Intrinsic Feedback. PhD thesis, TUM

Flame frequency response plays a key role in investigating combustion instability

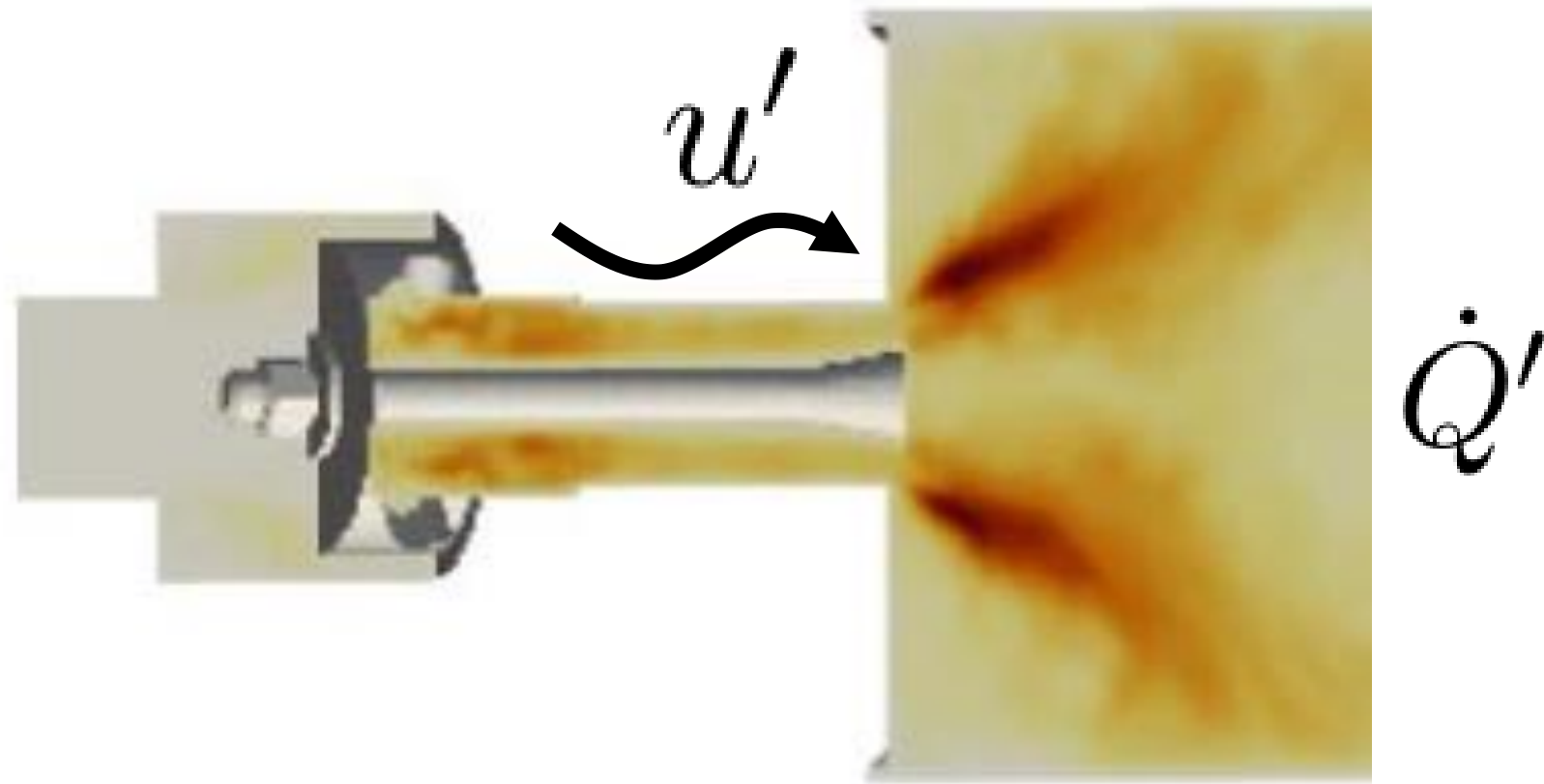


Merk, 2018^[2]

[2] M. Merk, W. Polifke, R. Gaudron, M. Gatti, C. Mirat, T. Schuller., 2018, AIAA Journal.

Guo et al. | CM⁴P, Porto, Portugal

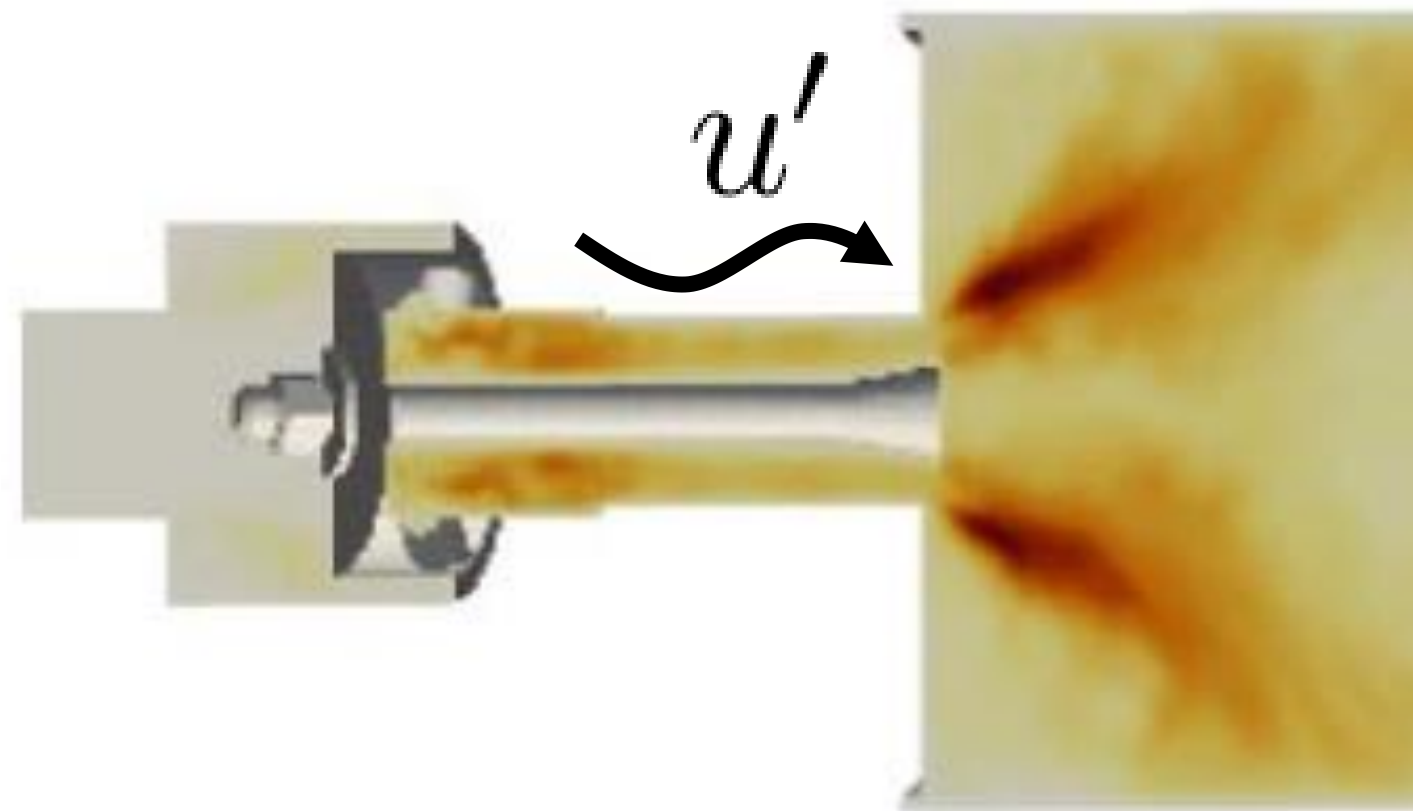
Flame frequency response plays a key role in investigating combustion instability



Merk, 2018^[2]

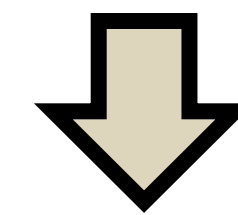
$$F(\omega) = \frac{\dot{Q}'(\omega)/\bar{\dot{Q}}}{u'(\omega)/\bar{u}}$$

Flame frequency response plays a key role in investigating combustion instability



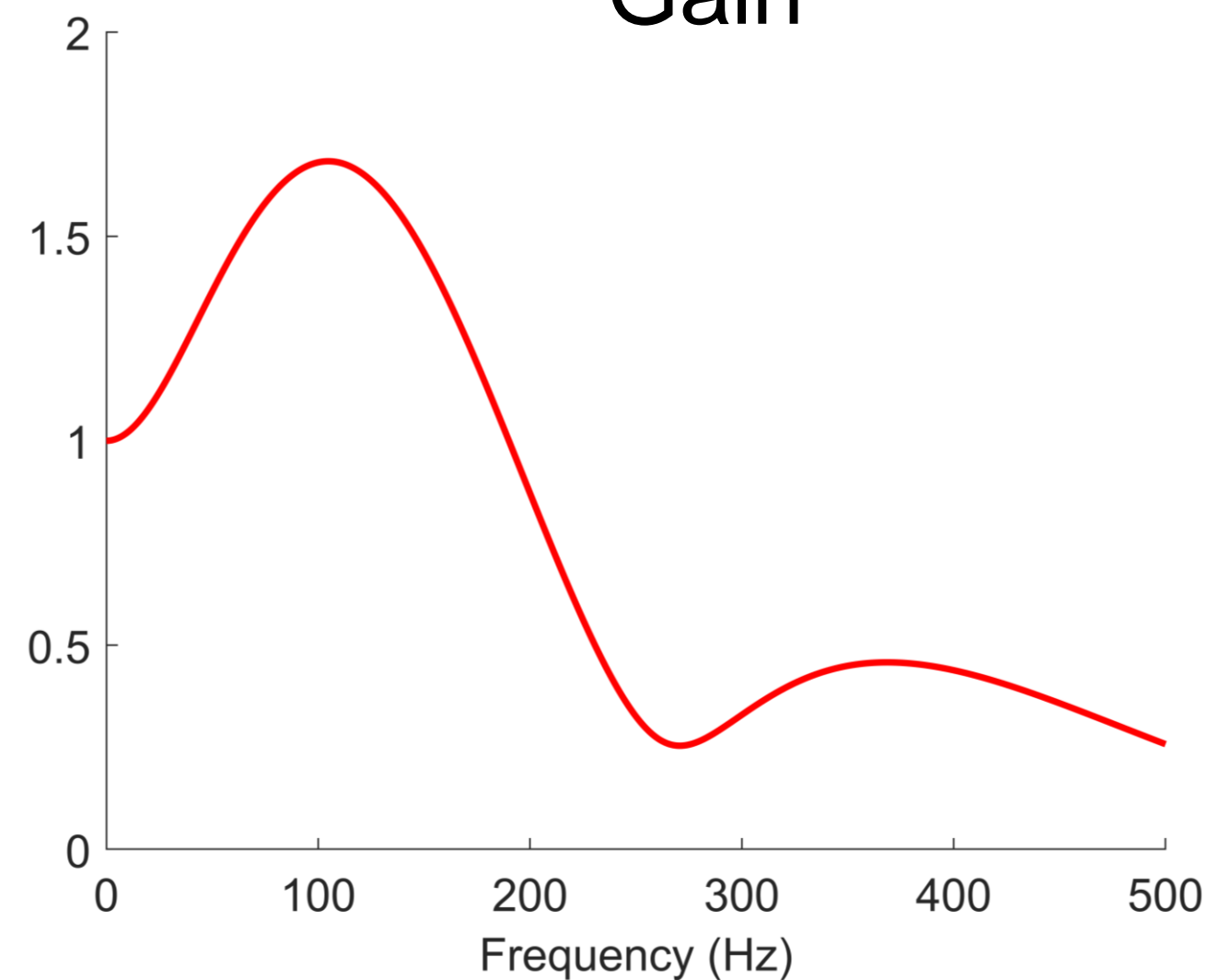
Merk, 2018^[2]

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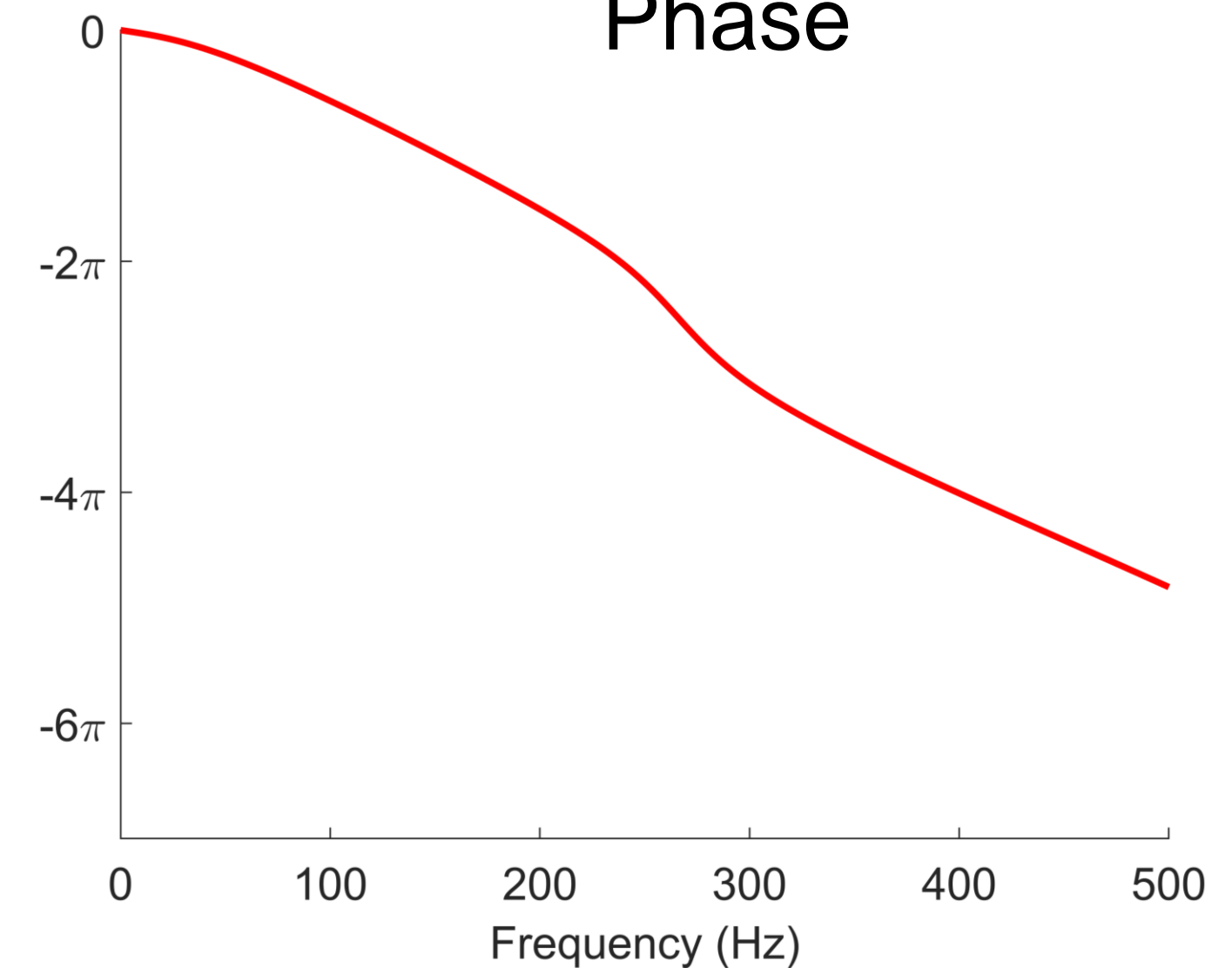


\dot{Q}'

Gain

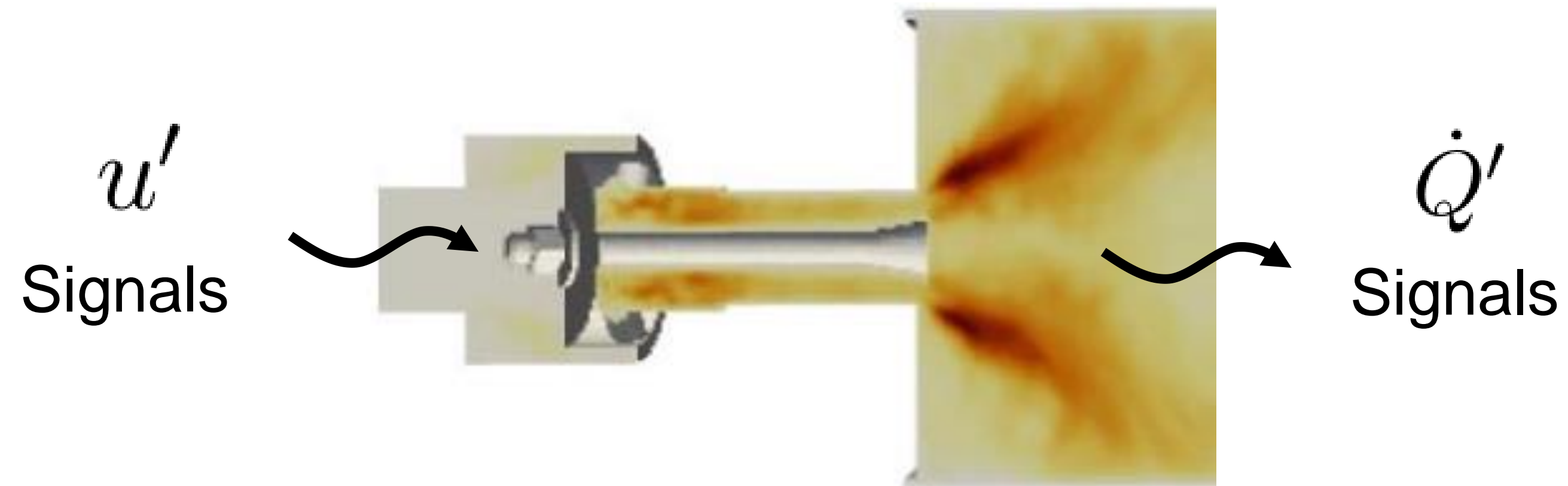


Phase



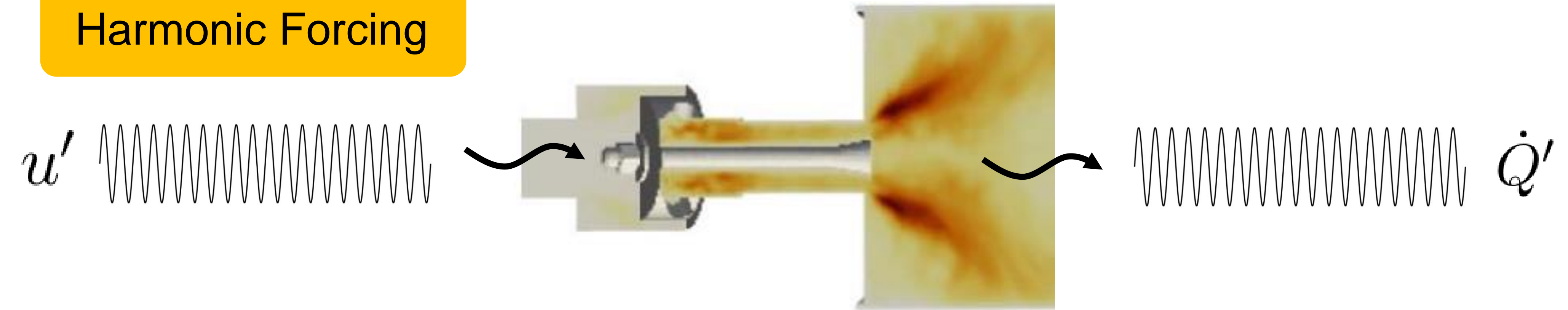
[2] M. Merk, W. Polifke, R. Gaudron, M. Gatti, C. Mirat, T. Schuller., 2018, AIAA Journal.

Flame frequency response can be derived from CFD simulations



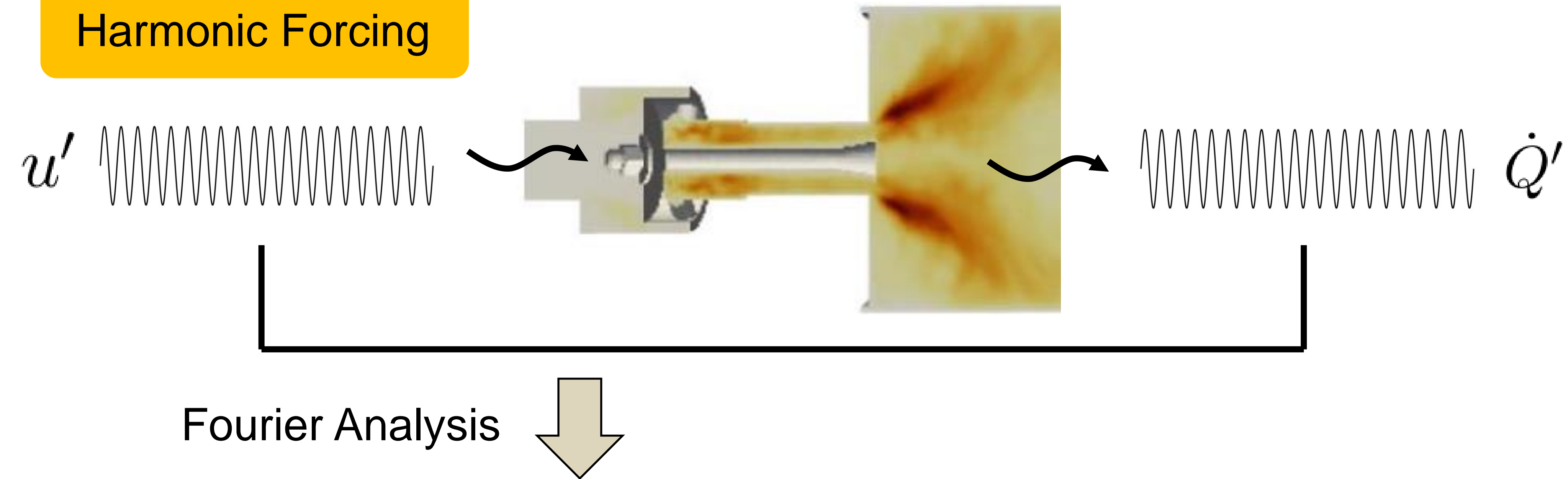
Harmonic forcing is highly accurate but only provides point-estimation

Harmonic Forcing



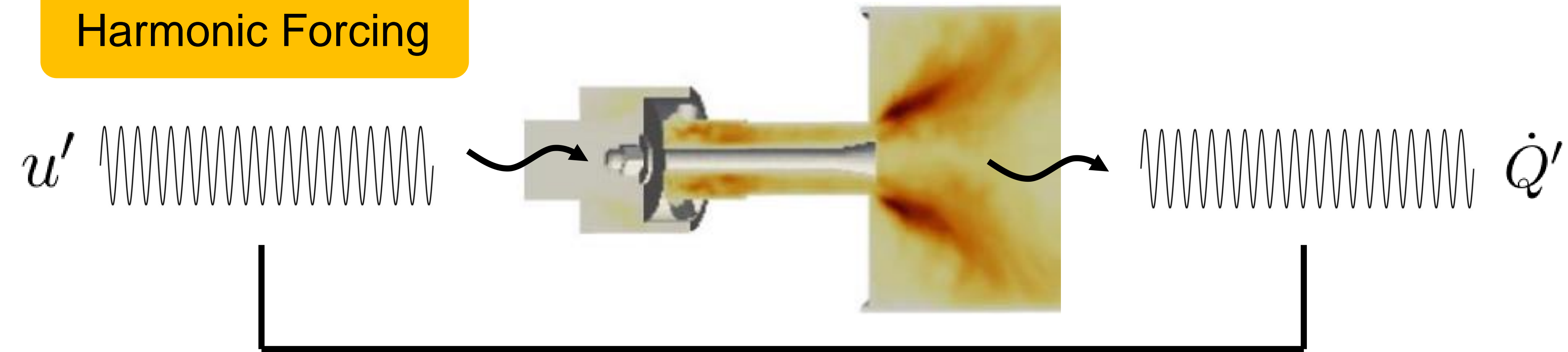
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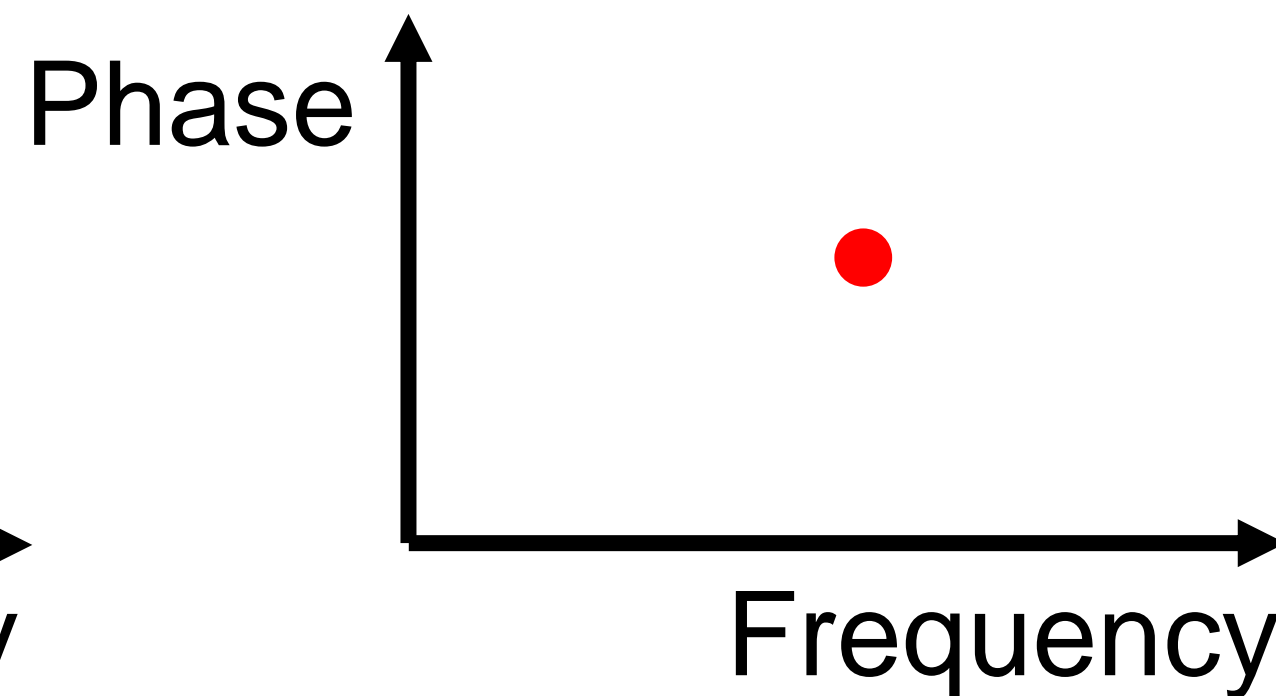
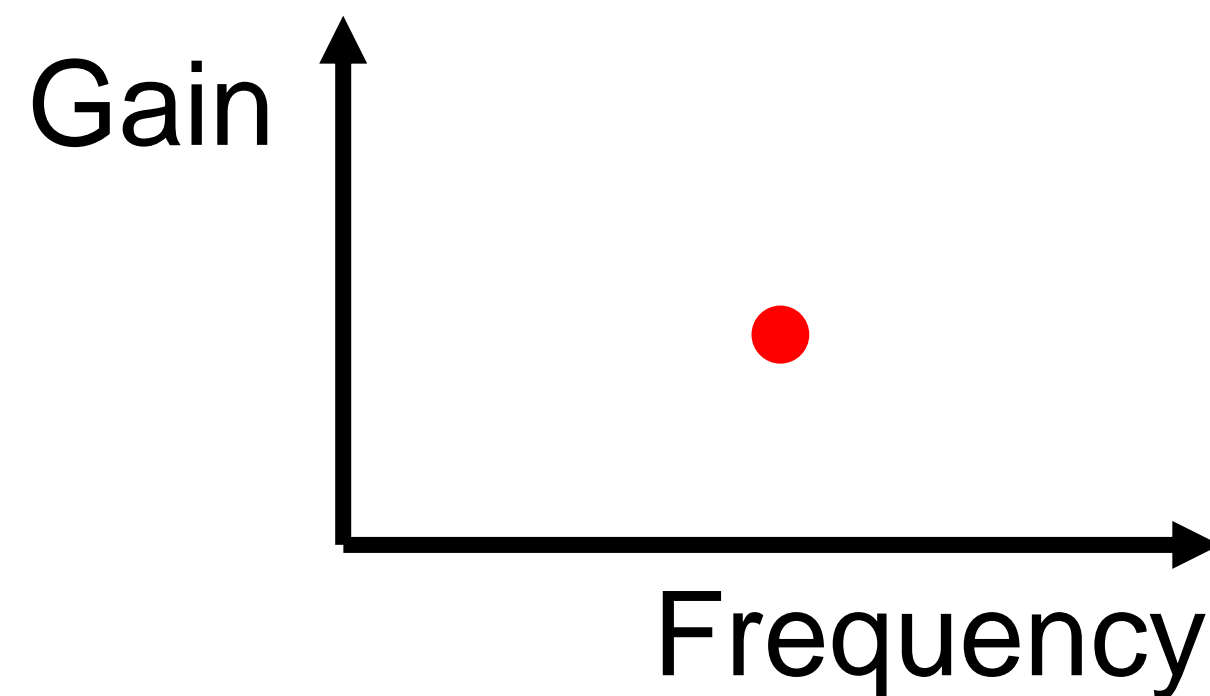
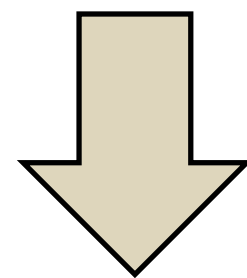


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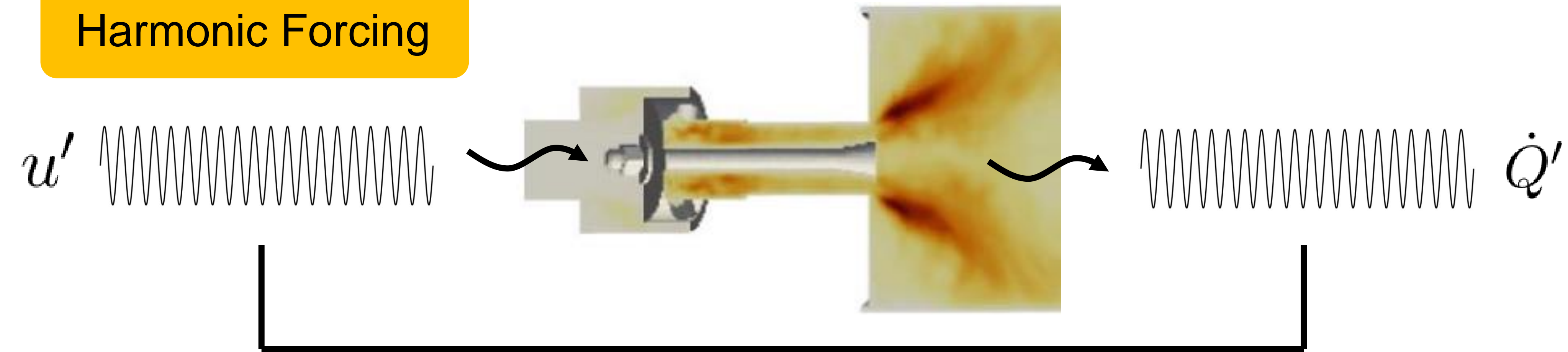


Fourier Analysis

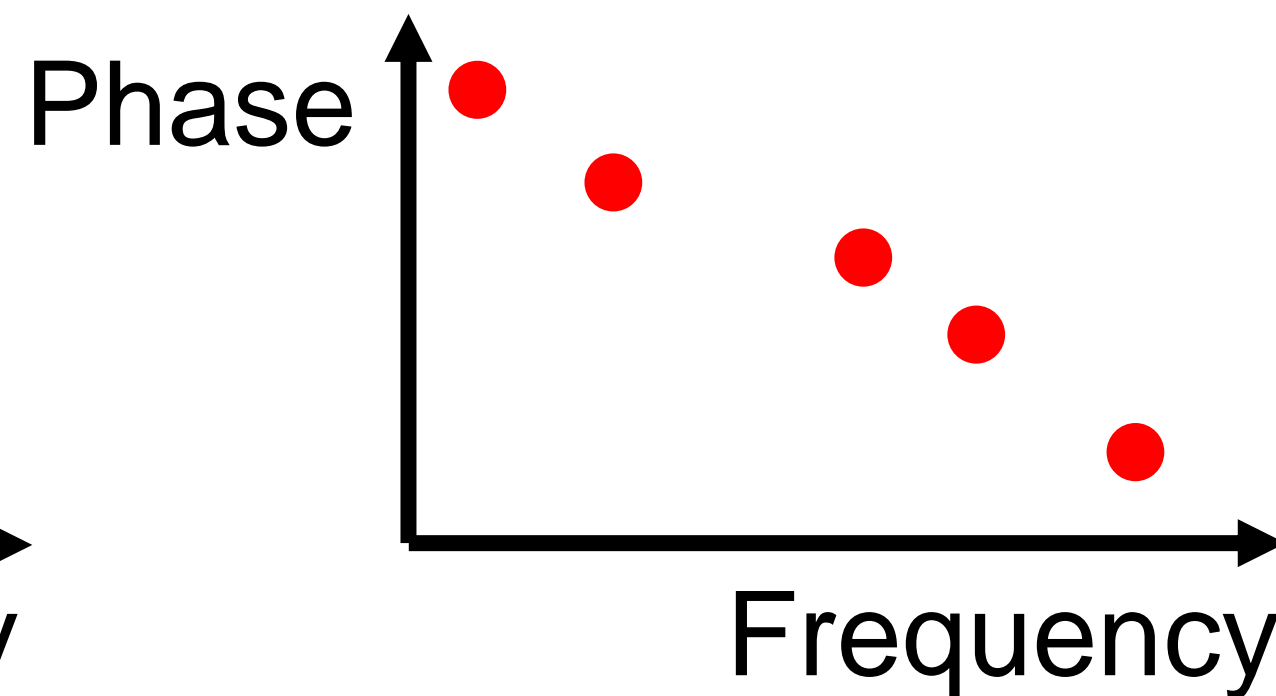
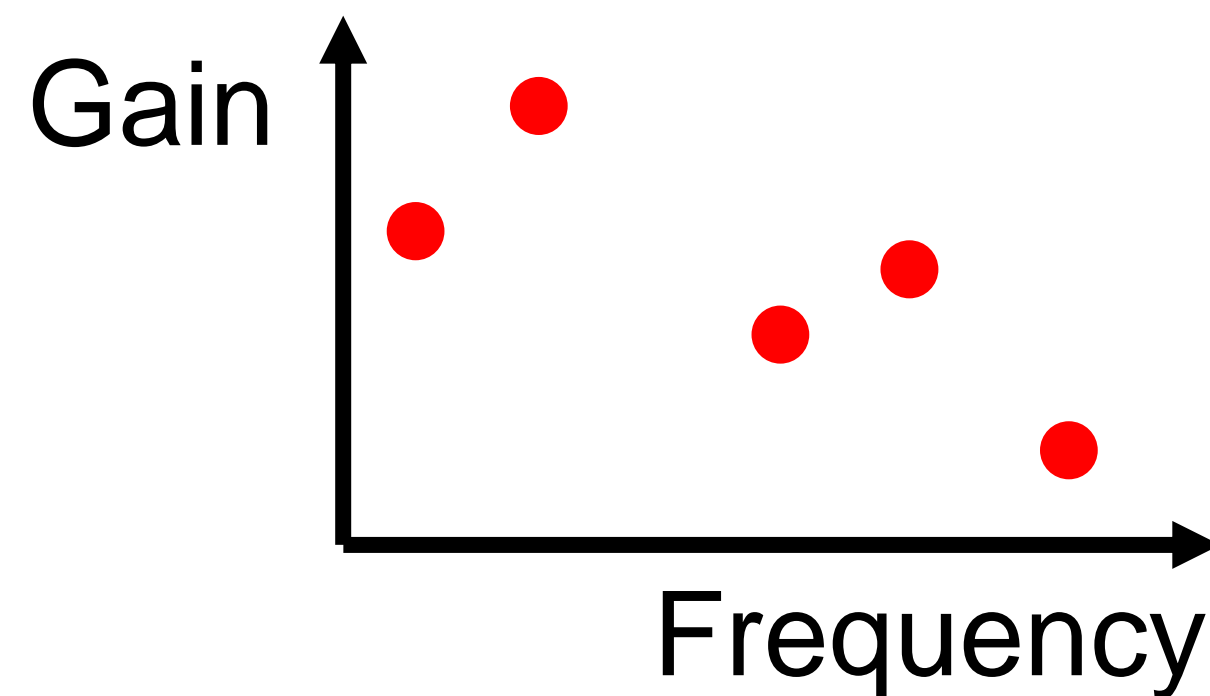
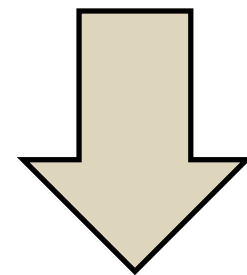


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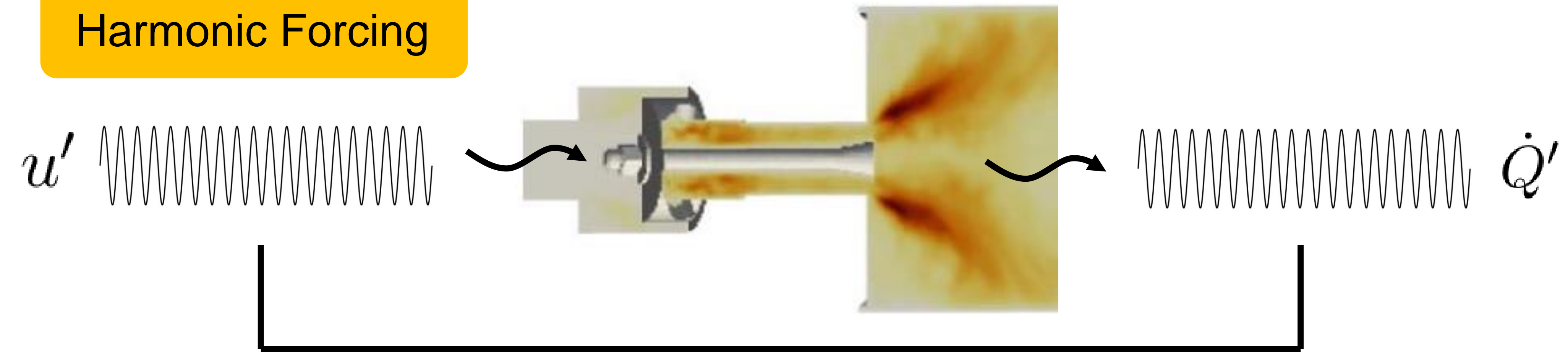


Fourier Analysis

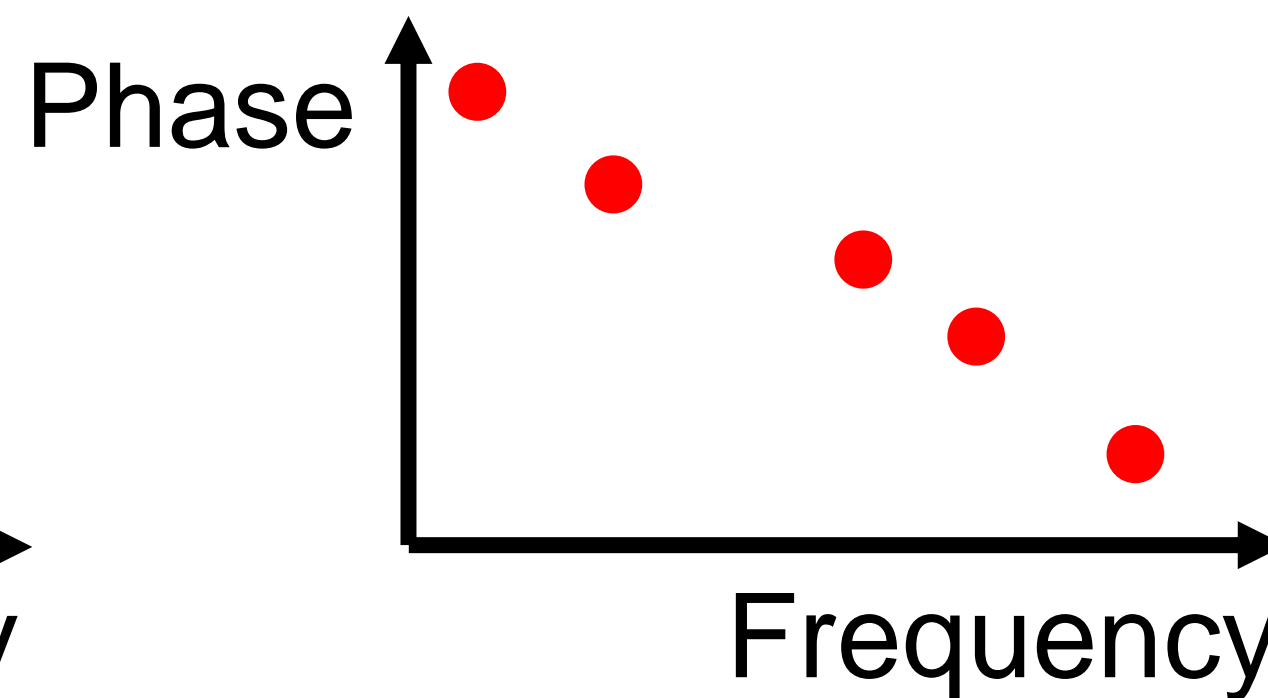
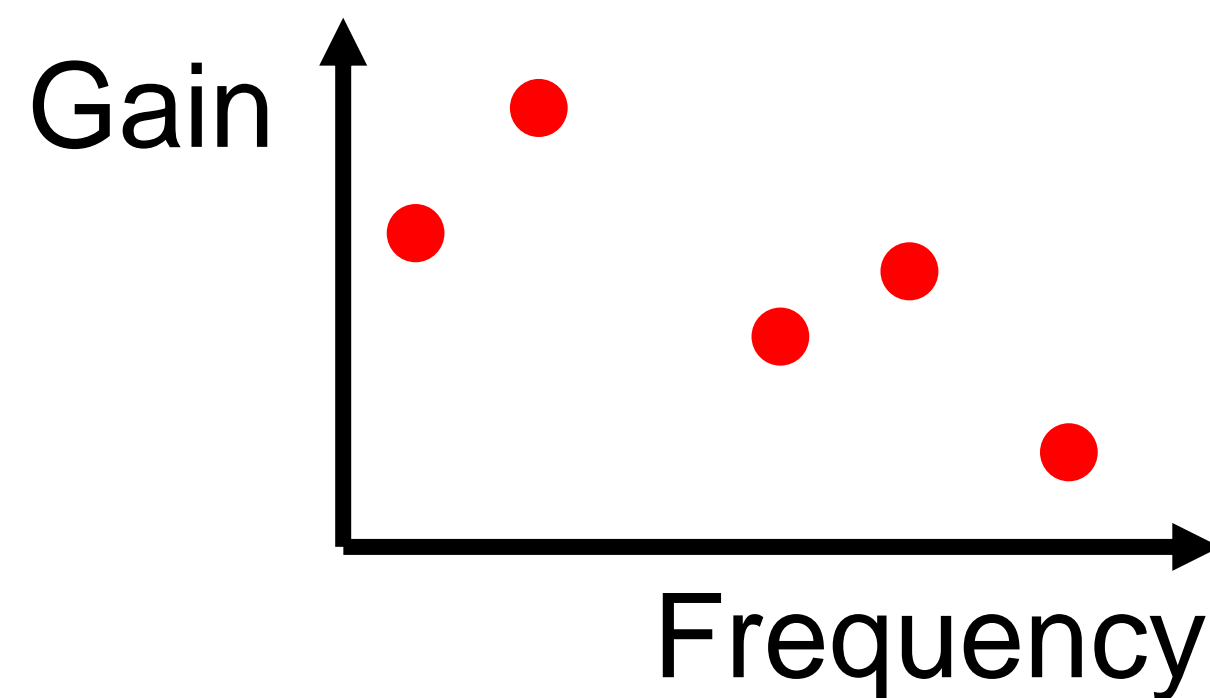
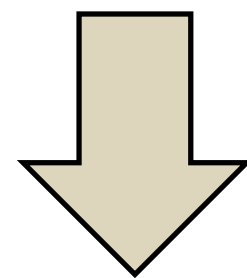


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Fourier Analysis

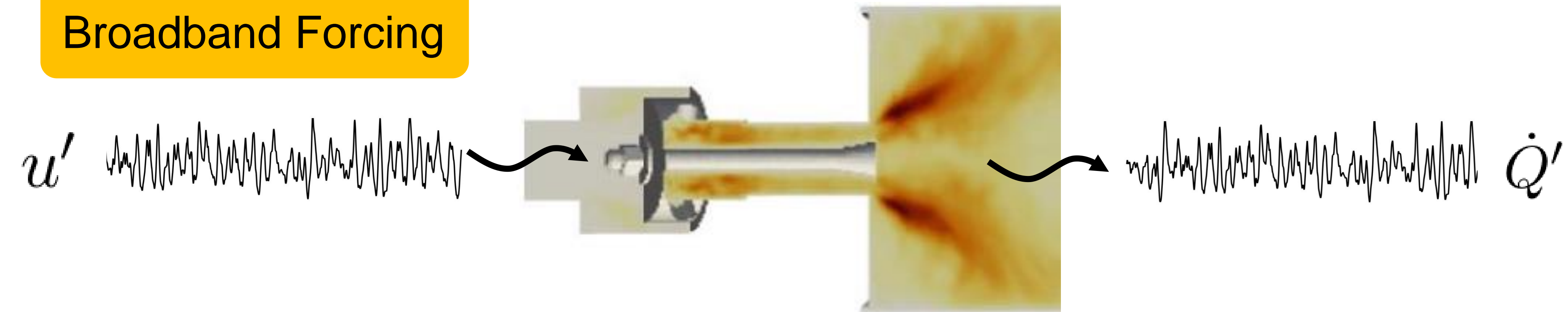


Time series length =

$$\sum_{i=1}^n \frac{1}{f_i} \times \text{excitation cycles}$$

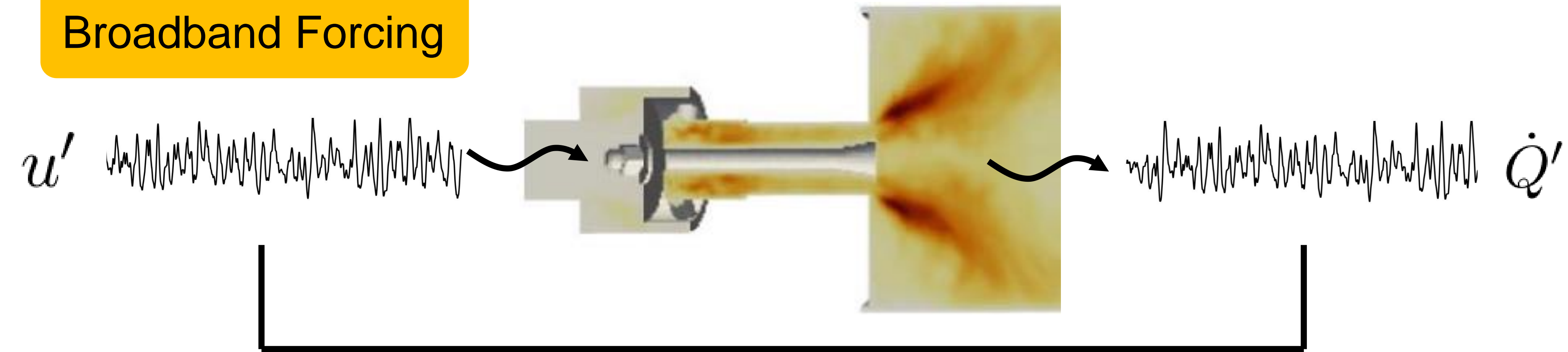
Broadband forcing provides complete frequency response but with uncertainty

Broadband Forcing

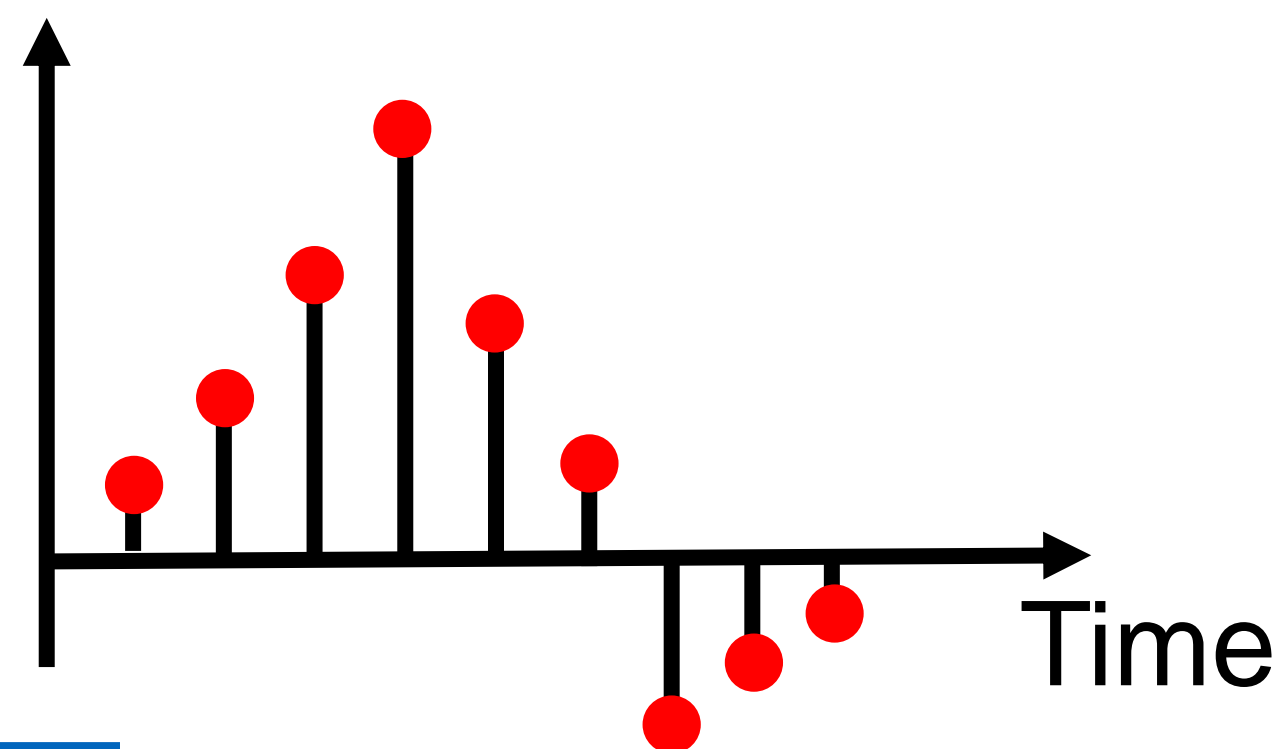


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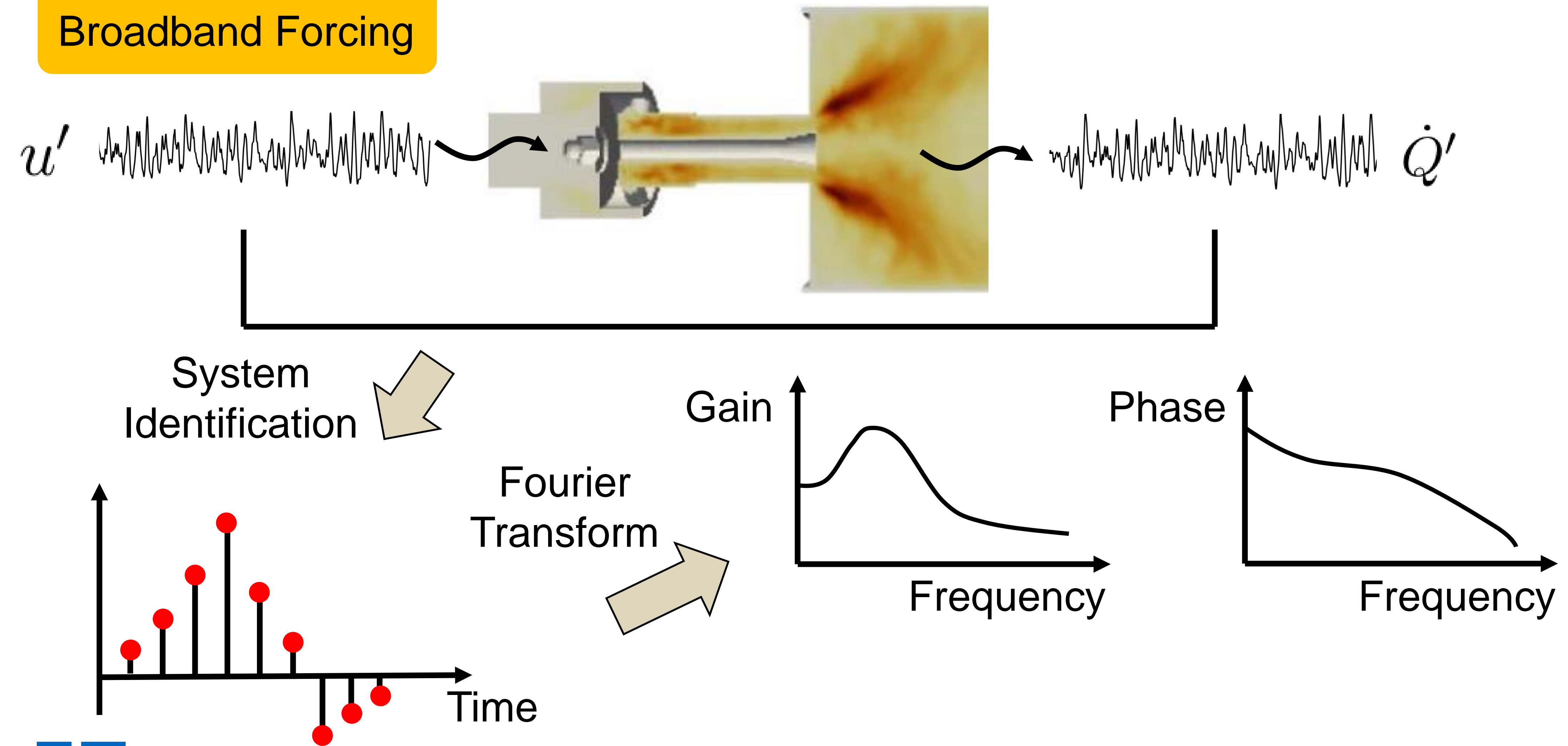


System
Identification



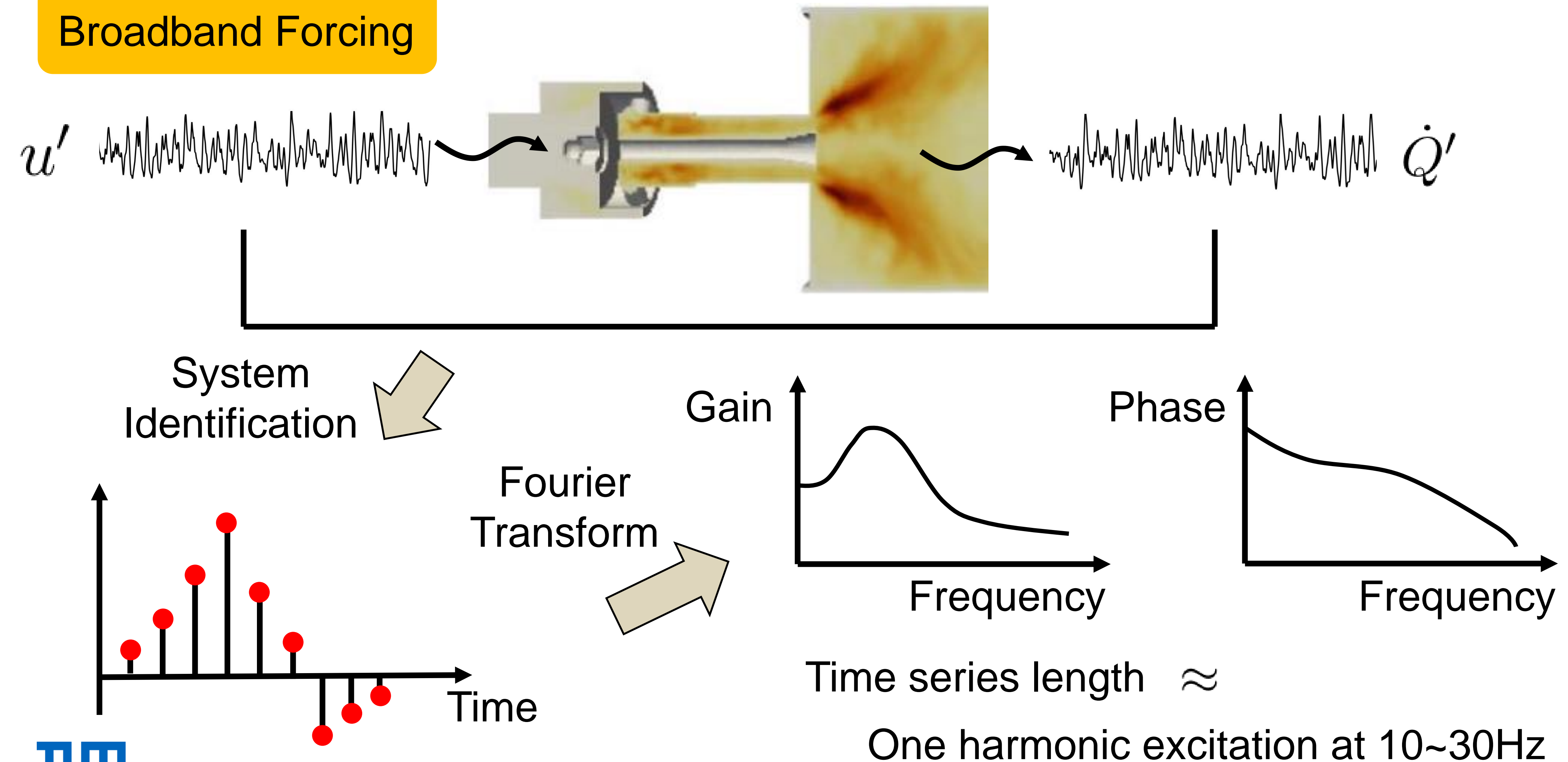
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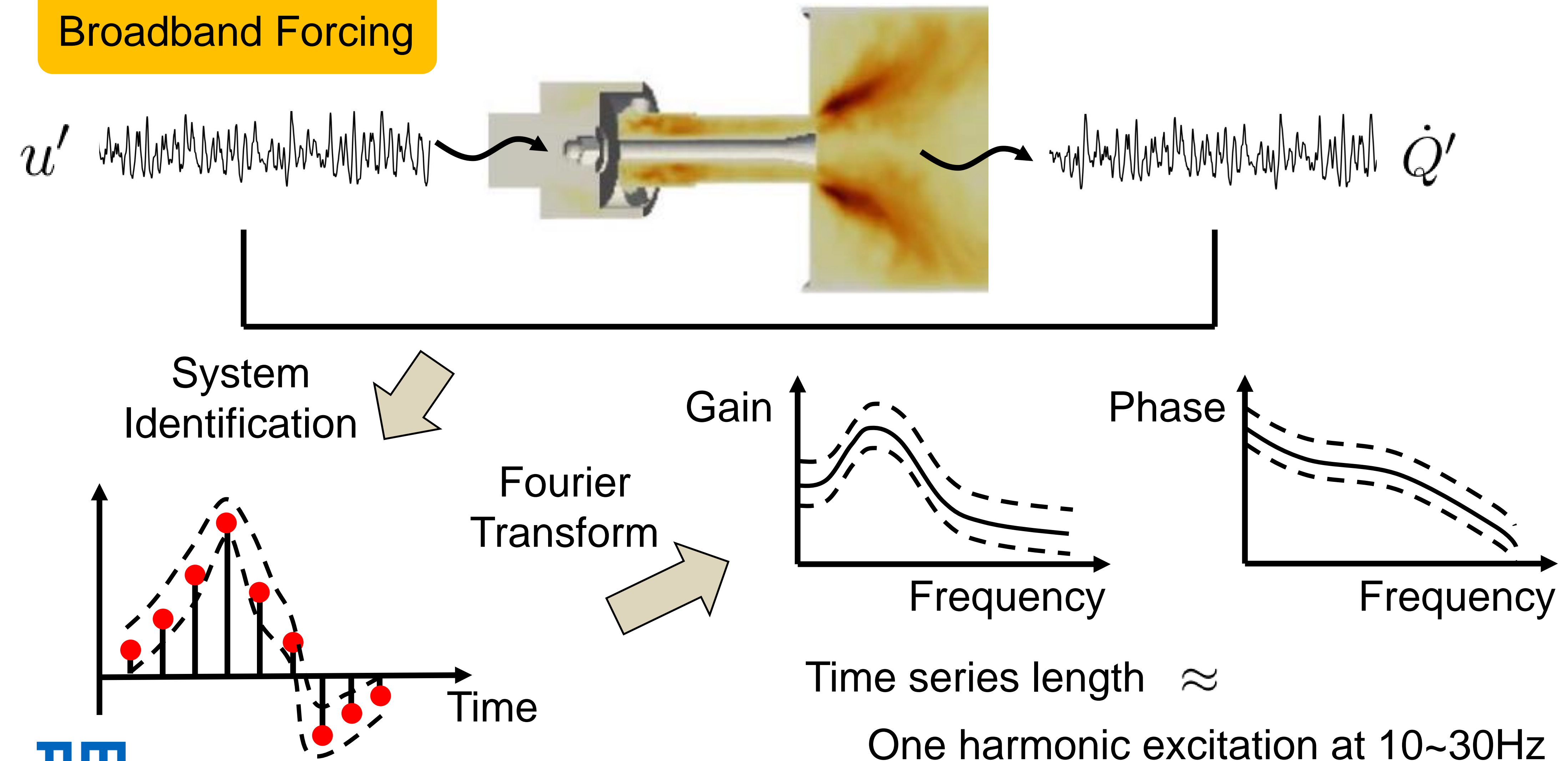
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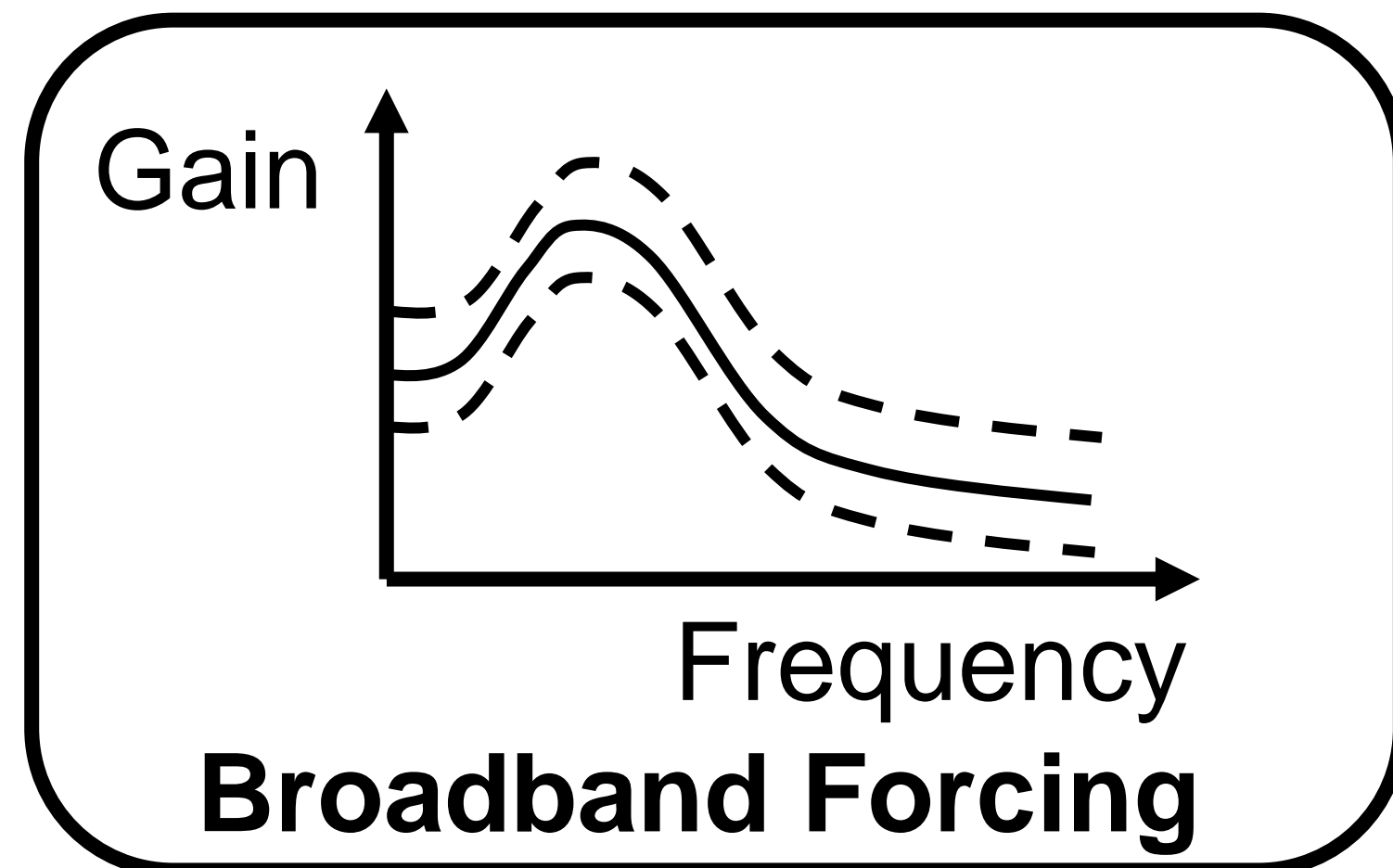
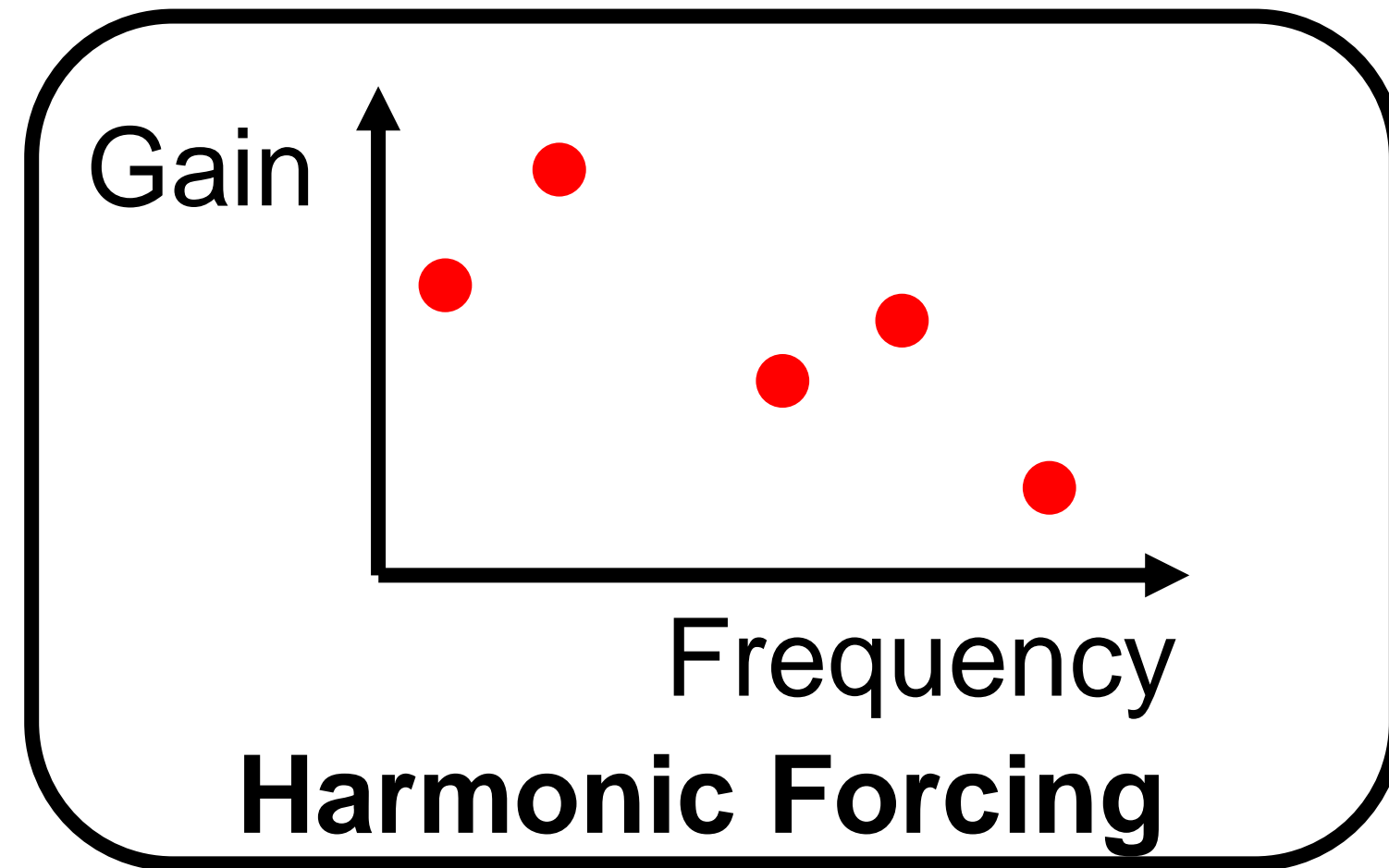


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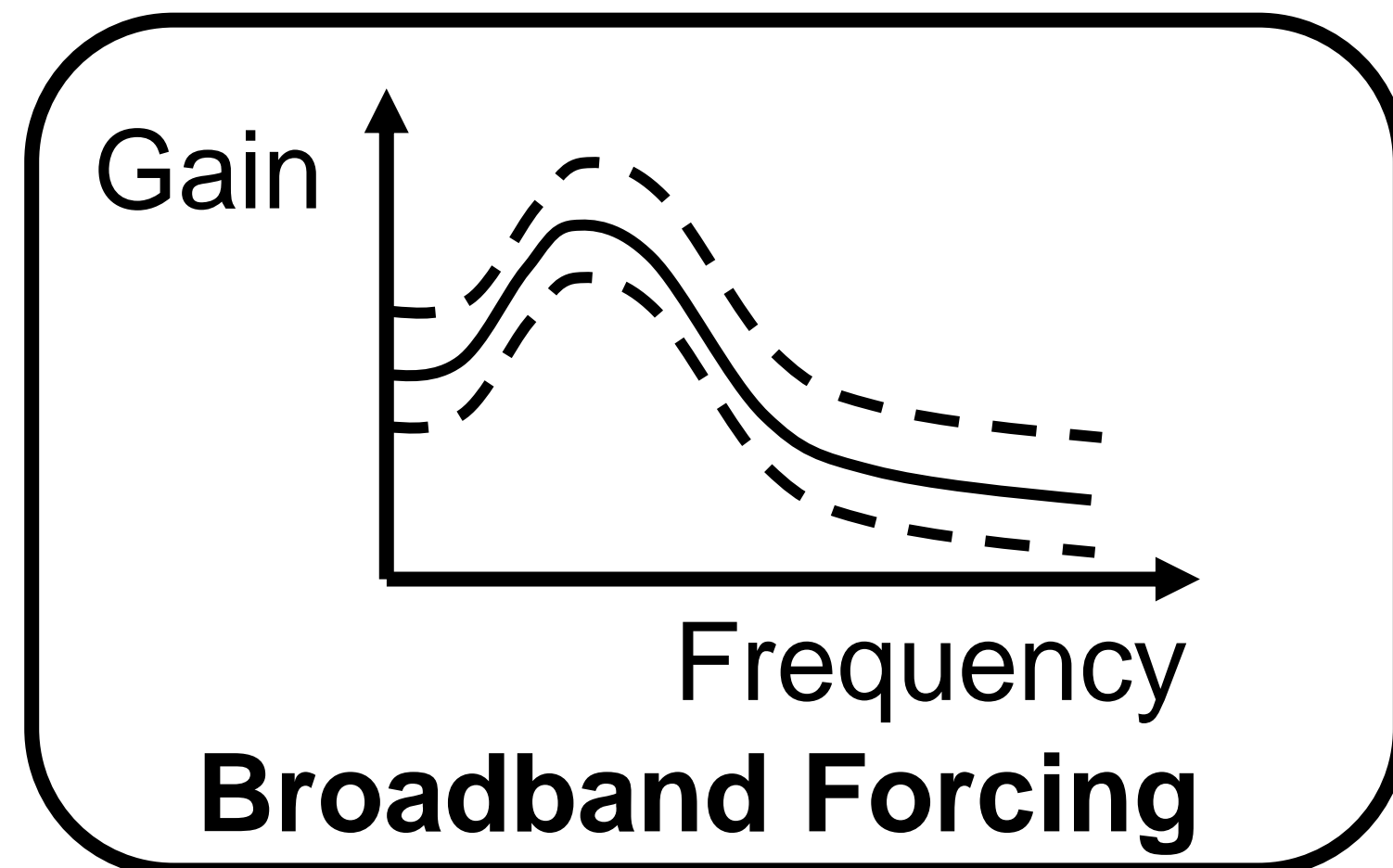
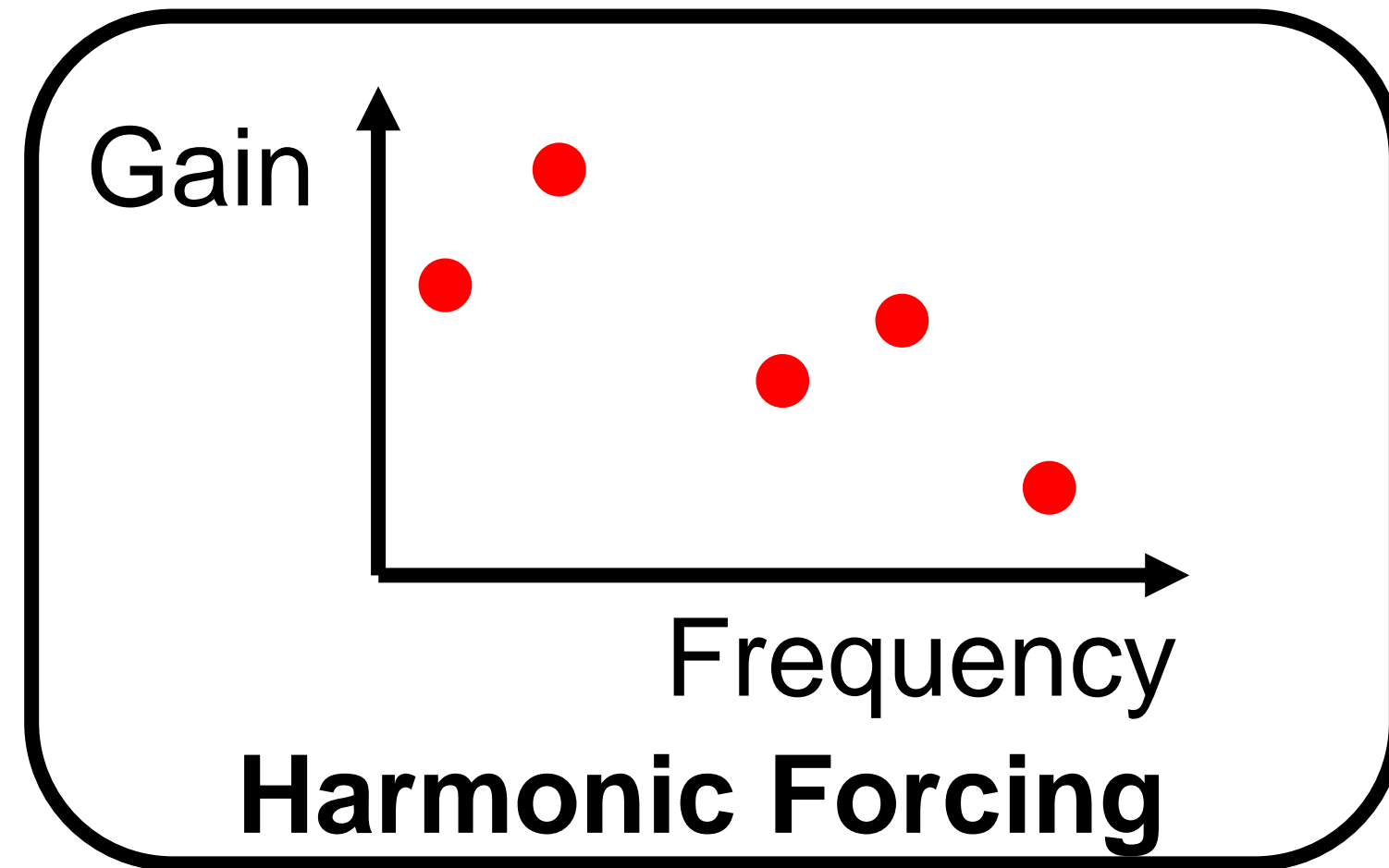
Broadband Forcing



Combining two methods may yield more accurate and robust frequency response identification

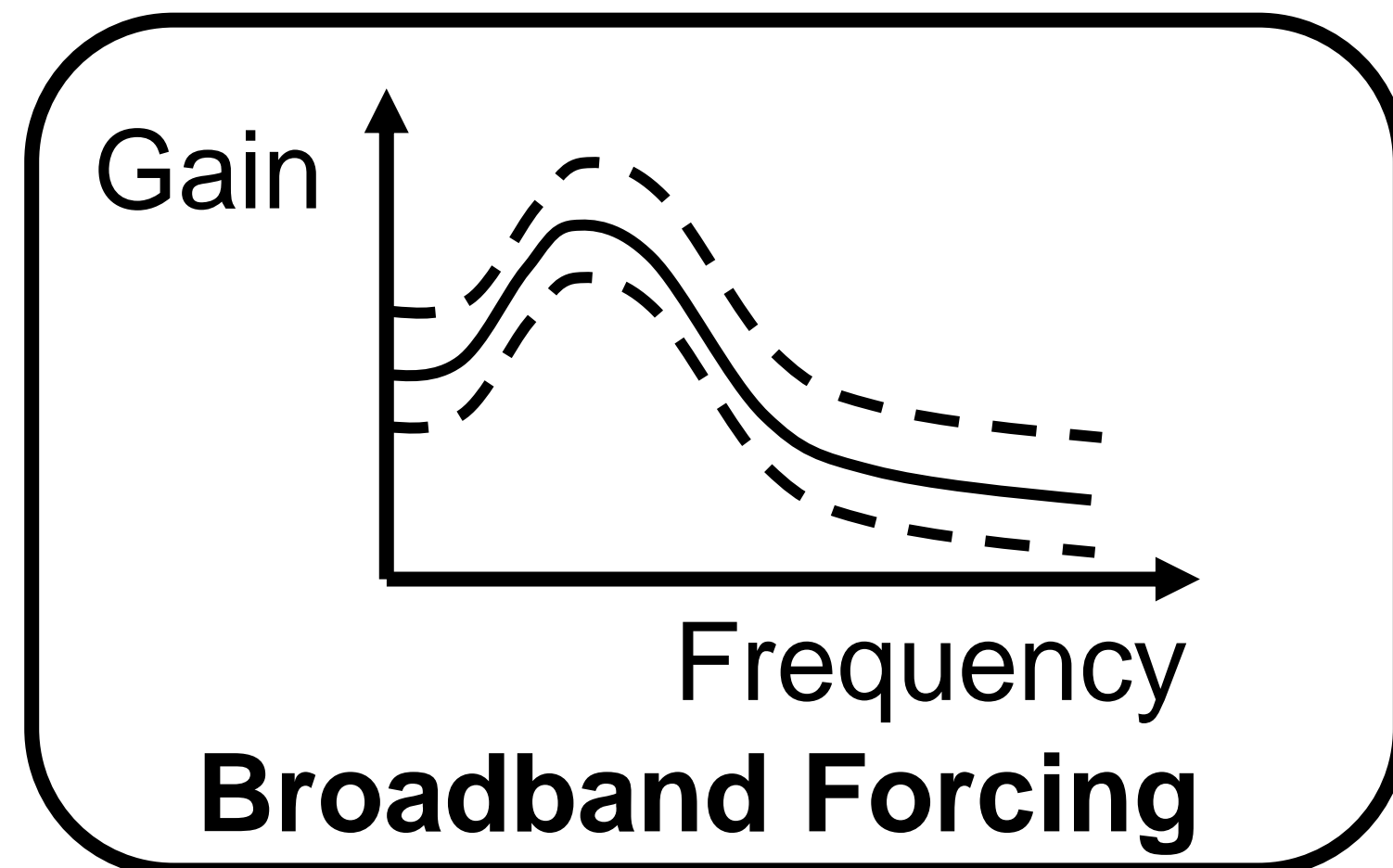
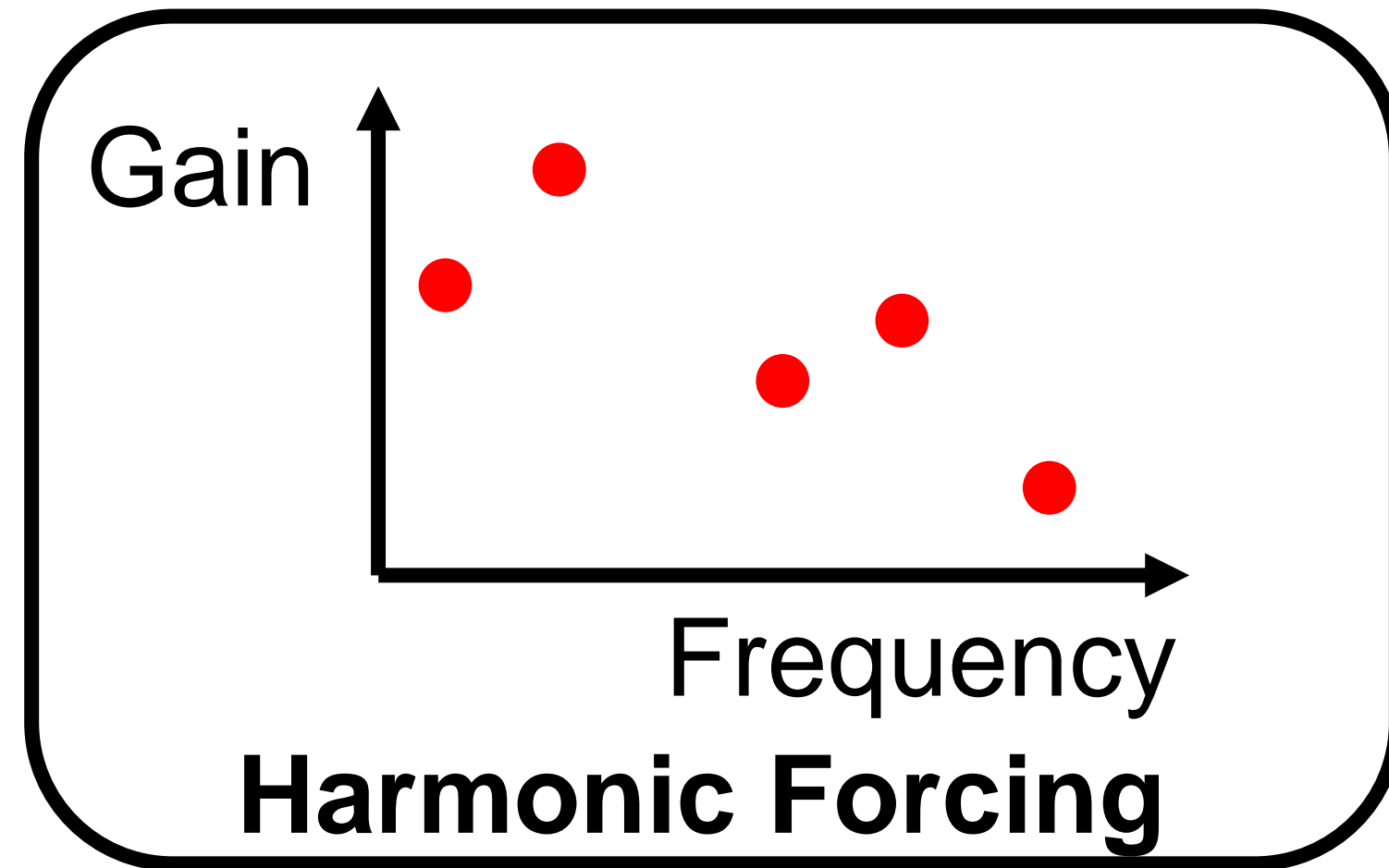


Combining two methods may yield more accurate and robust frequency response identification



→ A short time
(1/4 of recommendation)

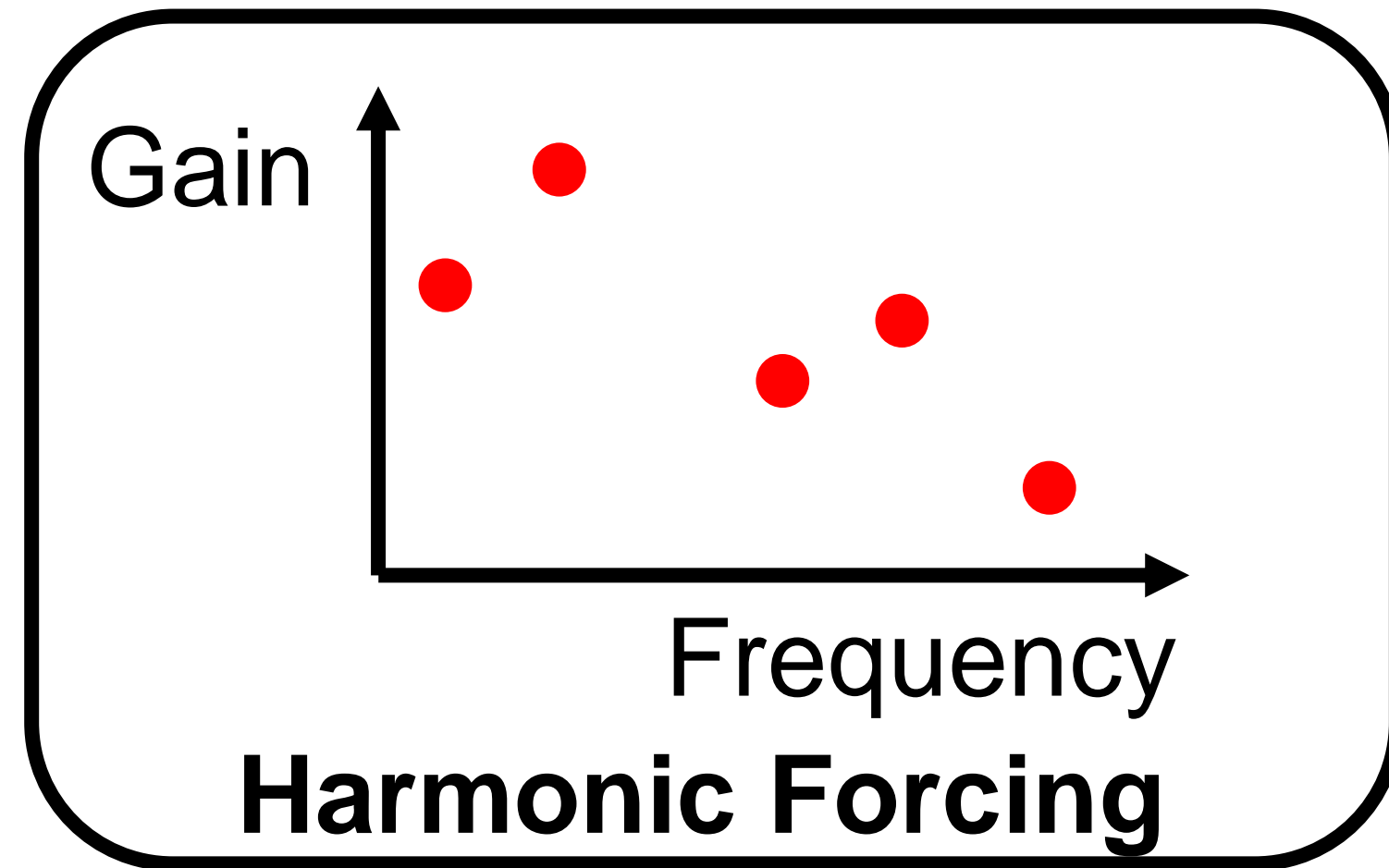
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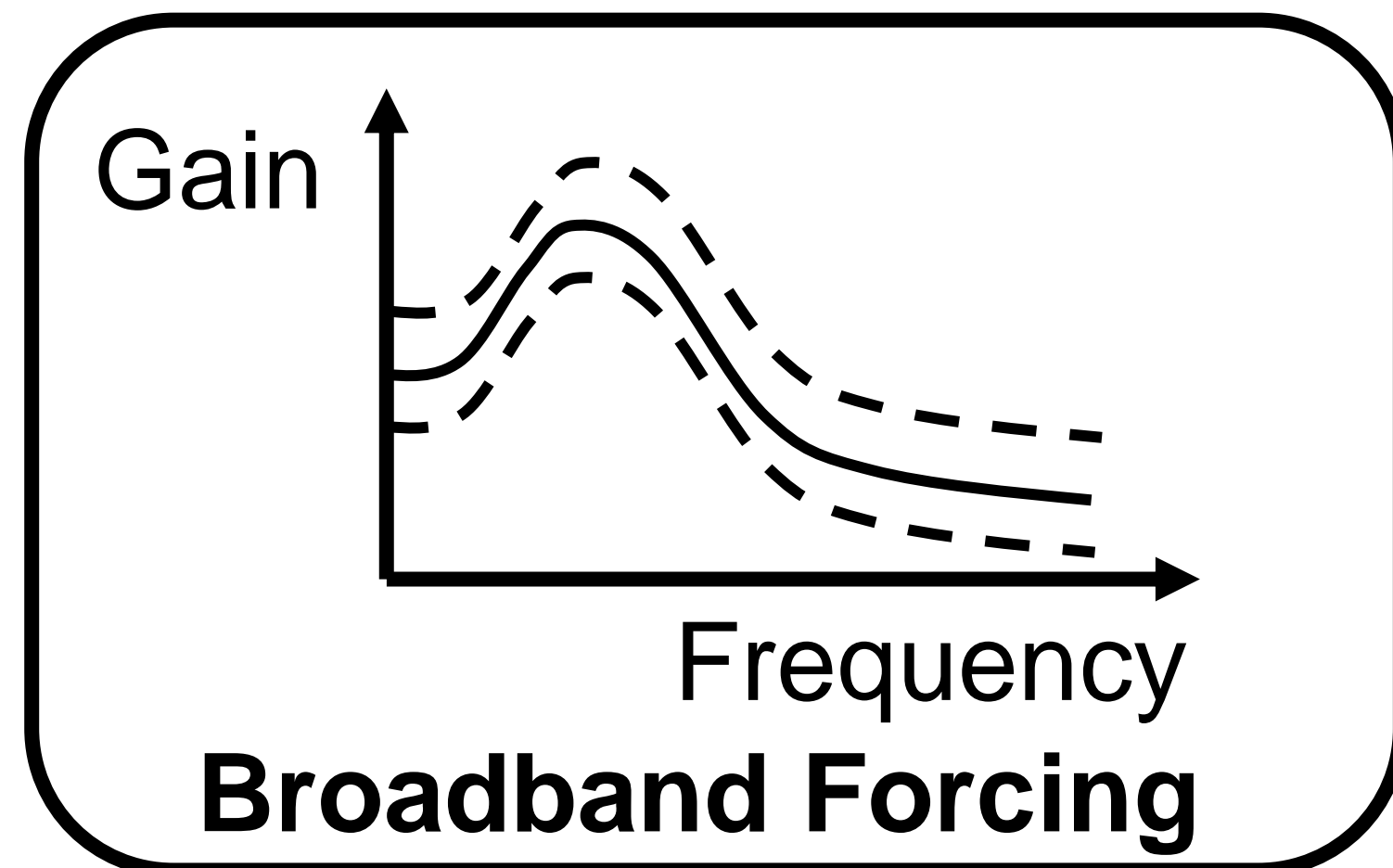
Low-fidelity

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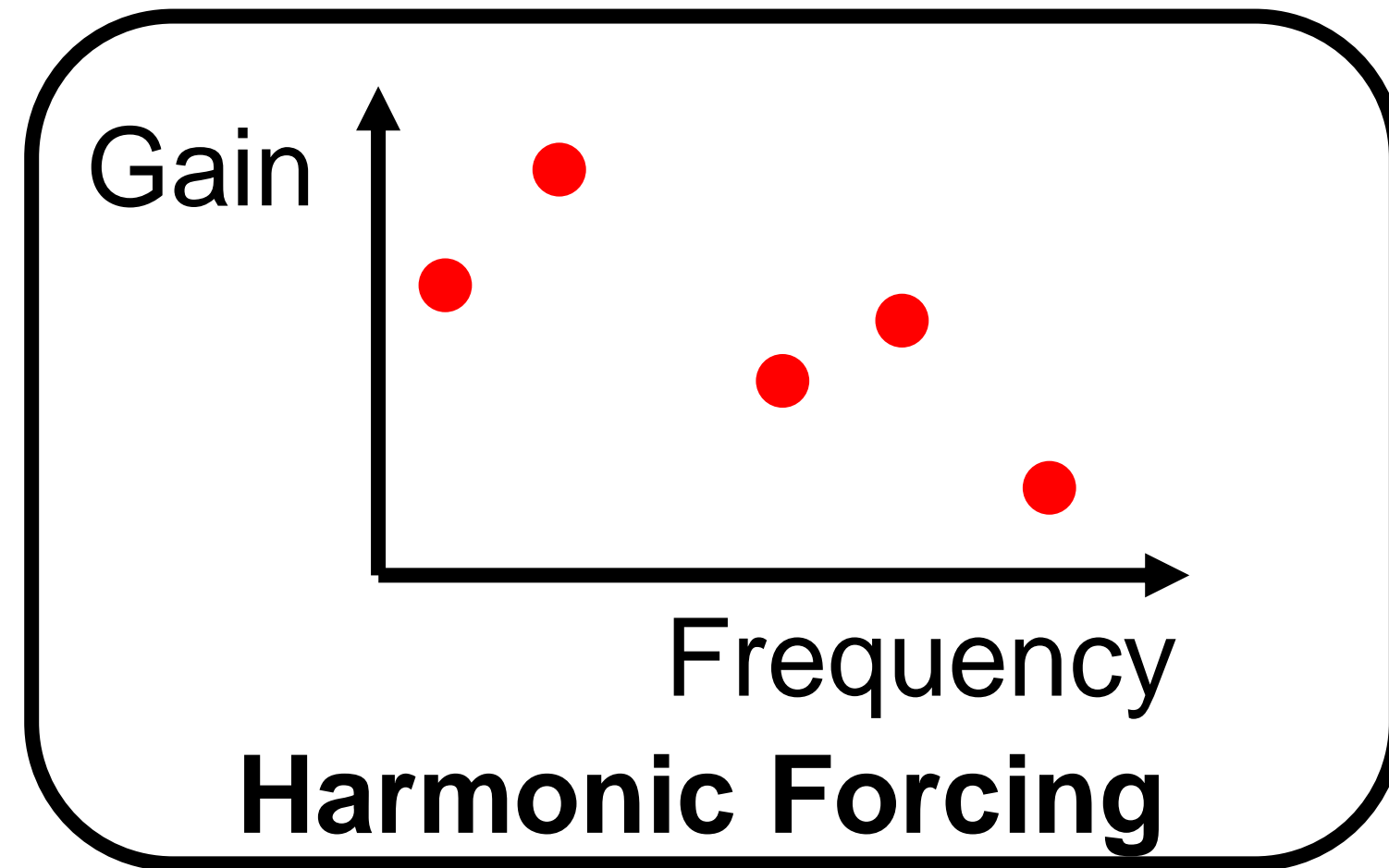
→ A few frequencies



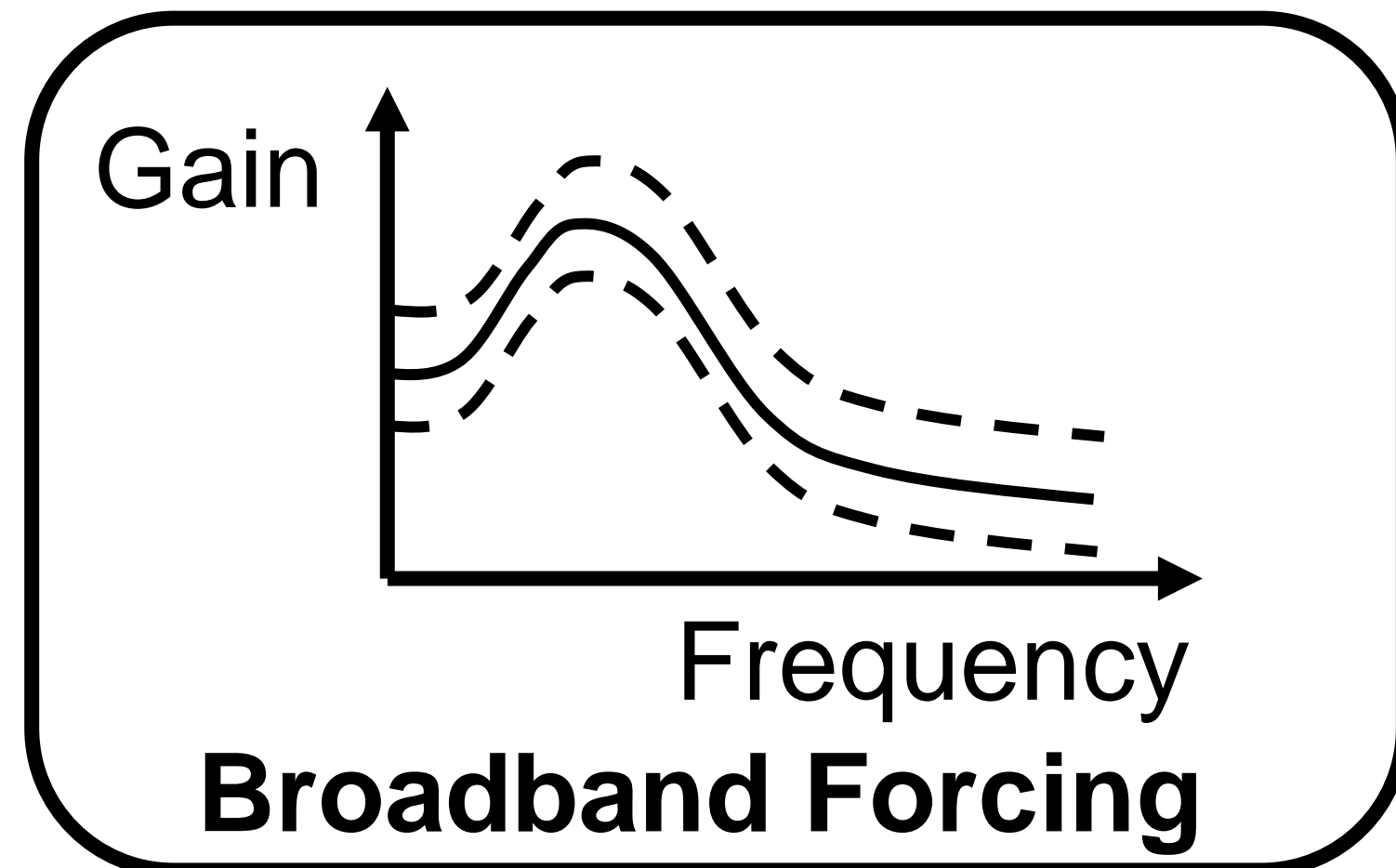
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Combining two methods may yield more accurate and robust frequency response identification



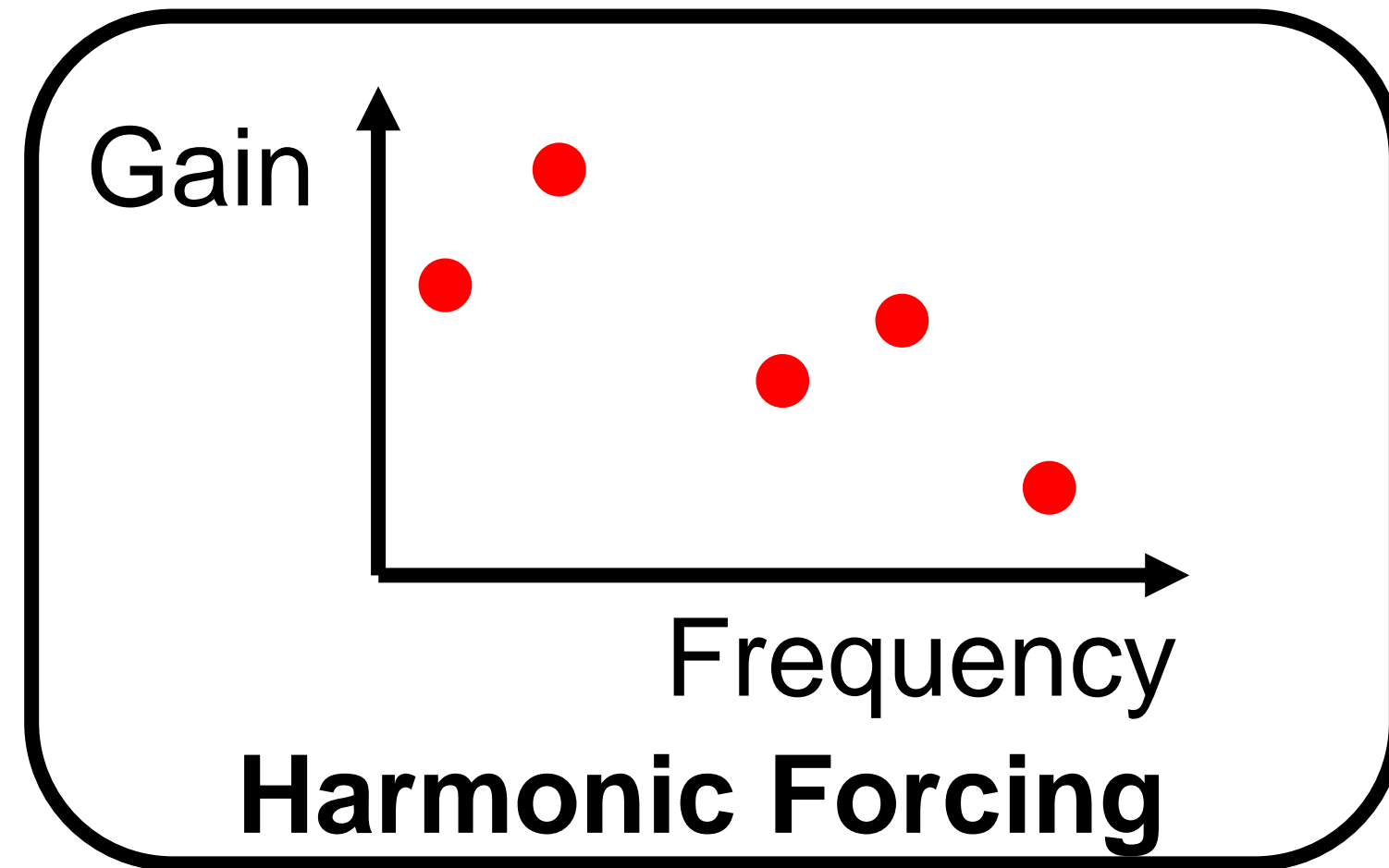
→ A few frequencies
High-fidelity



Low-fidelity

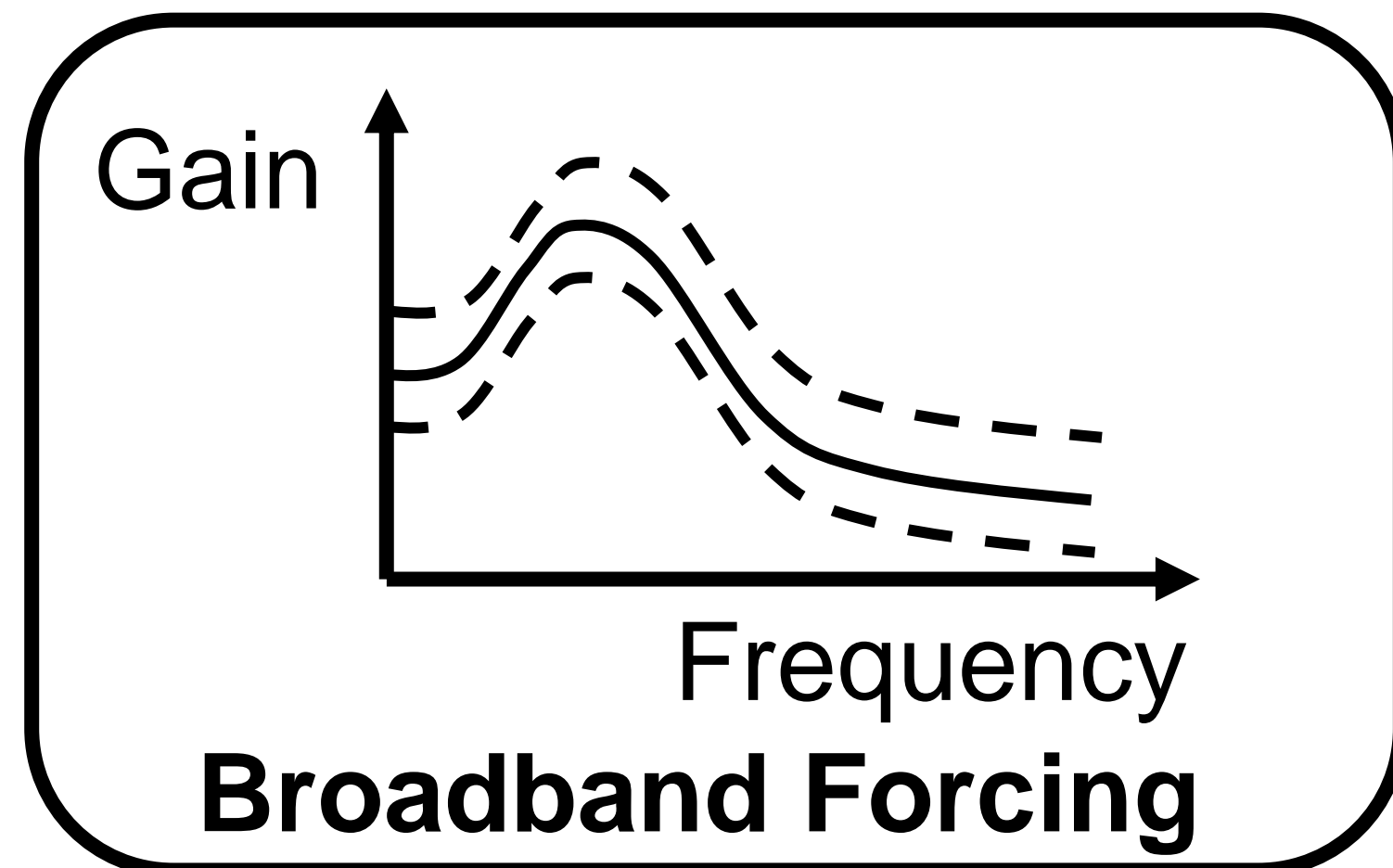
→ A short time
(1/4 of recommendation)

Combining two methods may yield more accurate and robust frequency response identification



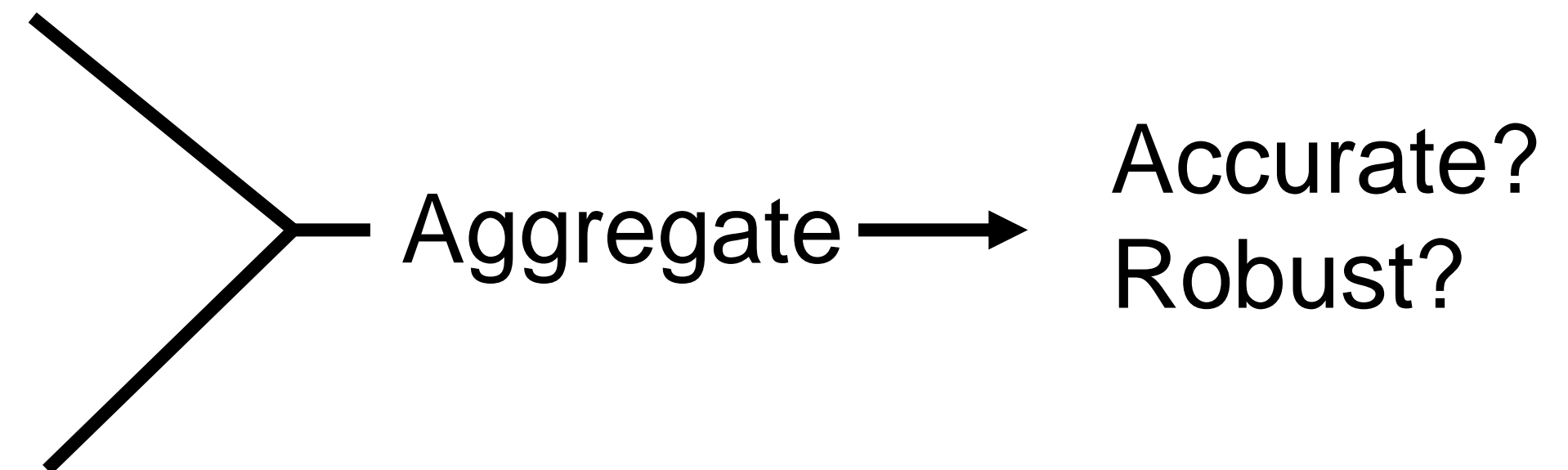
→ A few frequencies

High-fidelity



Low-fidelity

→ A short time
(1/4 of recommendation)



Presentation Overview

- Motivation
- Multi-fidelity Gaussian Process

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 - *How to aggregate different fidelities?*

- Motivation

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□ Motivation

□ Multi-fidelity Gaussian Process

→ *How to aggregate different fidelities?*

→ *How to combine uncertainties from individual fidelities?*

□ Case study

→ Set-up

→ Results & Discussions

- Motivation
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Gaussian Process uses unknown constant as its global trend

— Mean
■ Confidence interval



Prior

$$f(x) \sim \mathcal{GP}(\beta, k(x, x'))$$

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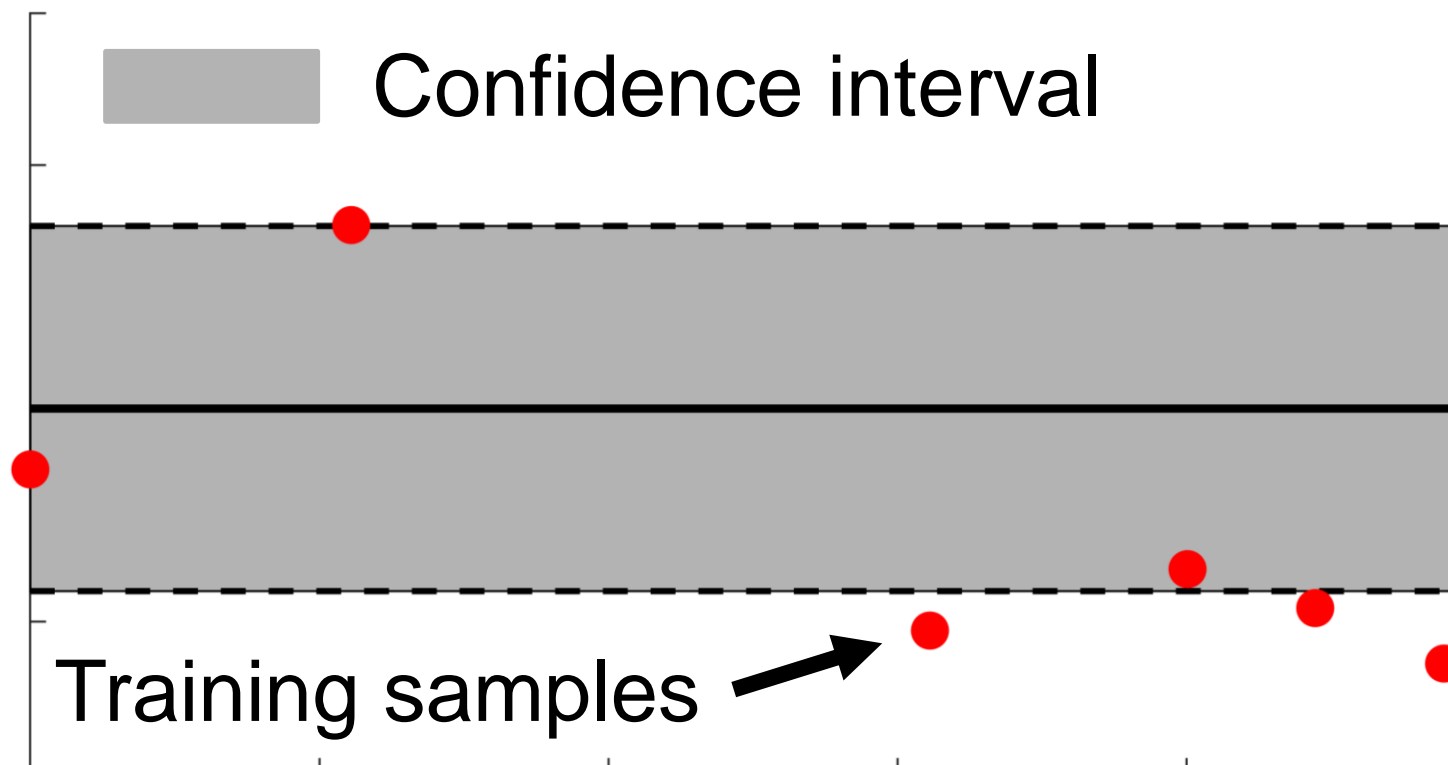
β : Constant

$$k(x, x') = \sigma^2 \exp(-\theta |x - x'|^2) \text{ : Kernel}$$

Gaussian Process uses unknown constant as its global trend

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Prior

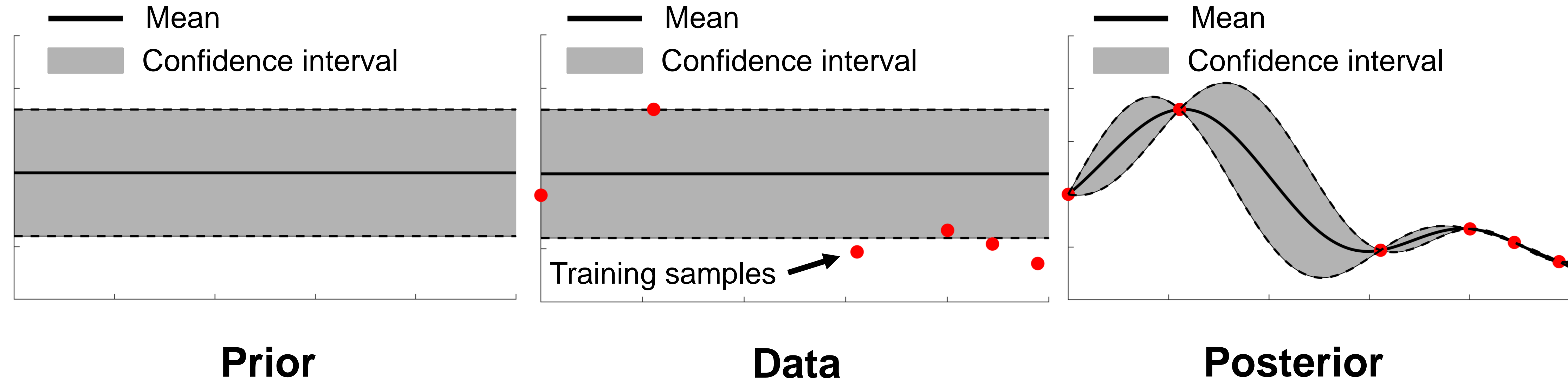
Data

$$f(x) \sim \mathcal{GP}(\beta, k(x, x'))$$

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$$k(x, x') = \sigma^2 \exp(-\theta |x - x'|^2) : \text{Kernel}$$

Gaussian Process uses unknown constant as its global trend



$$f(x) \sim \mathcal{GP}(\beta, k(x, x'))$$

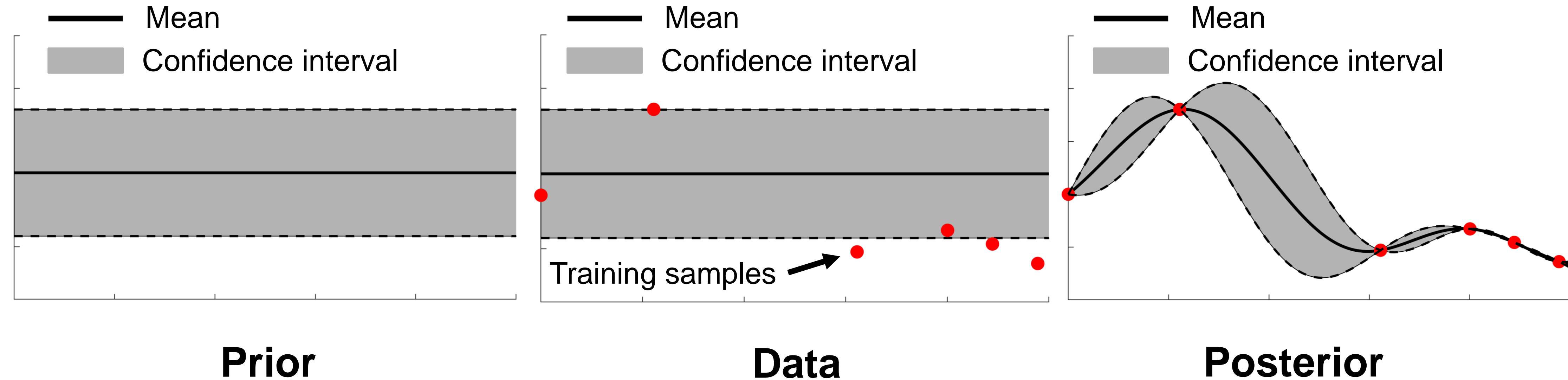


$$f^*(x) \sim \mathcal{GP}(m^*(x), k^*(x, x'))$$

β : Constant

$k(x, x') = \sigma^2 \exp(-\theta |x - x'|^2)$: Kernel

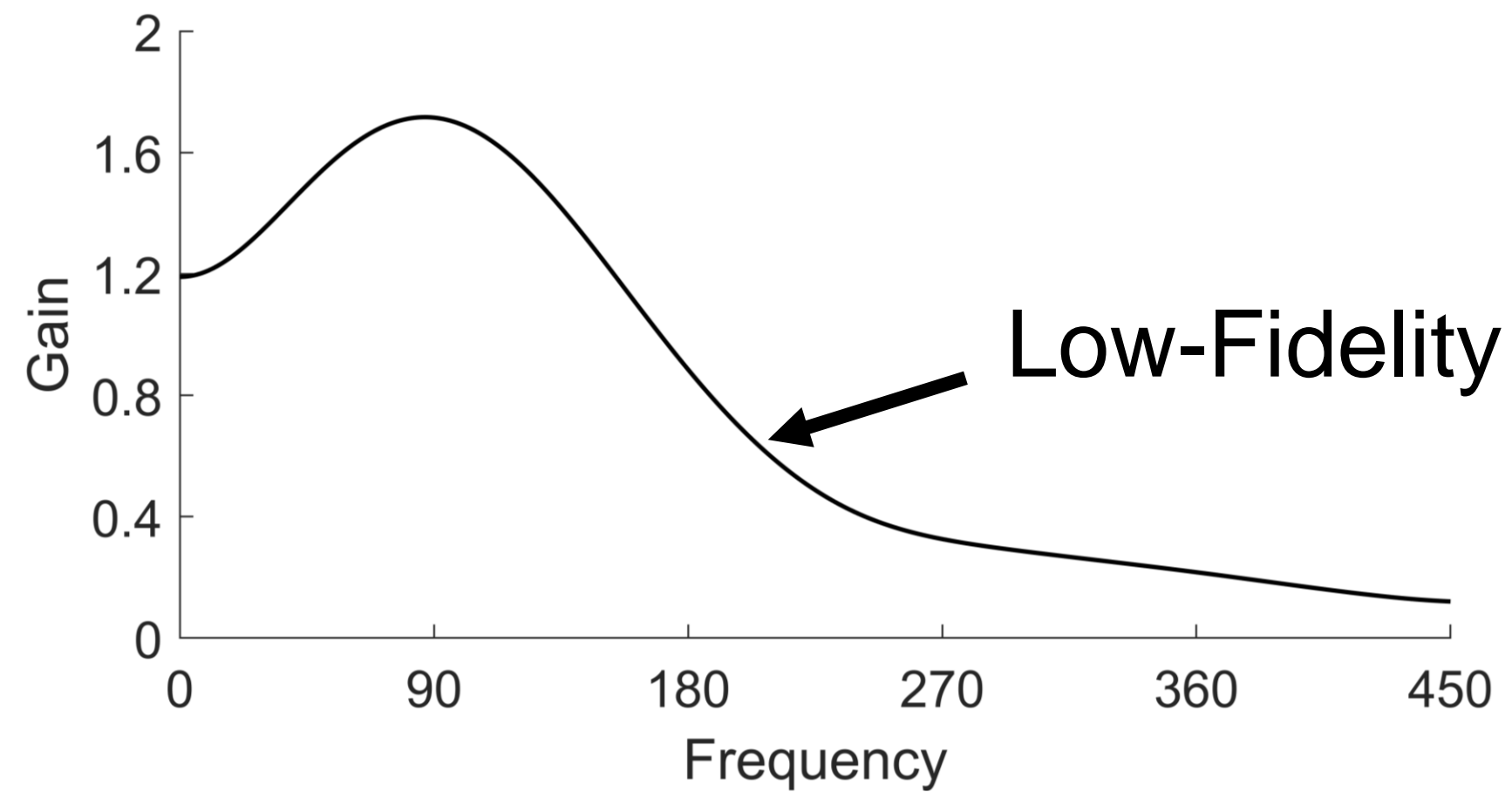
Multi-fidelity Gaussian Process uses low-fidelity results as its global trend



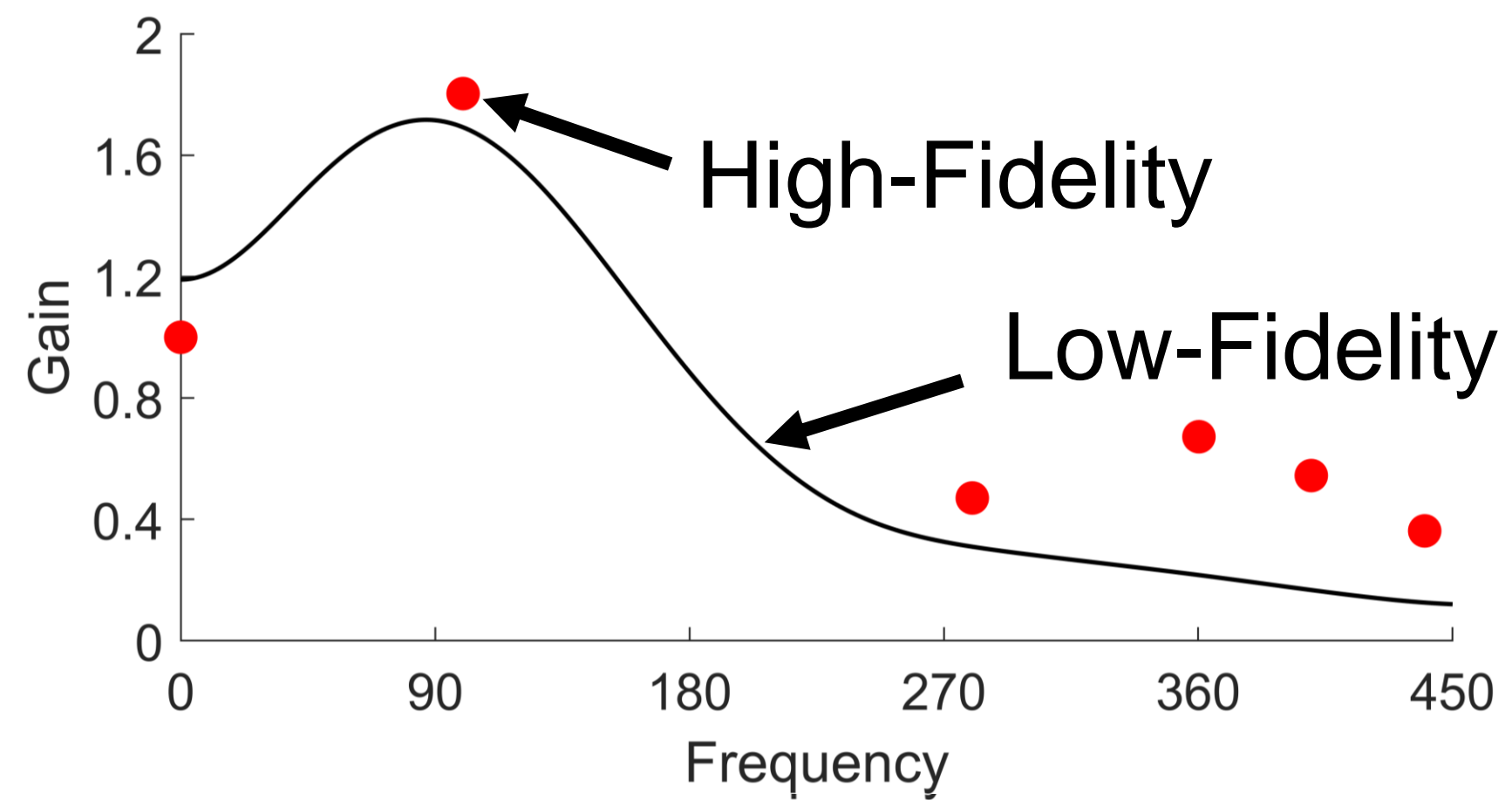
$$f(x) \sim \mathcal{GP}(\text{LoFi}(x), k(x, x')) \quad \Longrightarrow \quad f^*(x) \sim \mathcal{GP}(m^*(x), k^*(x, x'))$$

$$k(x, x') = \sigma^2 \exp(-\theta |x - x'|^2) : \text{Kernel}$$

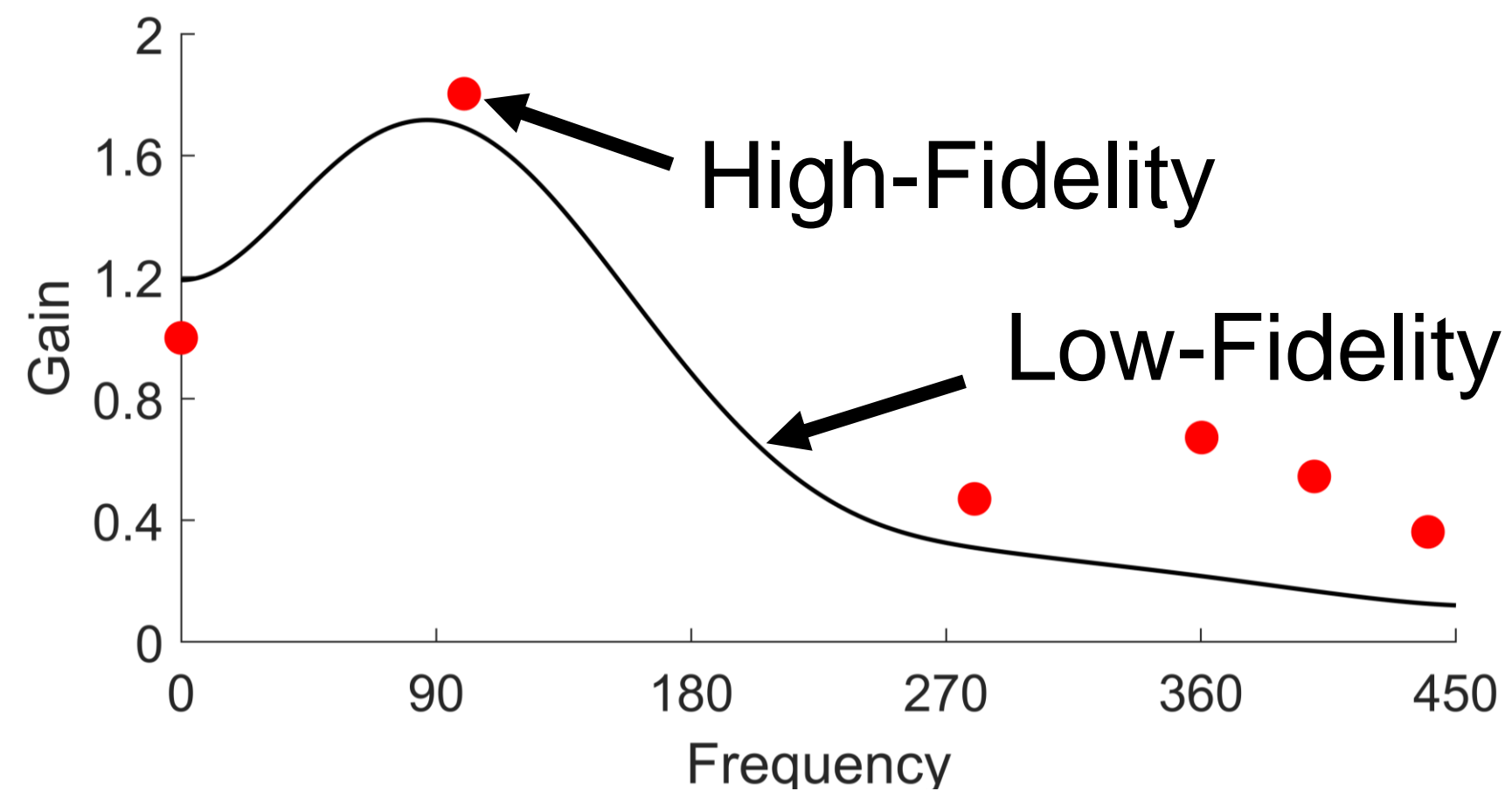
Multi-fidelity Gaussian Process is employed to fuse results from both fidelities



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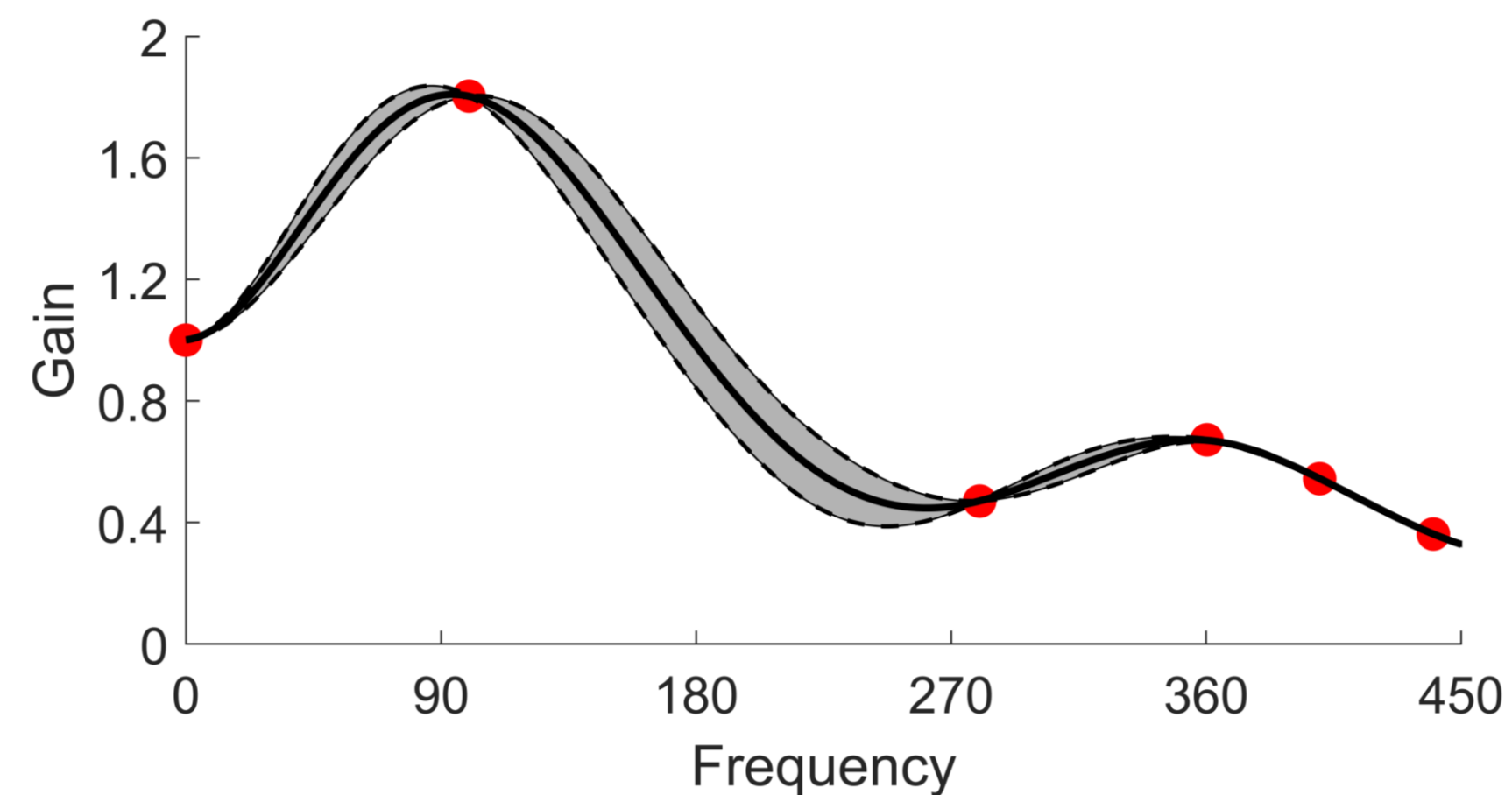
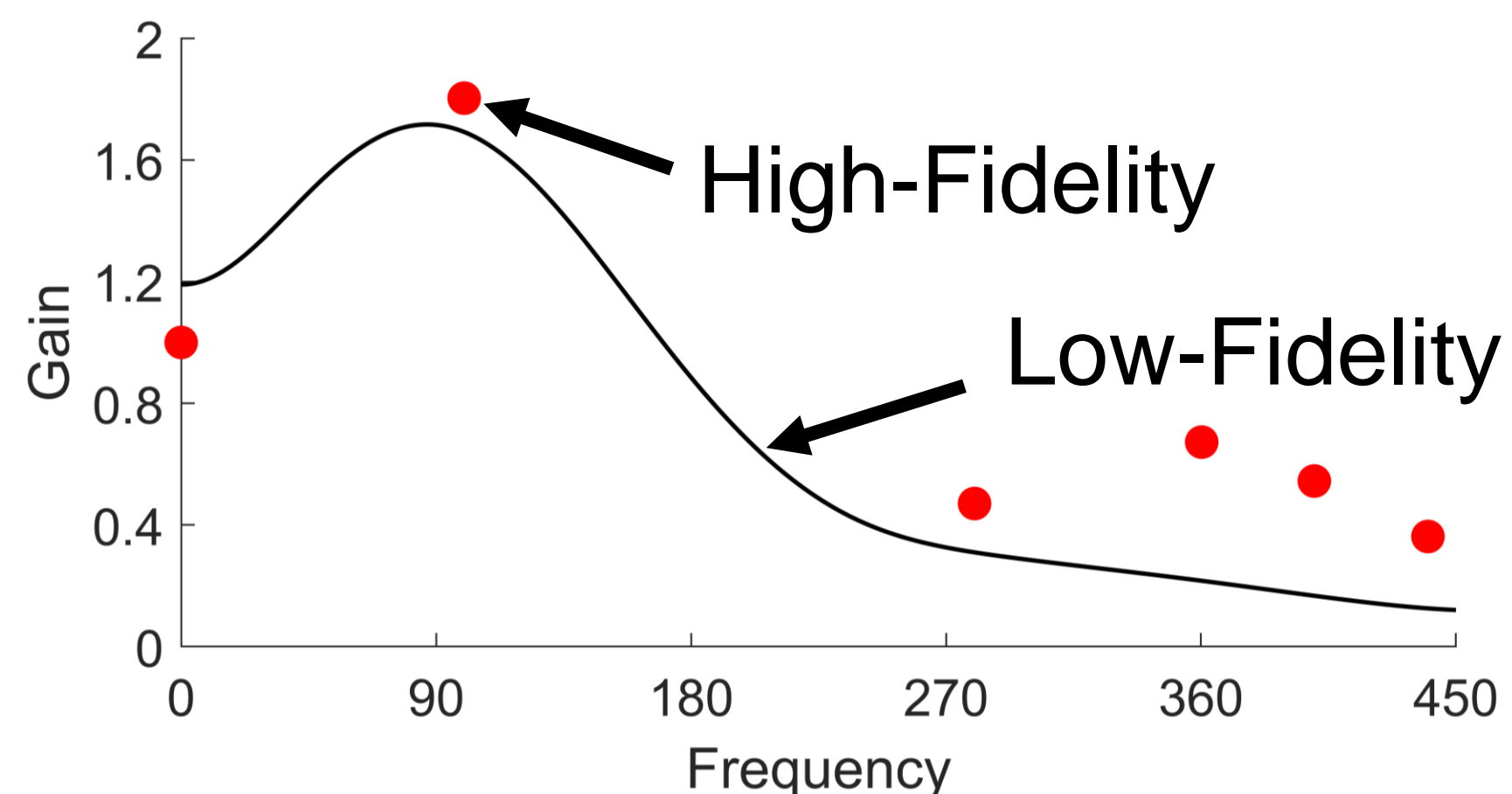


Multi-fidelity Gaussian Process is employed to fuse results from both fidelities



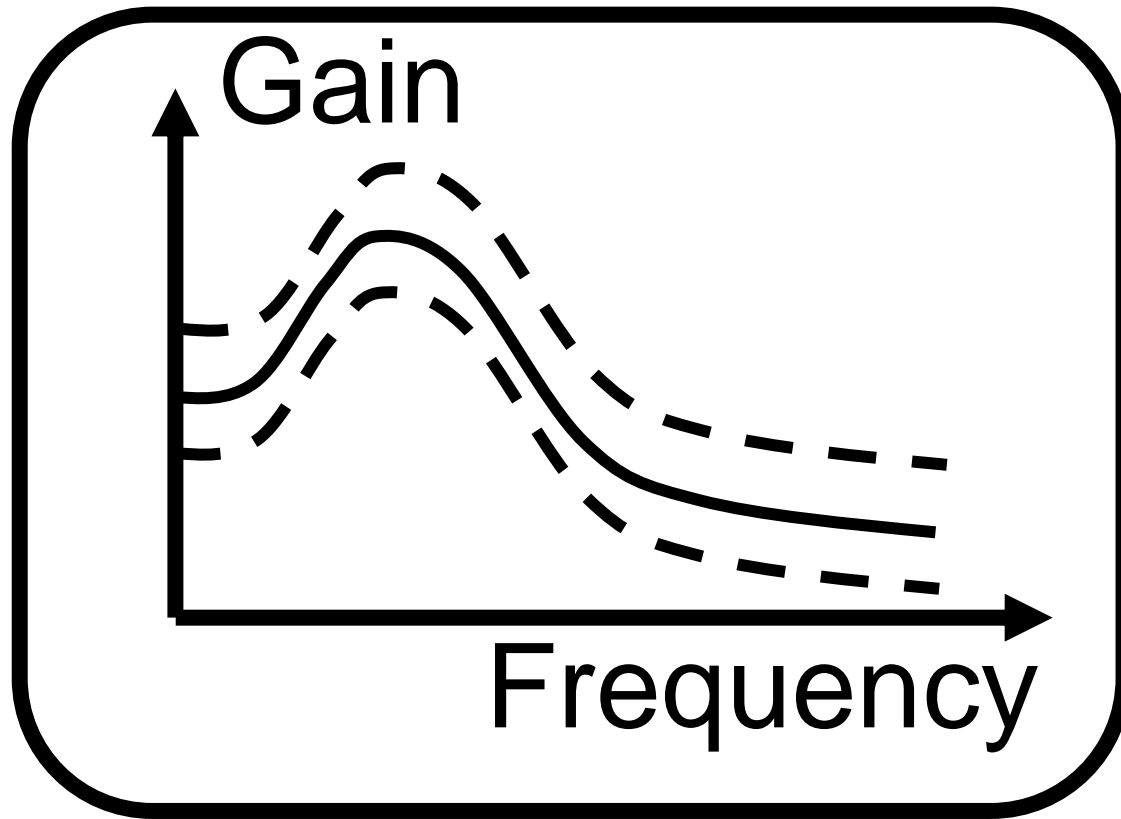
$$f(x) \sim \mathcal{GP}(\text{LoFi}(x), k(x, x'))$$

Multi-fidelity Gaussian Process is employed to fuse results from both fidelities

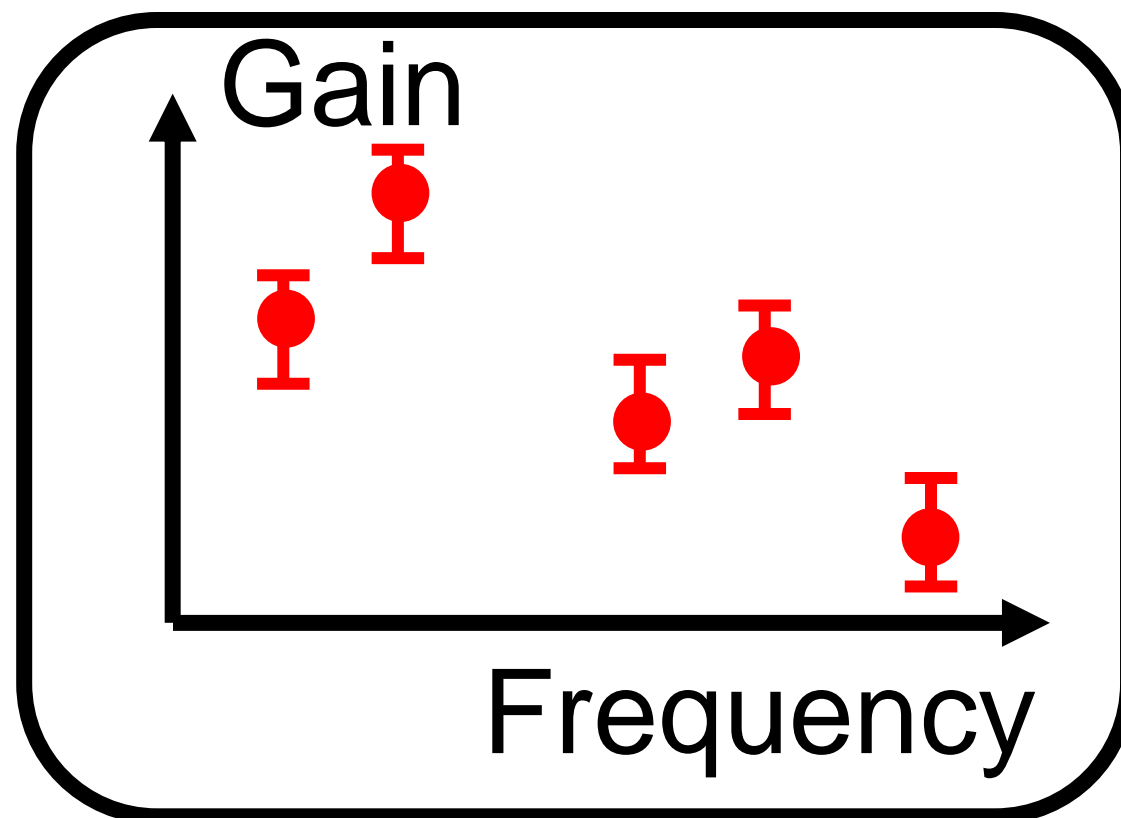


$$f(x) \sim \mathcal{GP}(\text{LoFi}(x), k(x, x')) \quad \Rightarrow \quad f^*(x) \sim \mathcal{GP}(m^*(x), k^*(x, x'))$$

We propose a bootstrapping procedure to account for uncertainties from both fidelities



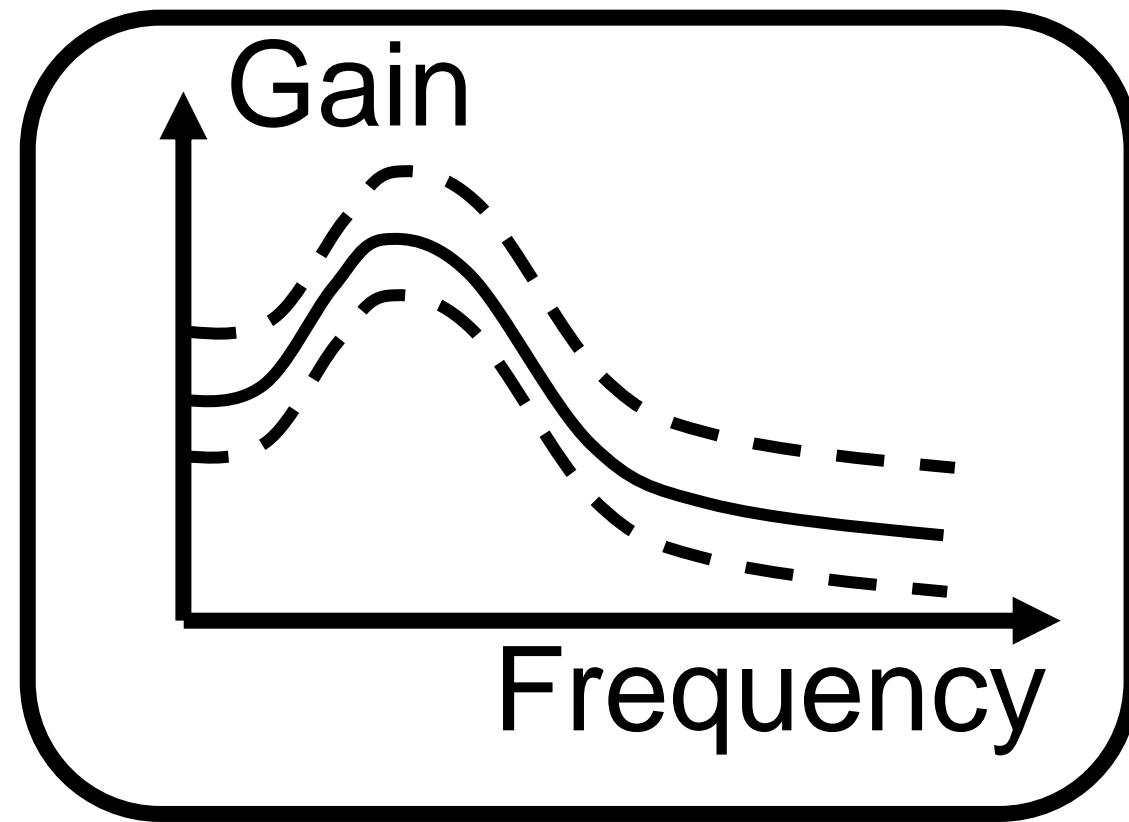
Low-Fidelity



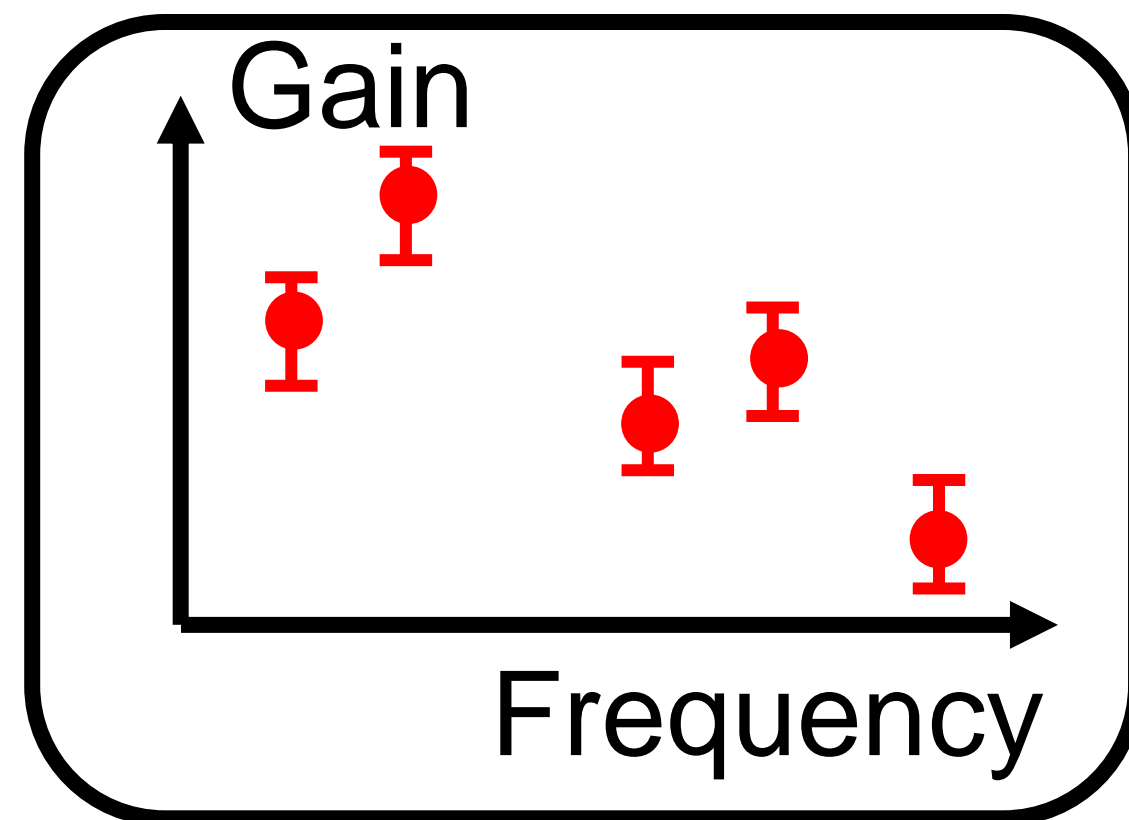
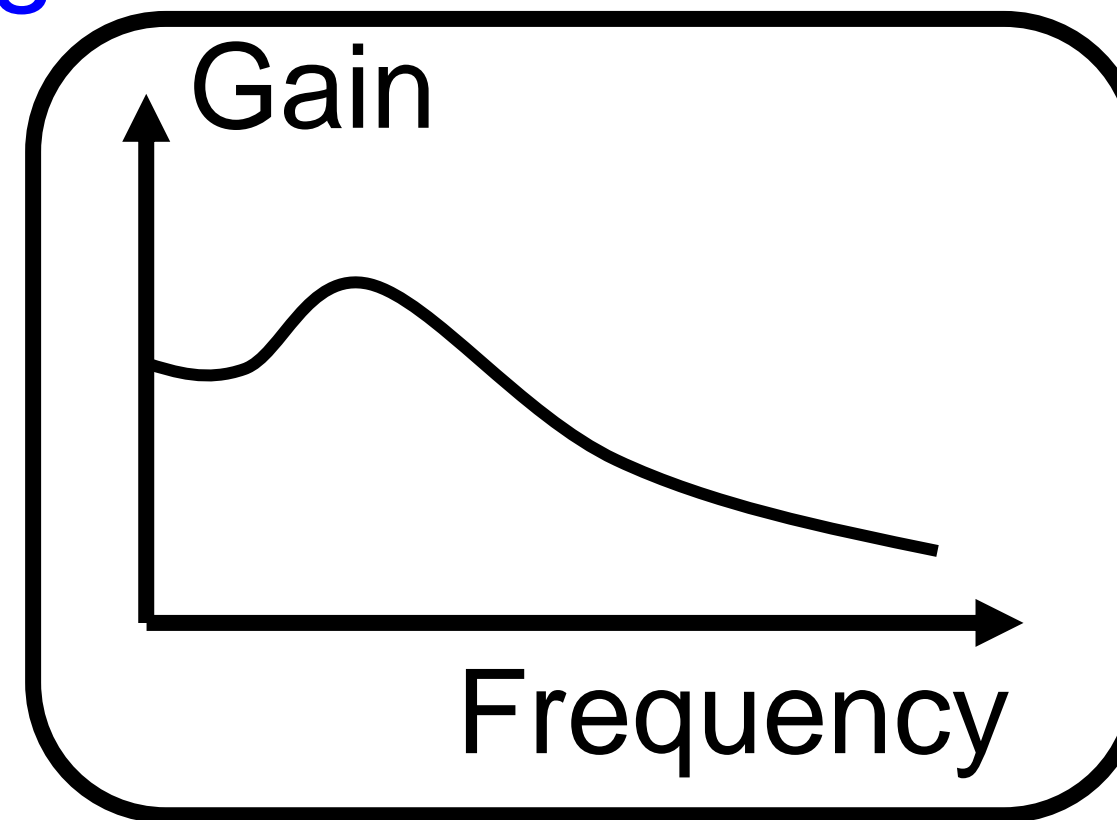
High-Fidelity

We propose a bootstrapping procedure to account for uncertainties from both fidelities

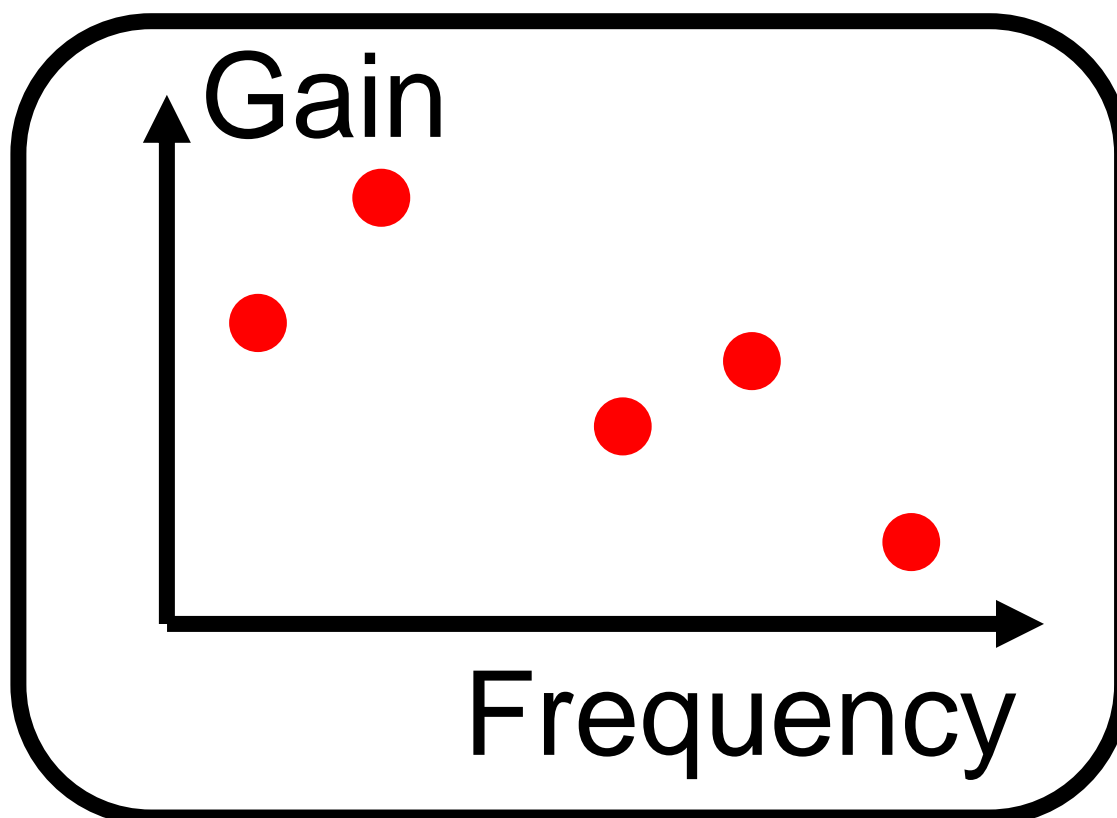
Realizations



Low-Fidelity

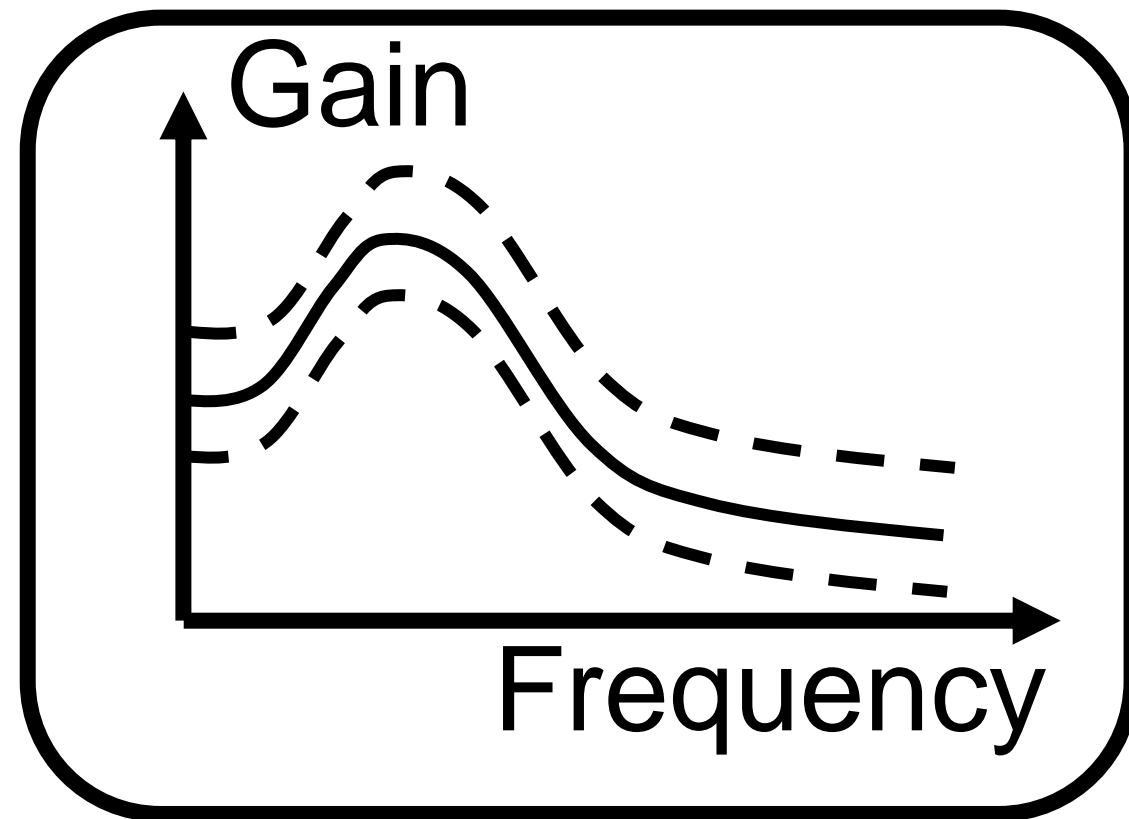


High-Fidelity

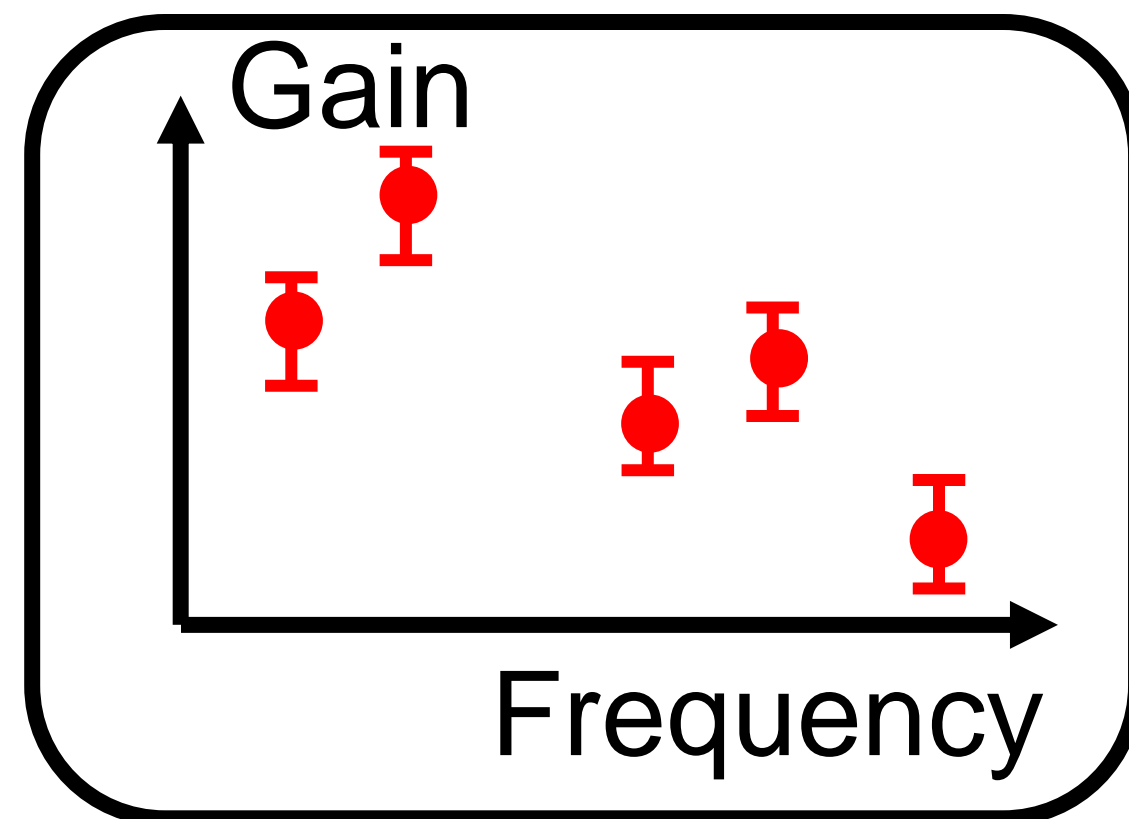


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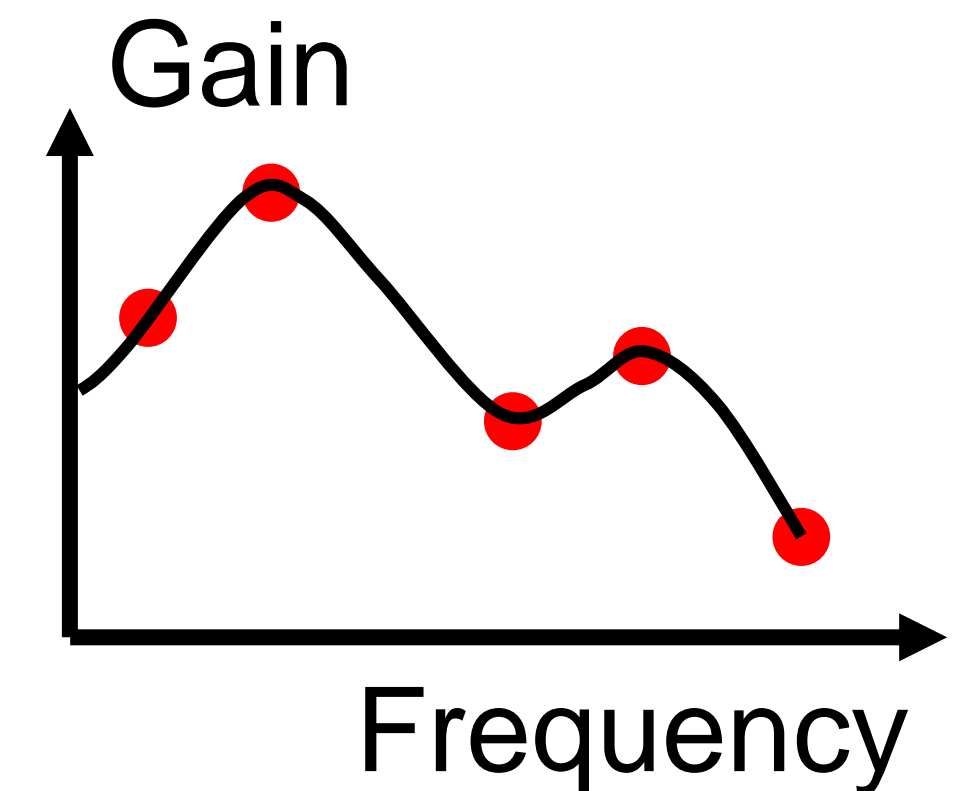
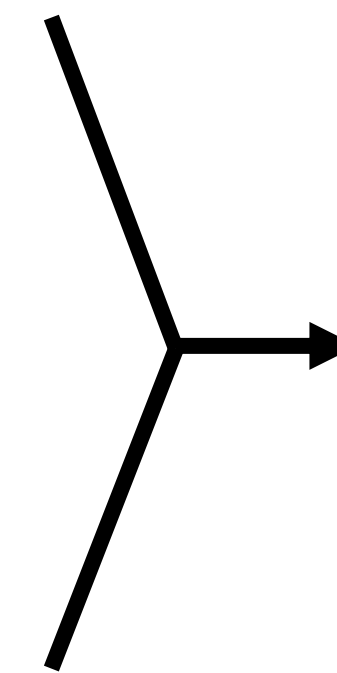
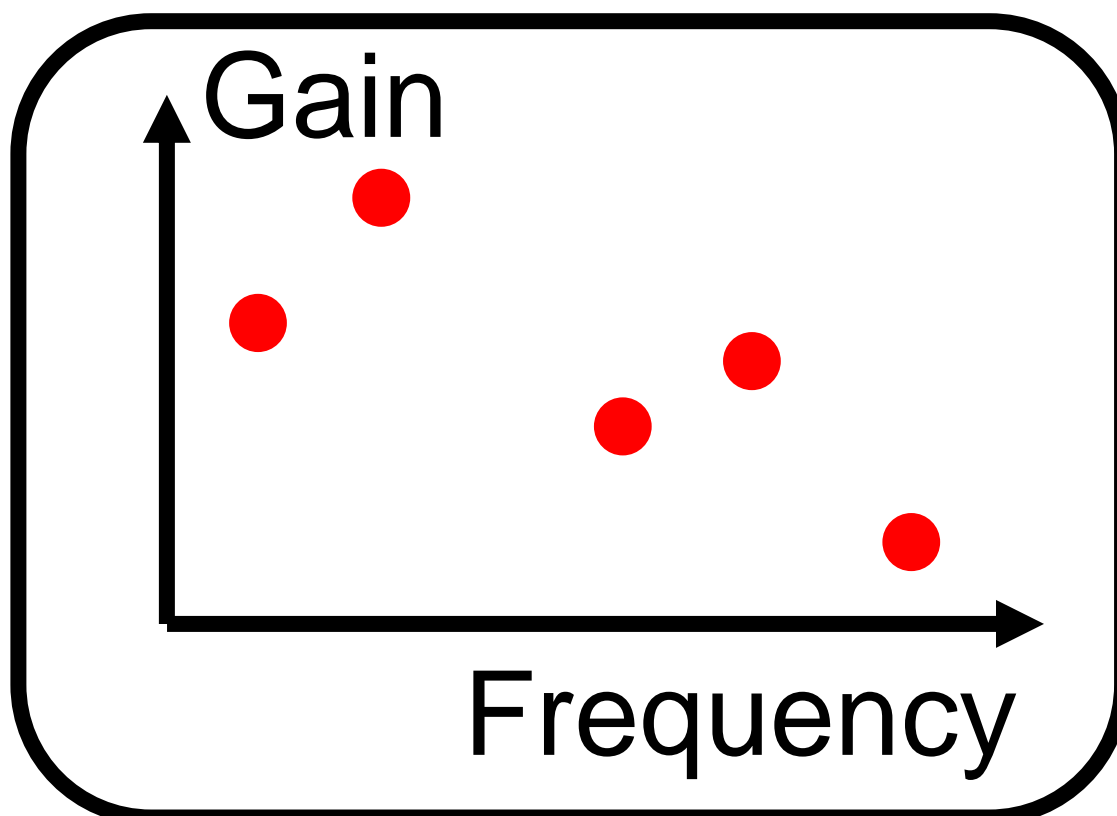
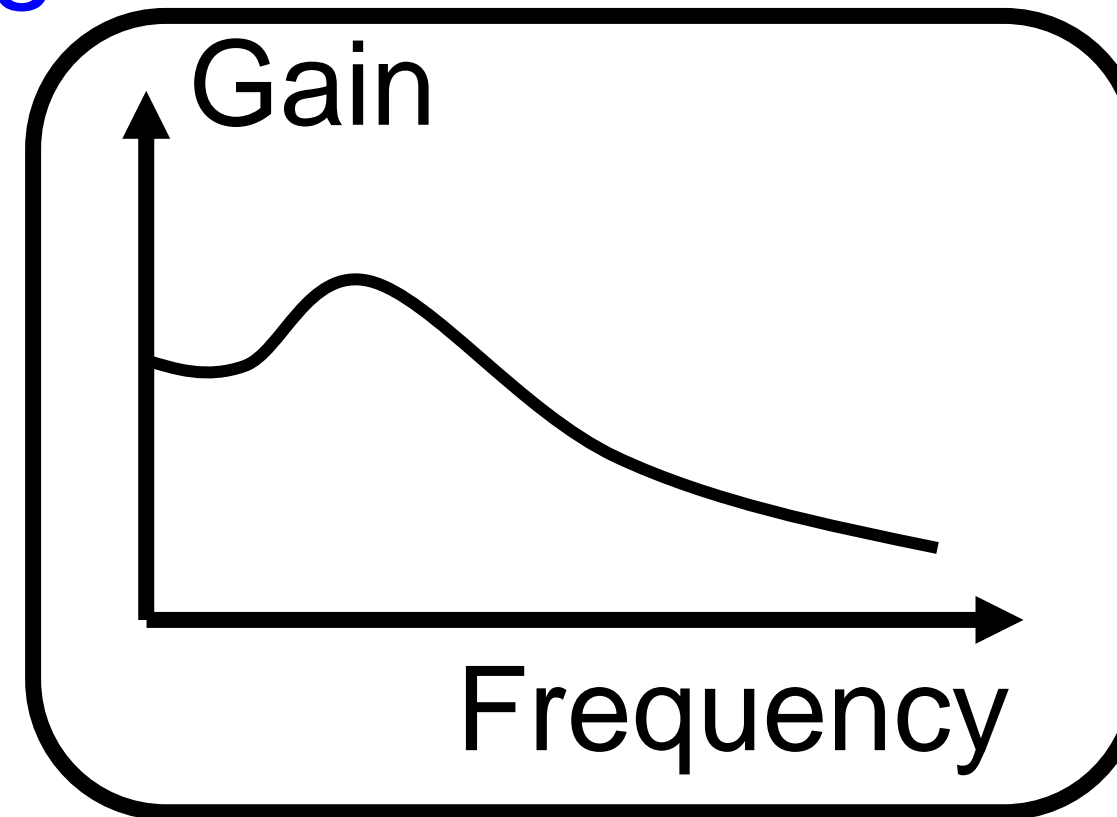
Realizations



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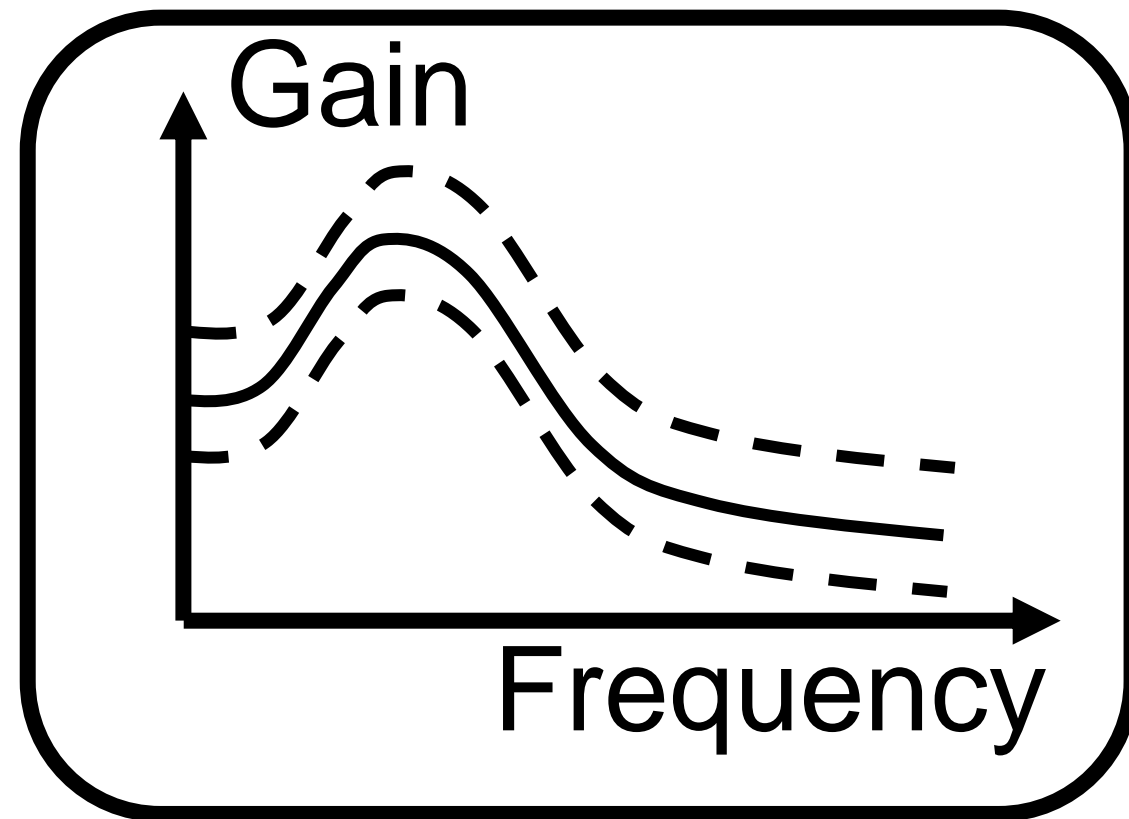


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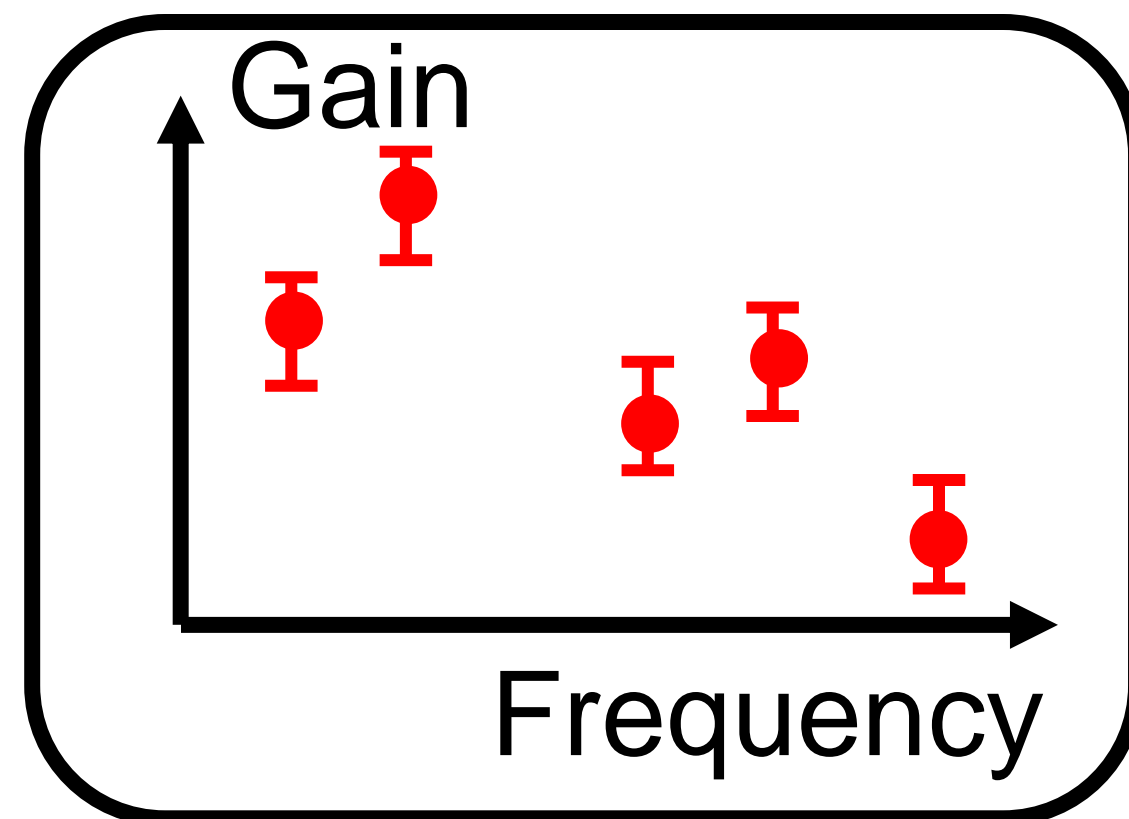


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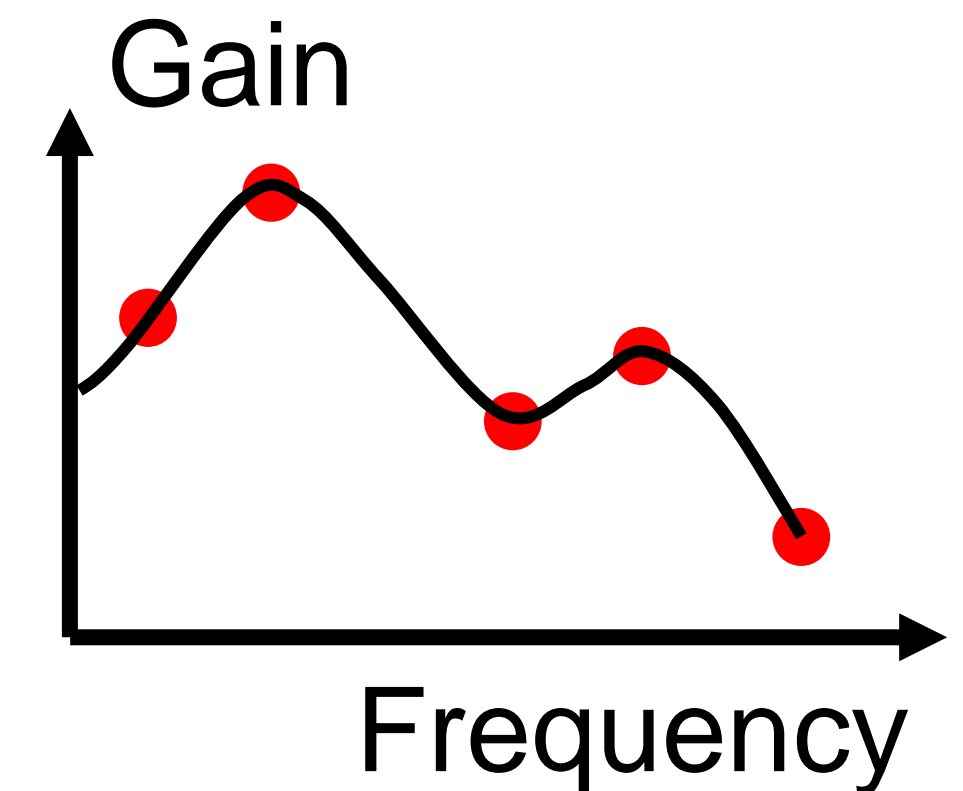
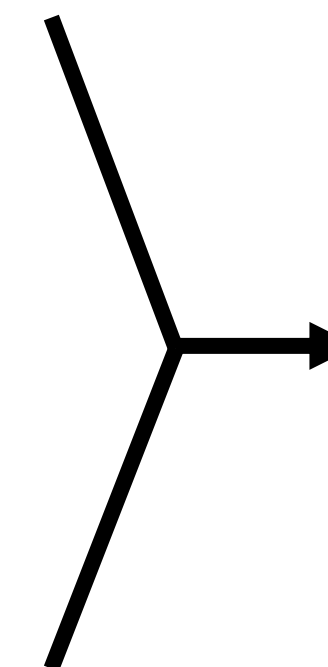
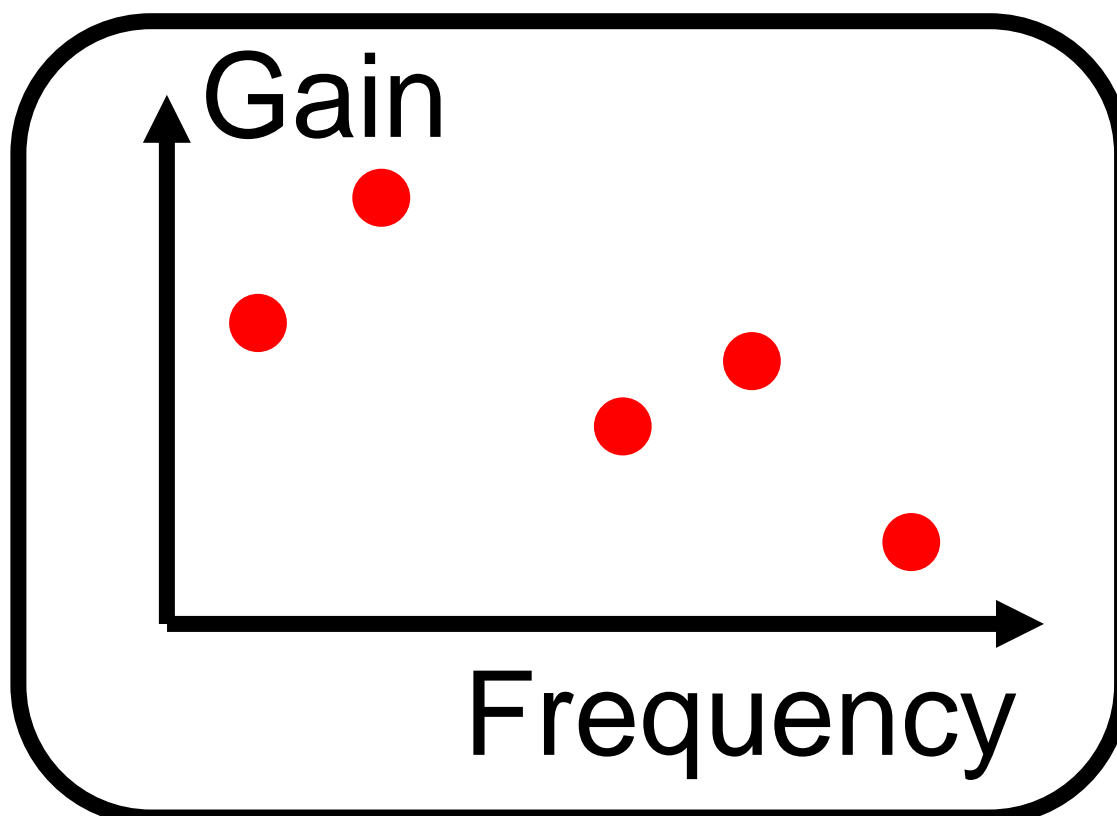
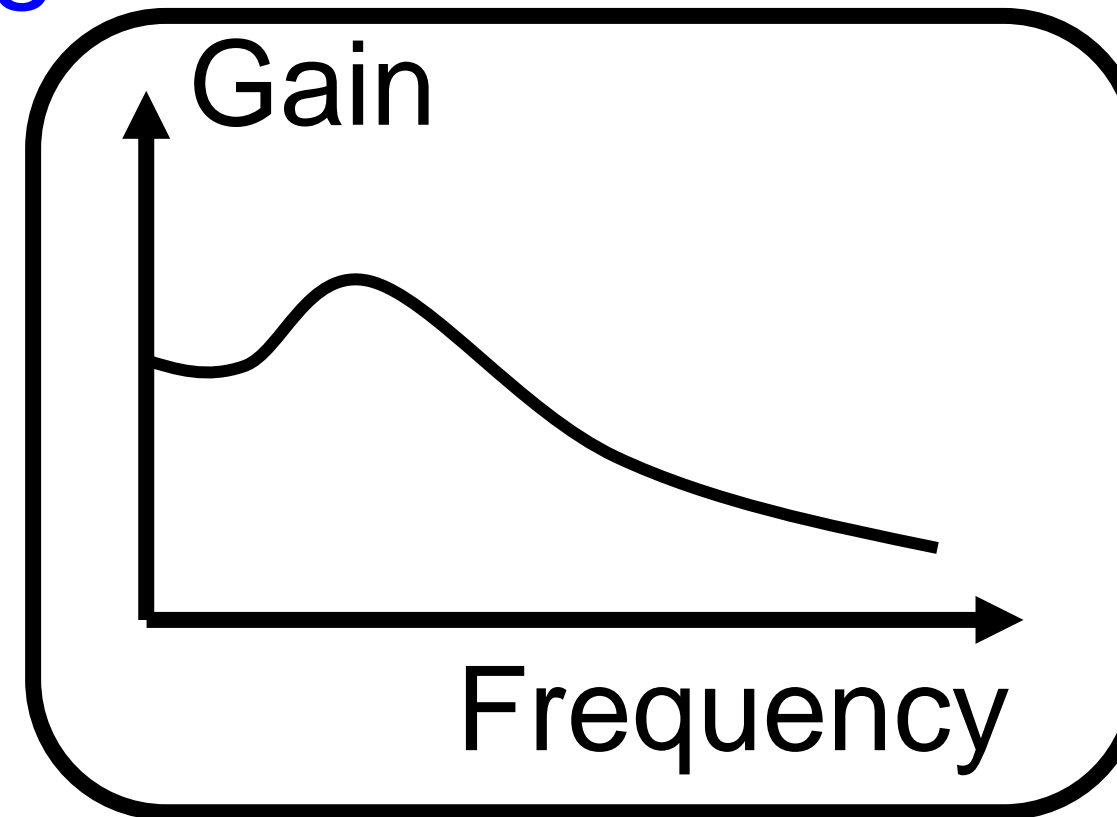
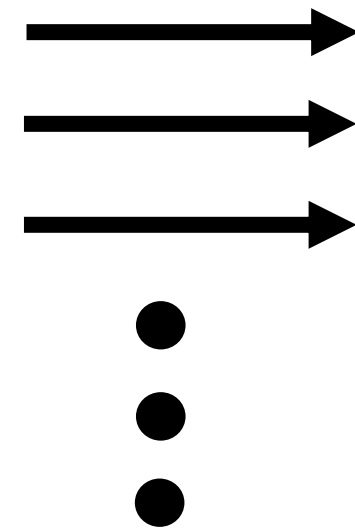
Realizations



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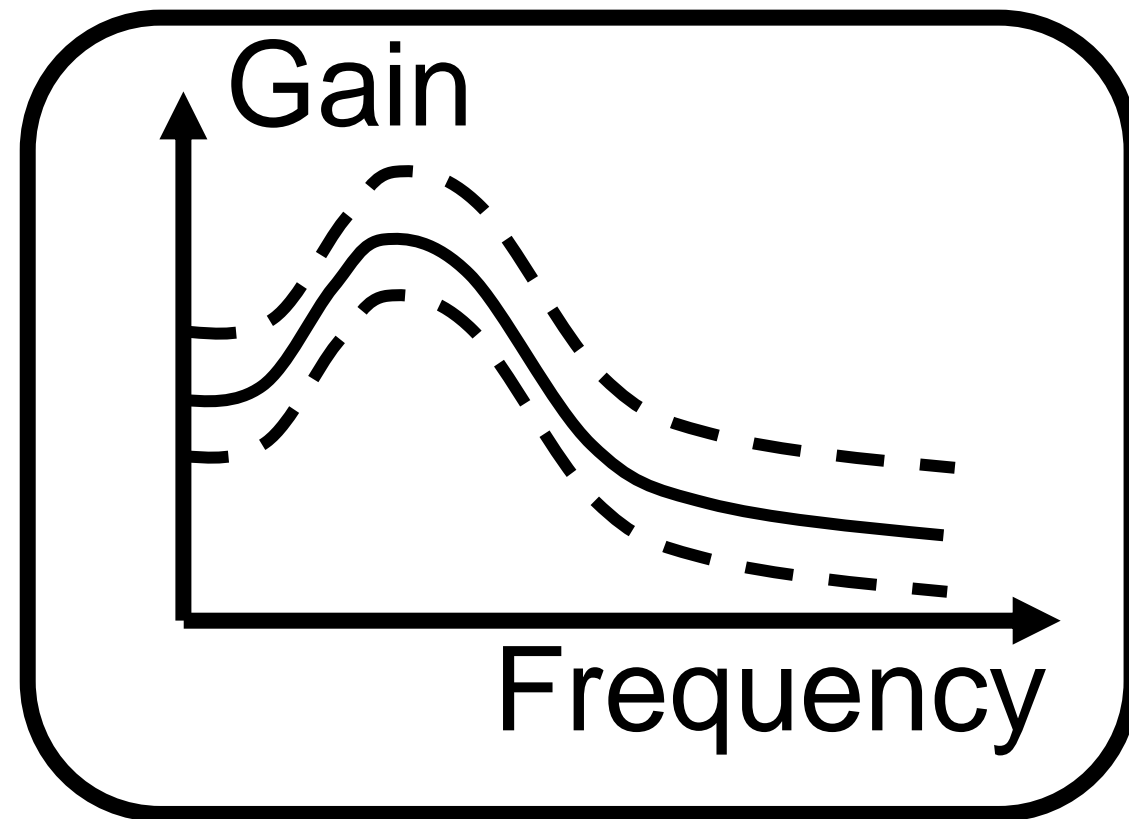


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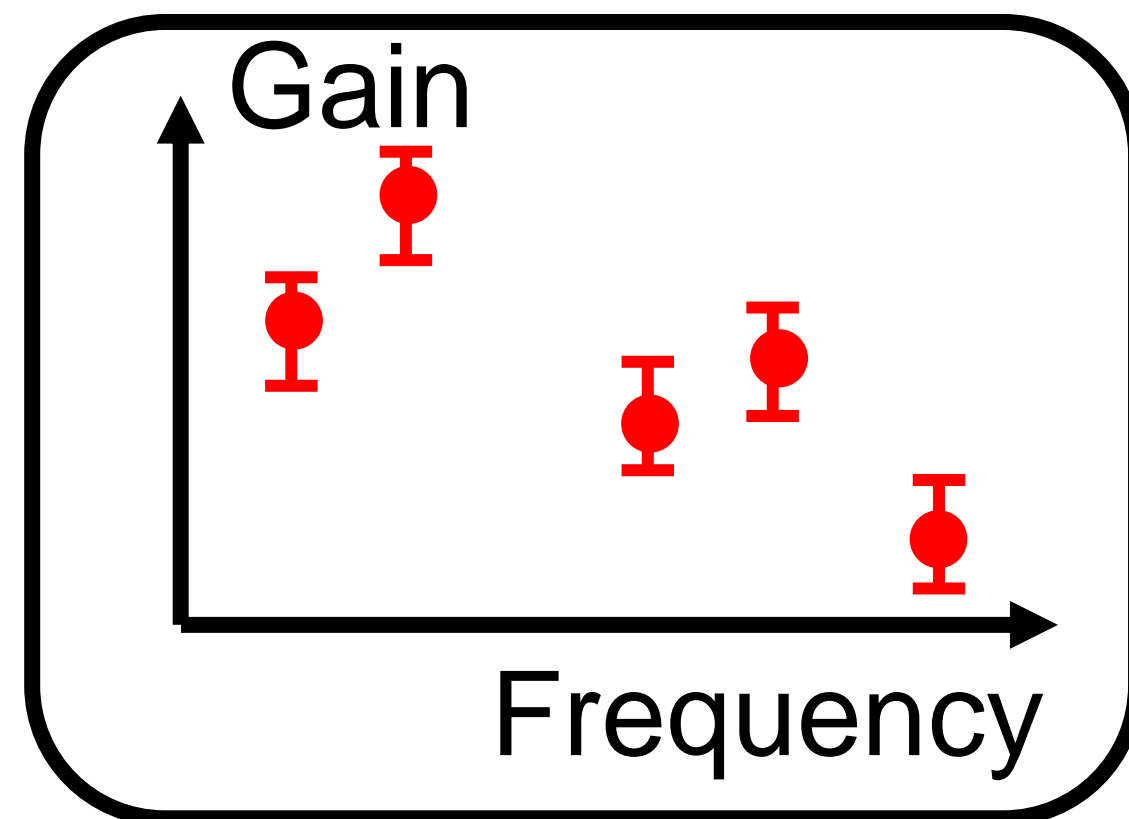


We propose a bootstrapping procedure to account for uncertainties from both fidelities

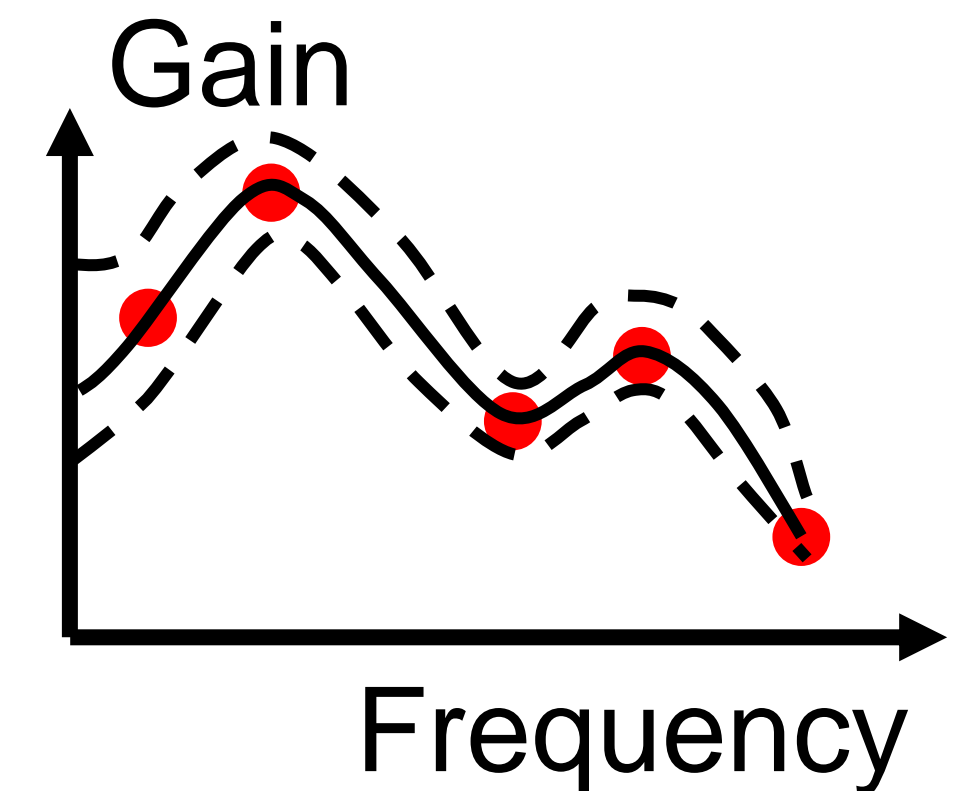
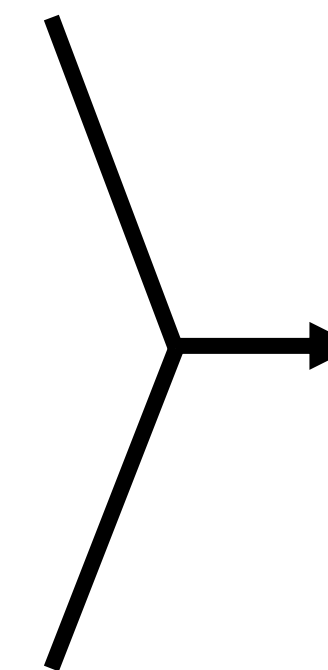
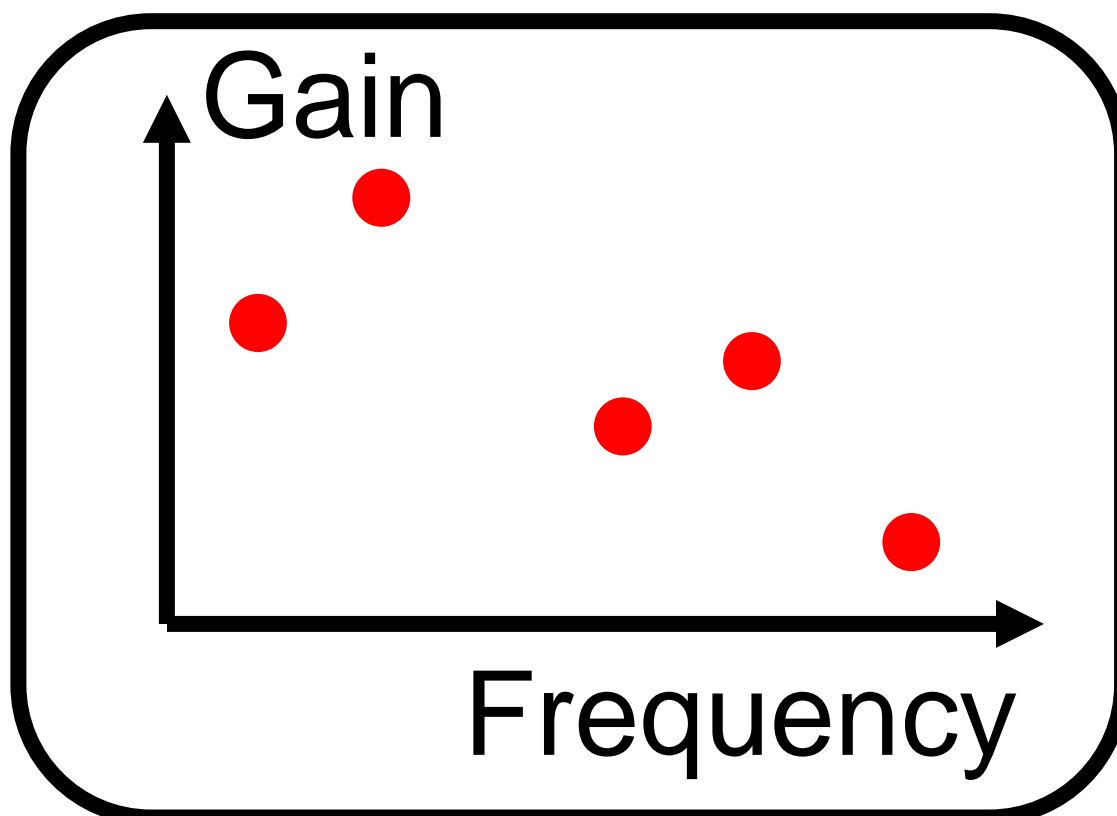
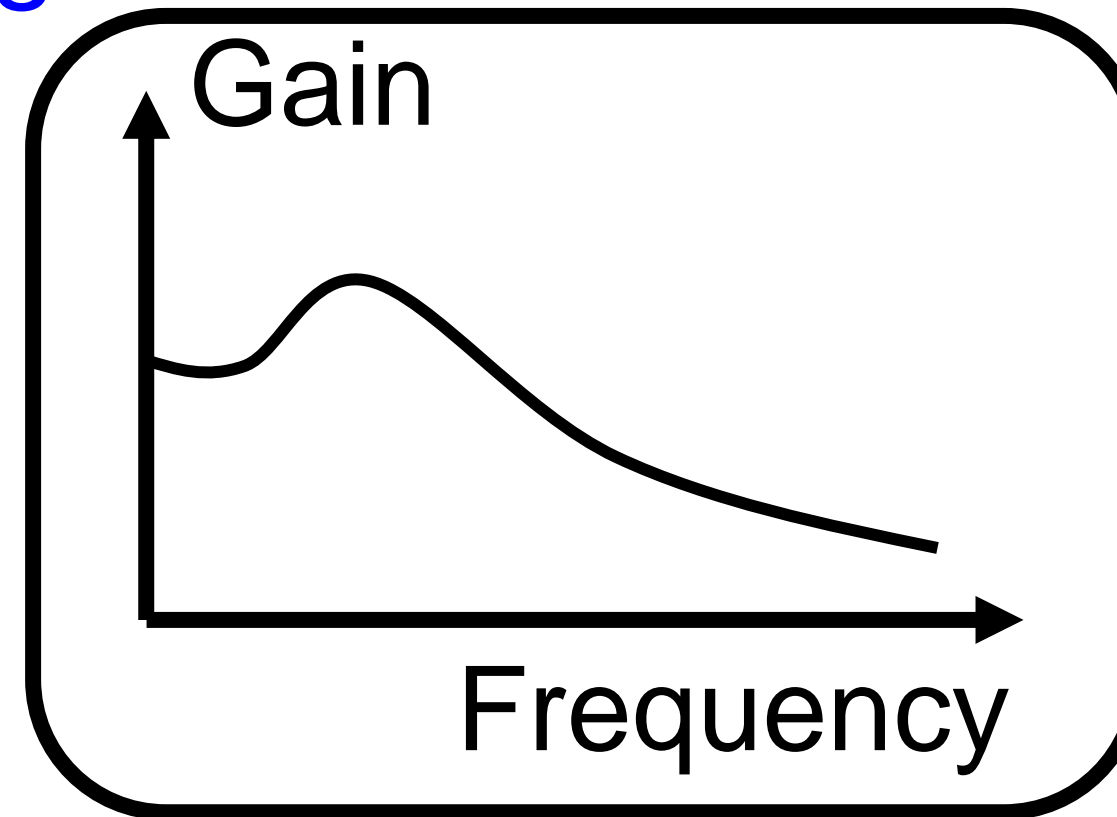
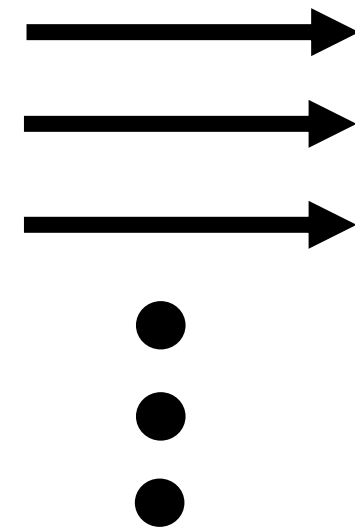
Realizations



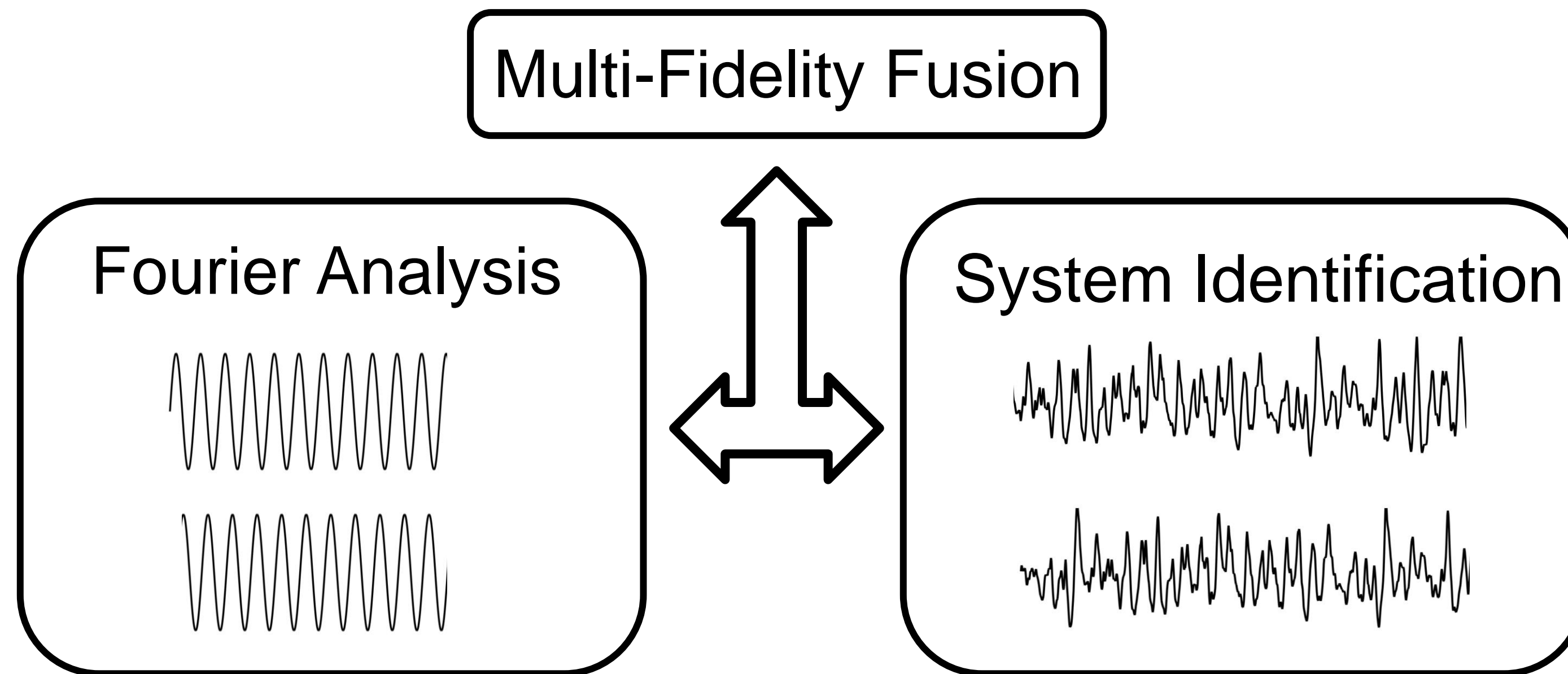
Low-Fidelity



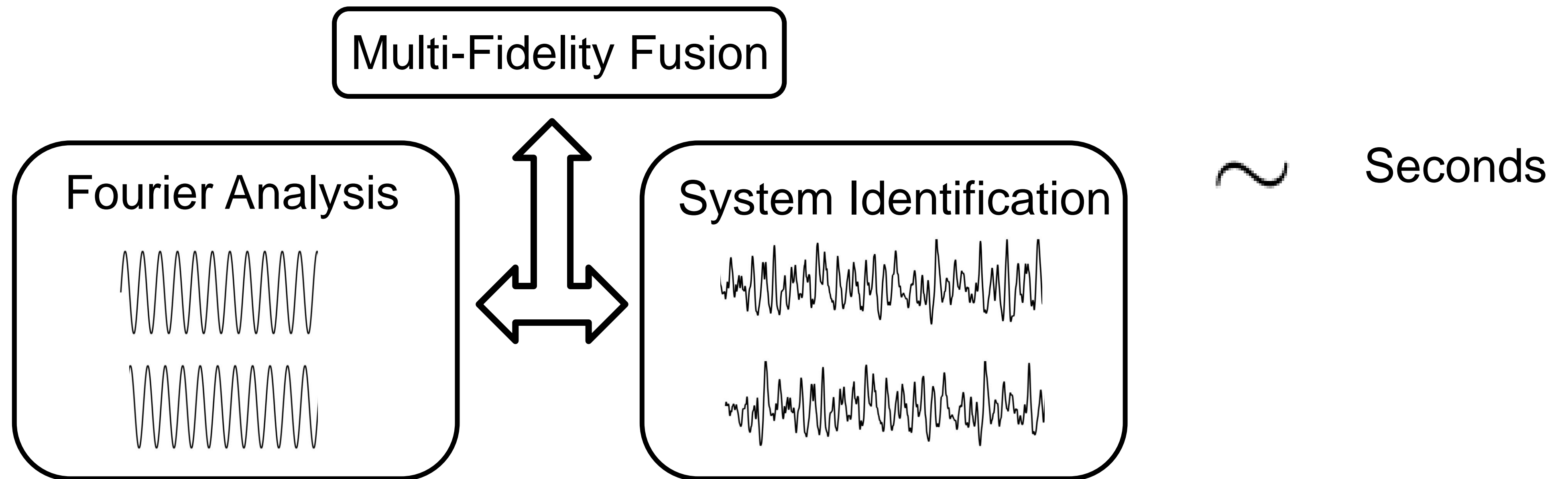
High-Fidelity



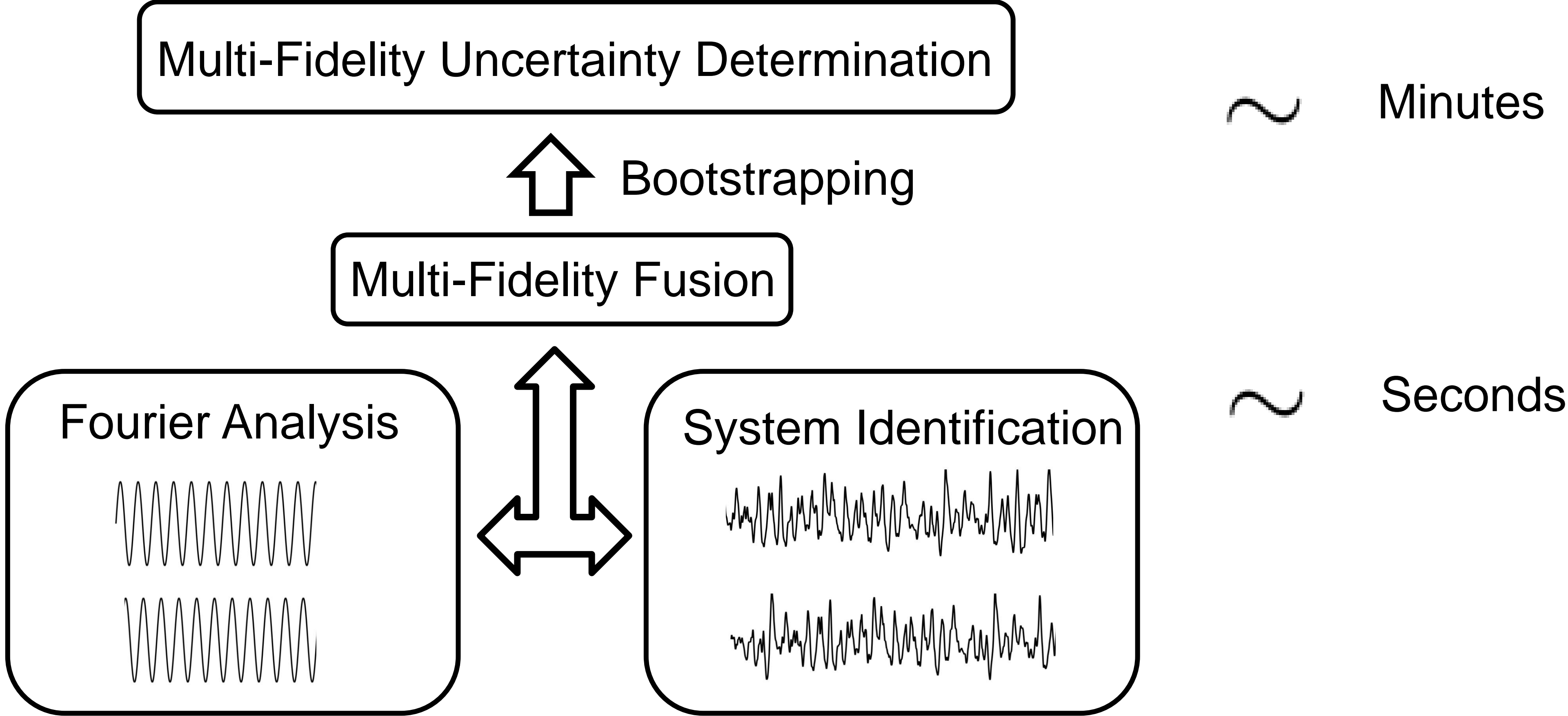
The costs of multi-fidelity analysis is negligible compared with CFD simulations



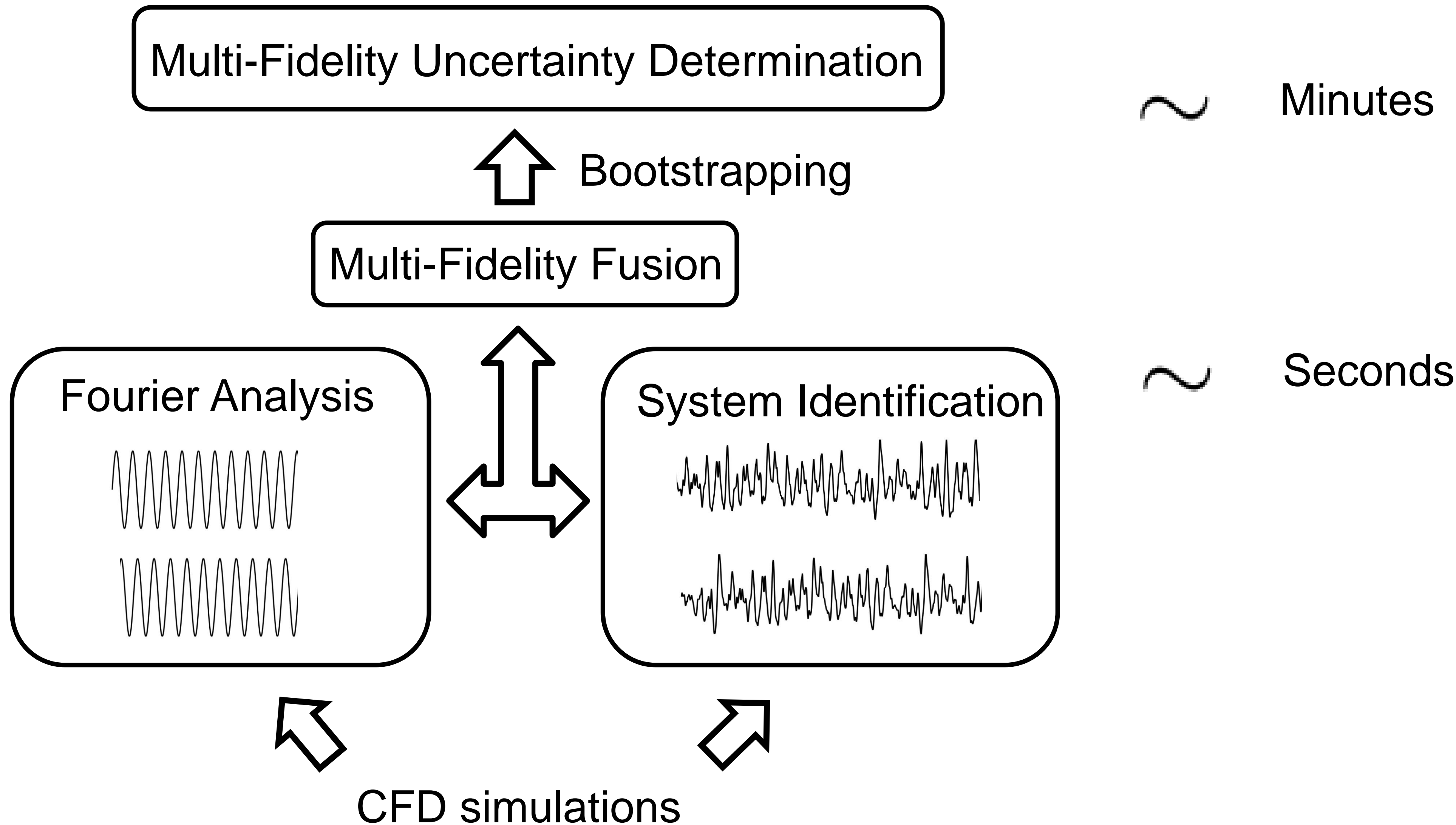
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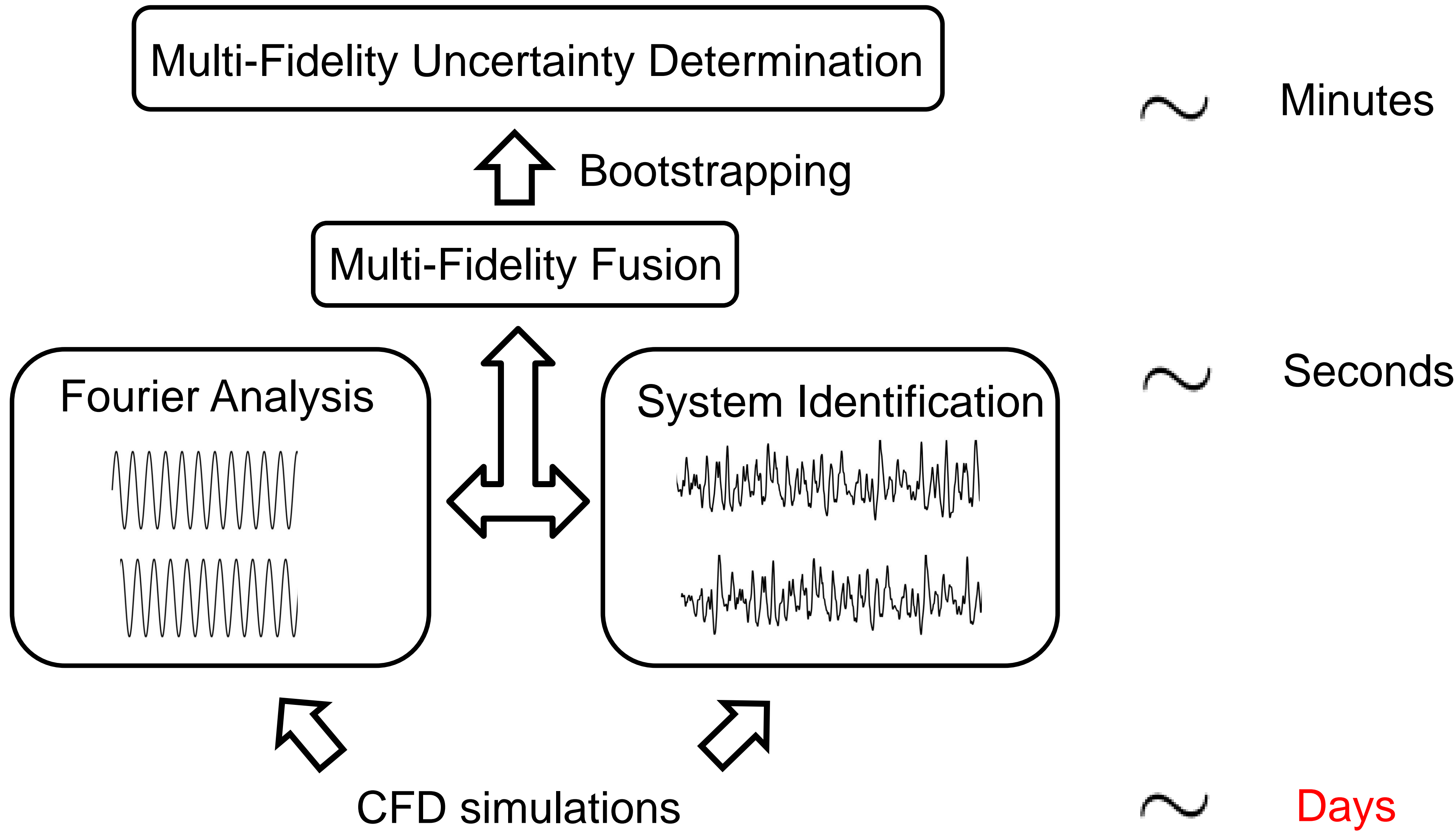
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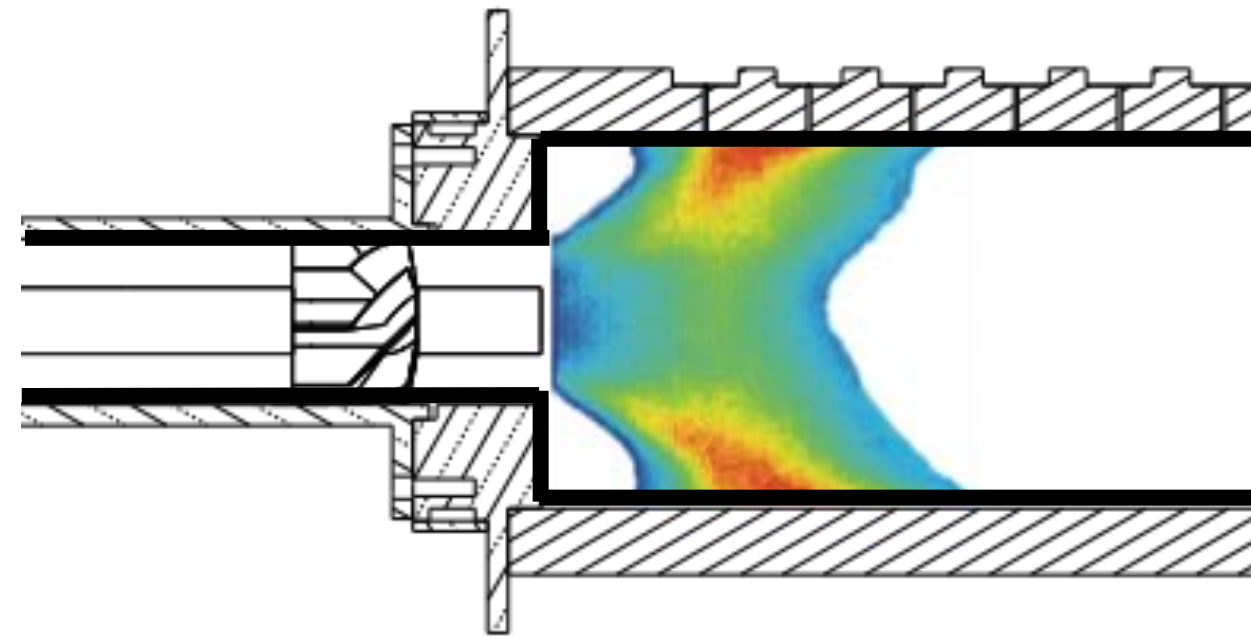


The costs of multi-fidelity analysis is negligible compared with CFD simulations



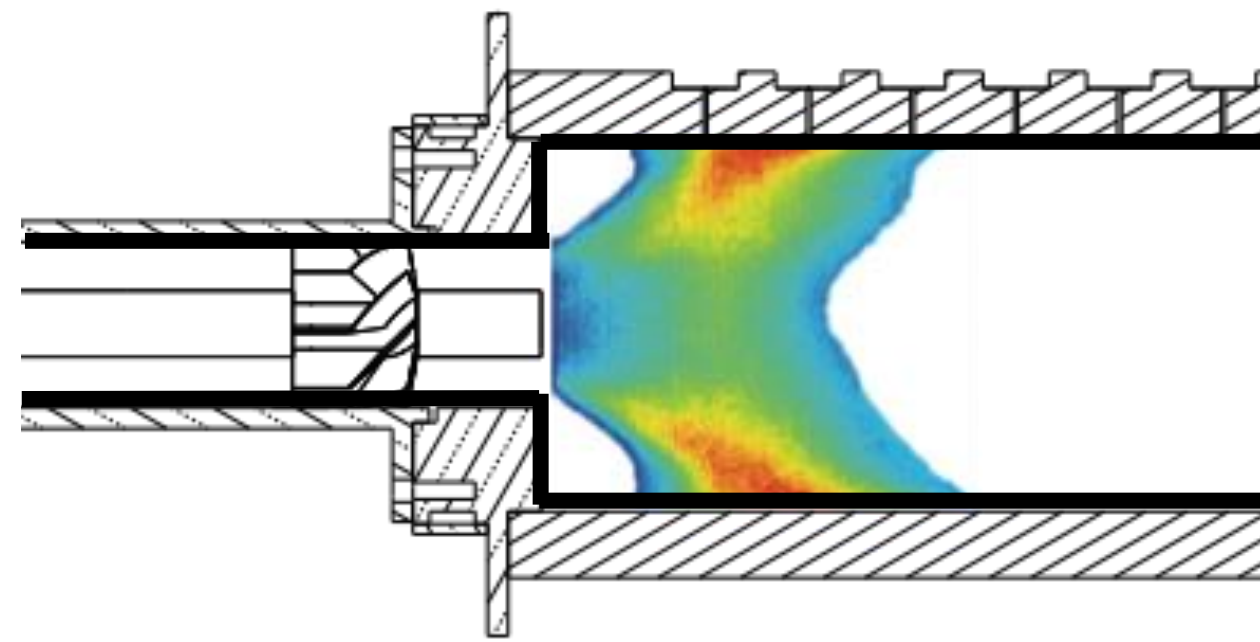
- Motivation
- Multi-fidelity Gaussian Process
 - How to aggregate different fidelities?
 - How to combine uncertainties from individual fidelities?
- Case study
 - Set-up
 - Results & Discussions
- Conclusion & Outlook

We force a combustor network model to identify flame frequency response

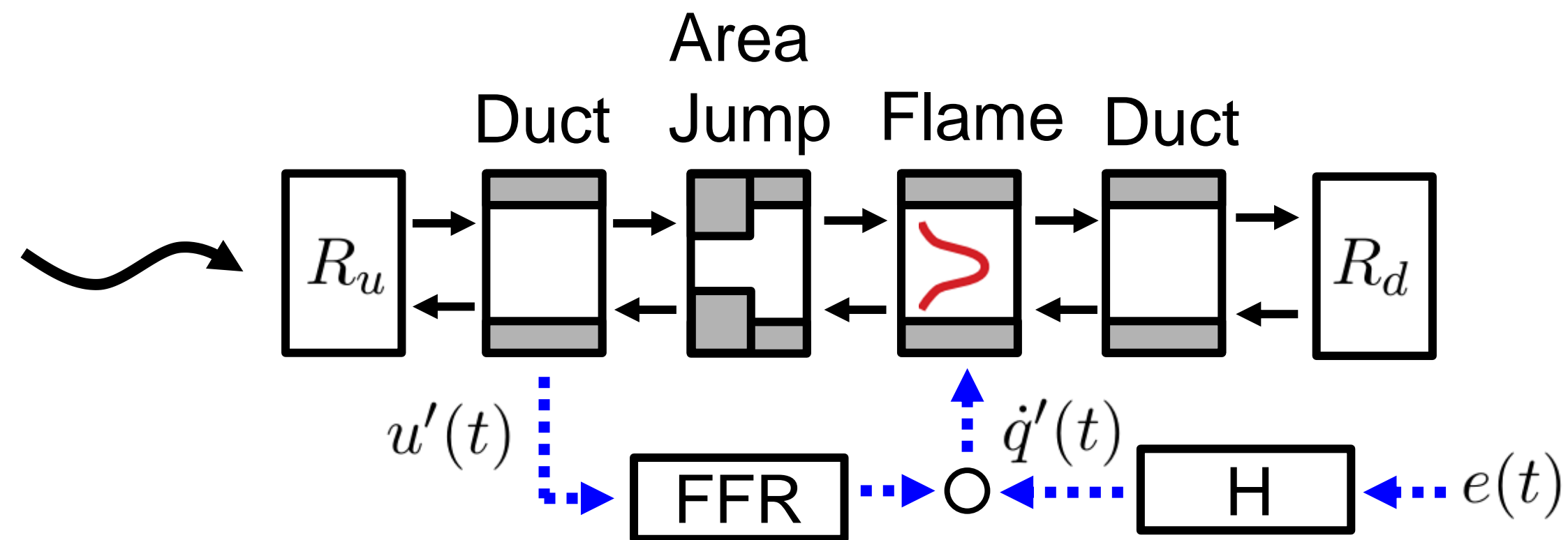


Premixed swirl burner

We force a combustor network model to identify flame frequency response

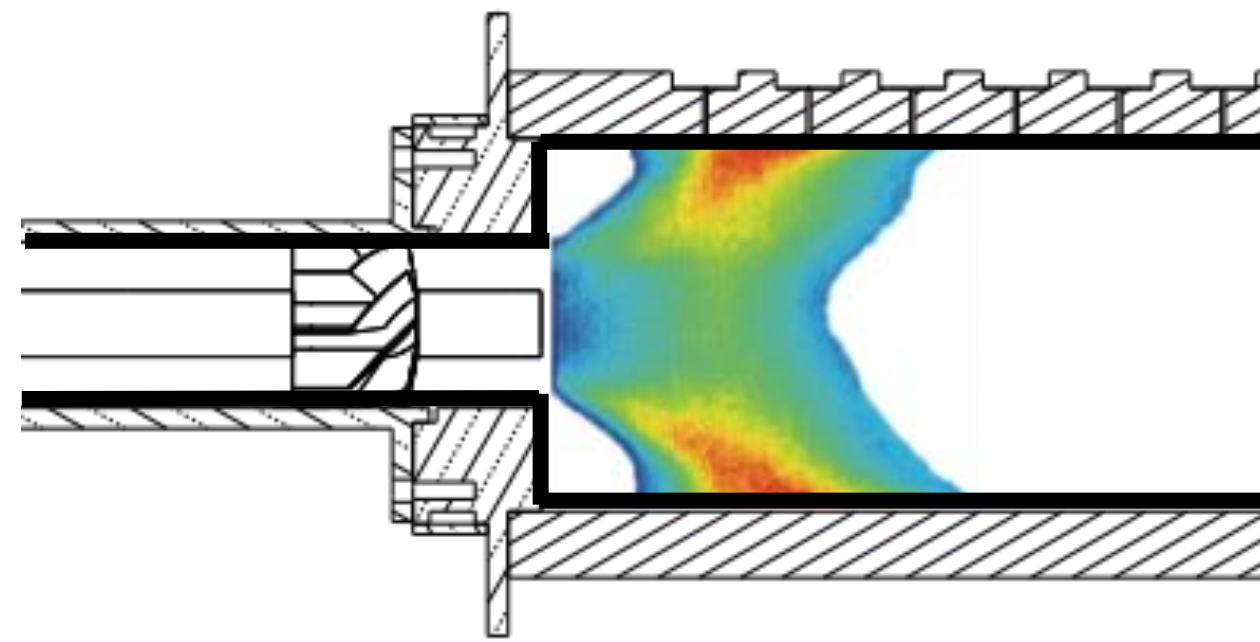


Premixed swirl burner

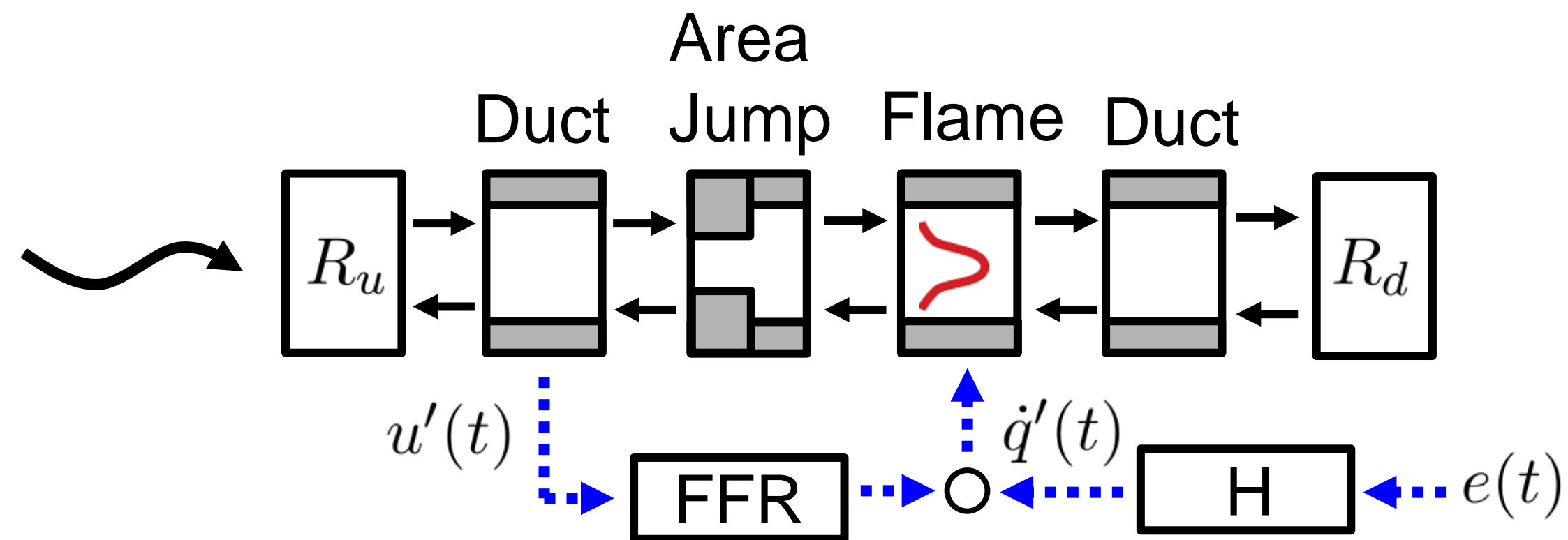


Network model

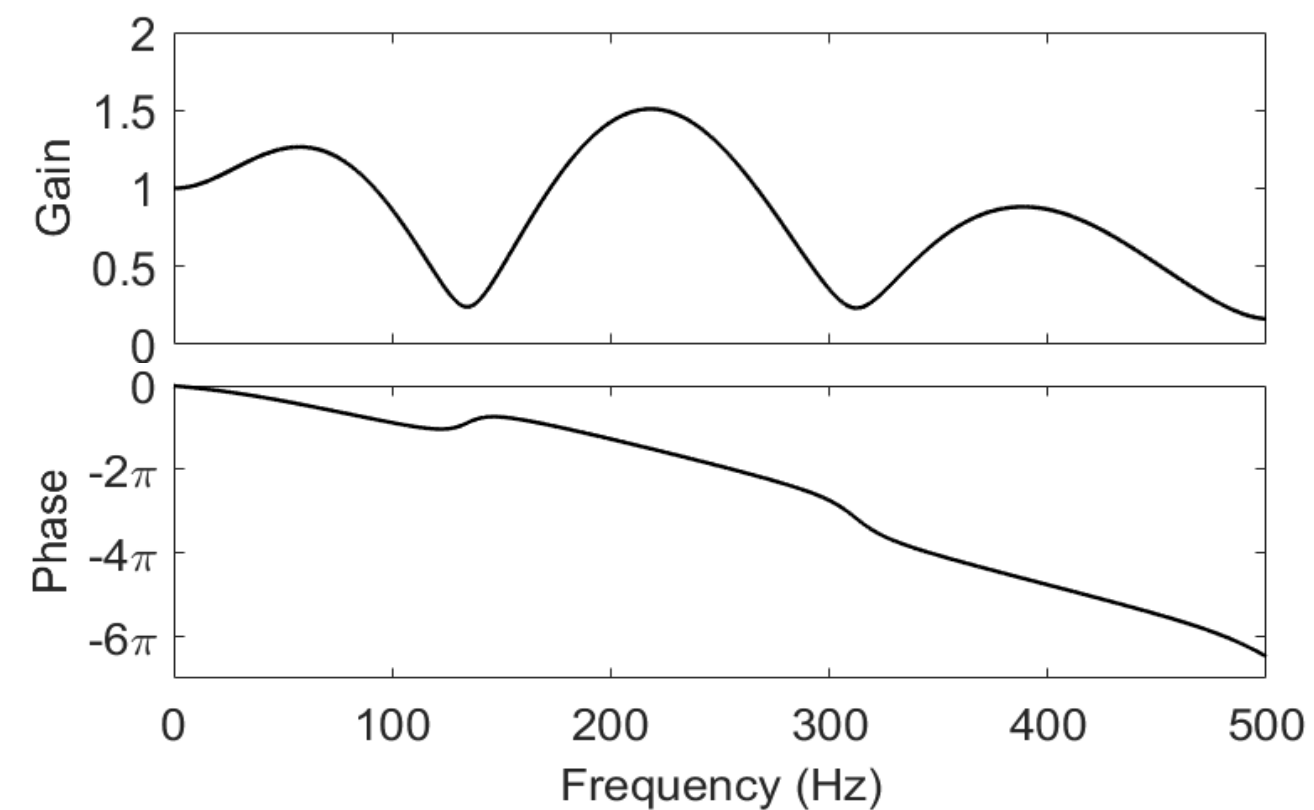
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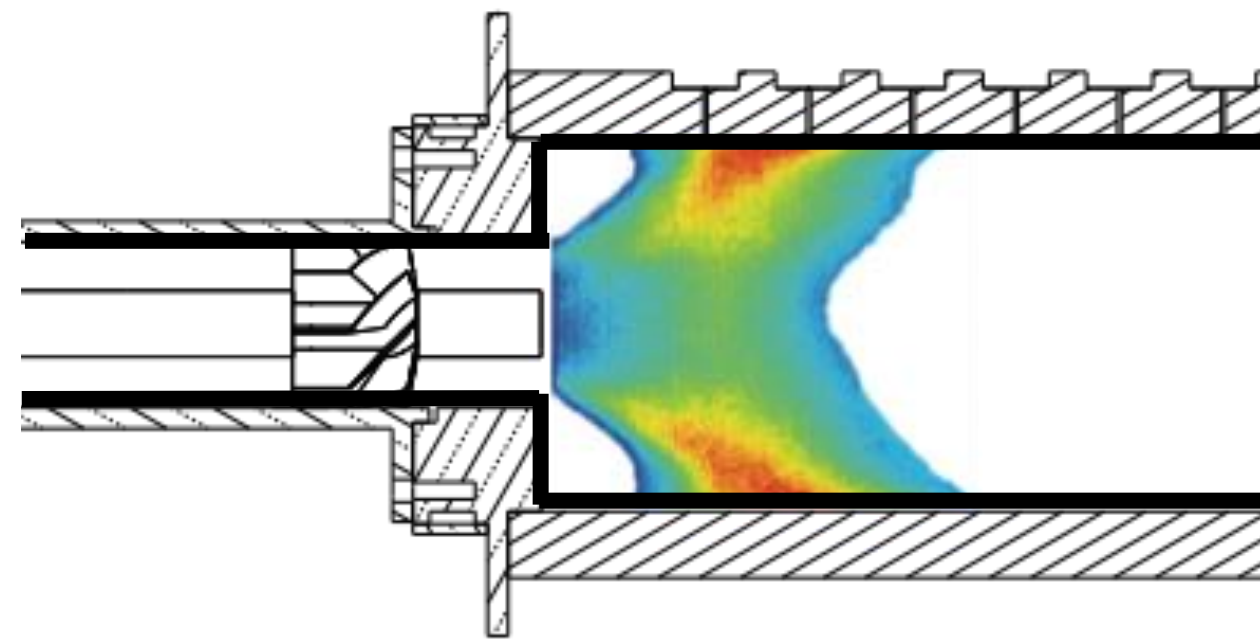
Premixed swirl burner



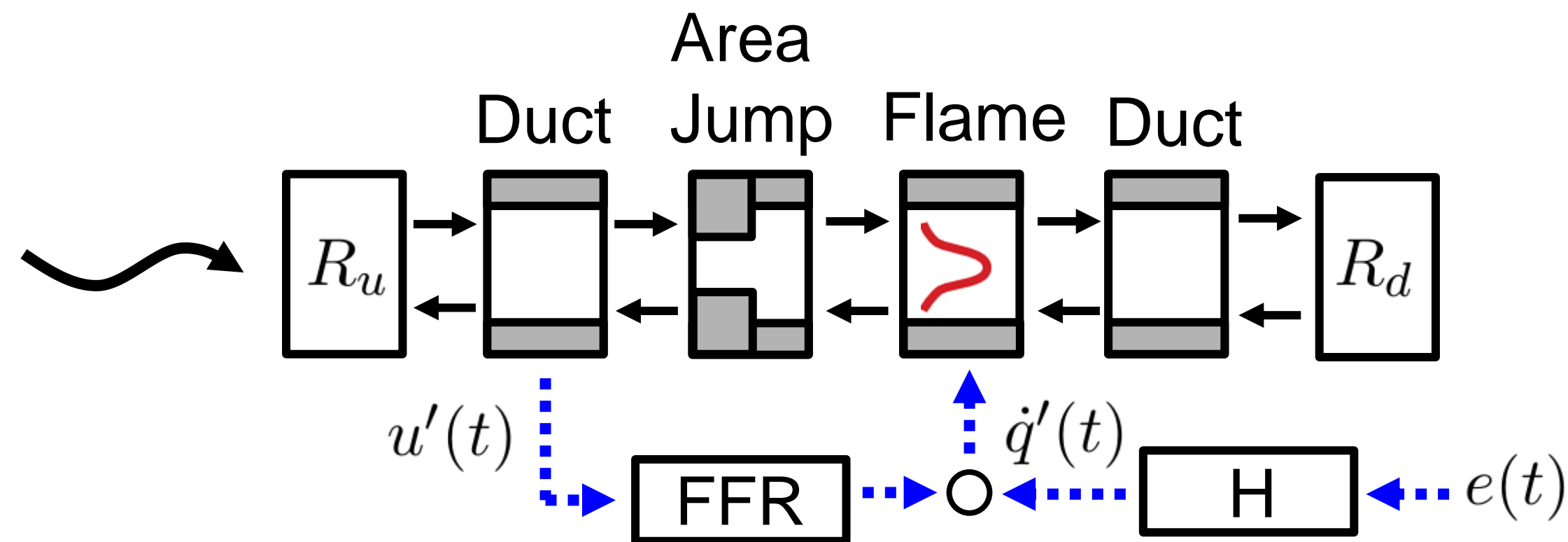
Network model



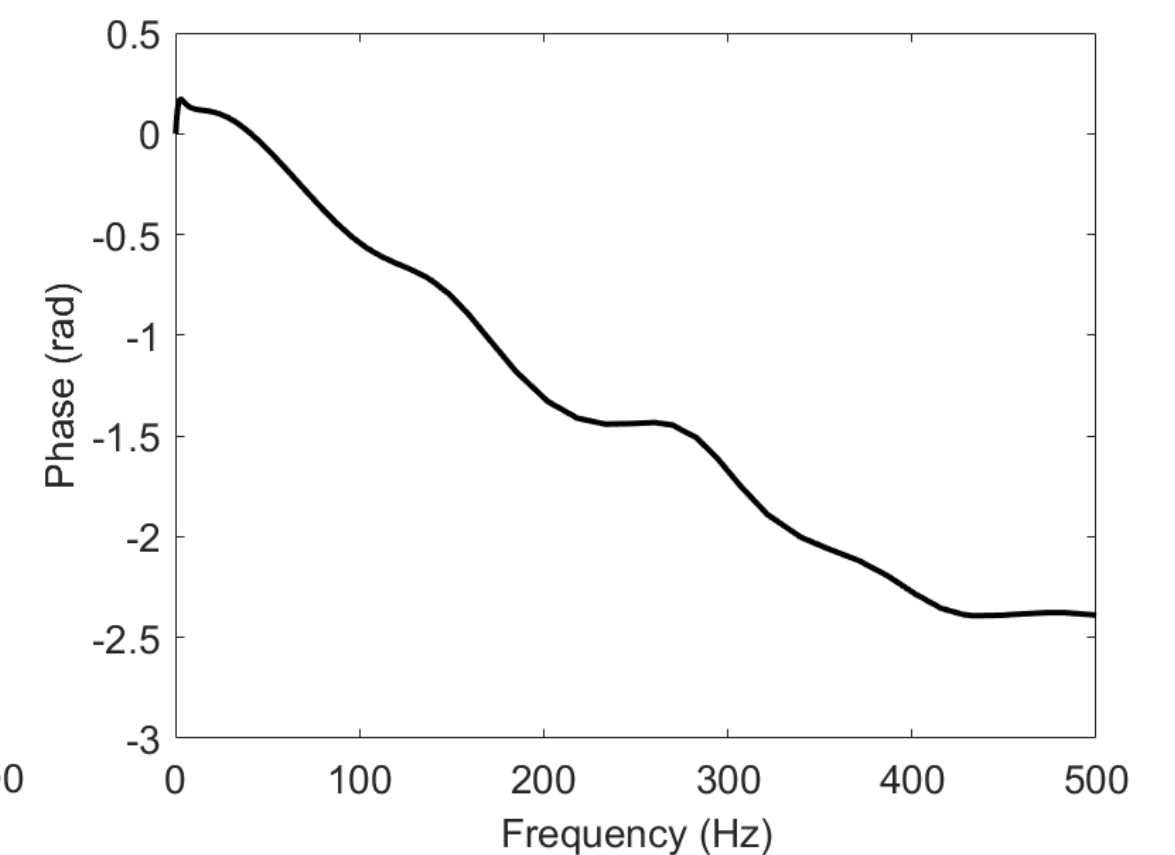
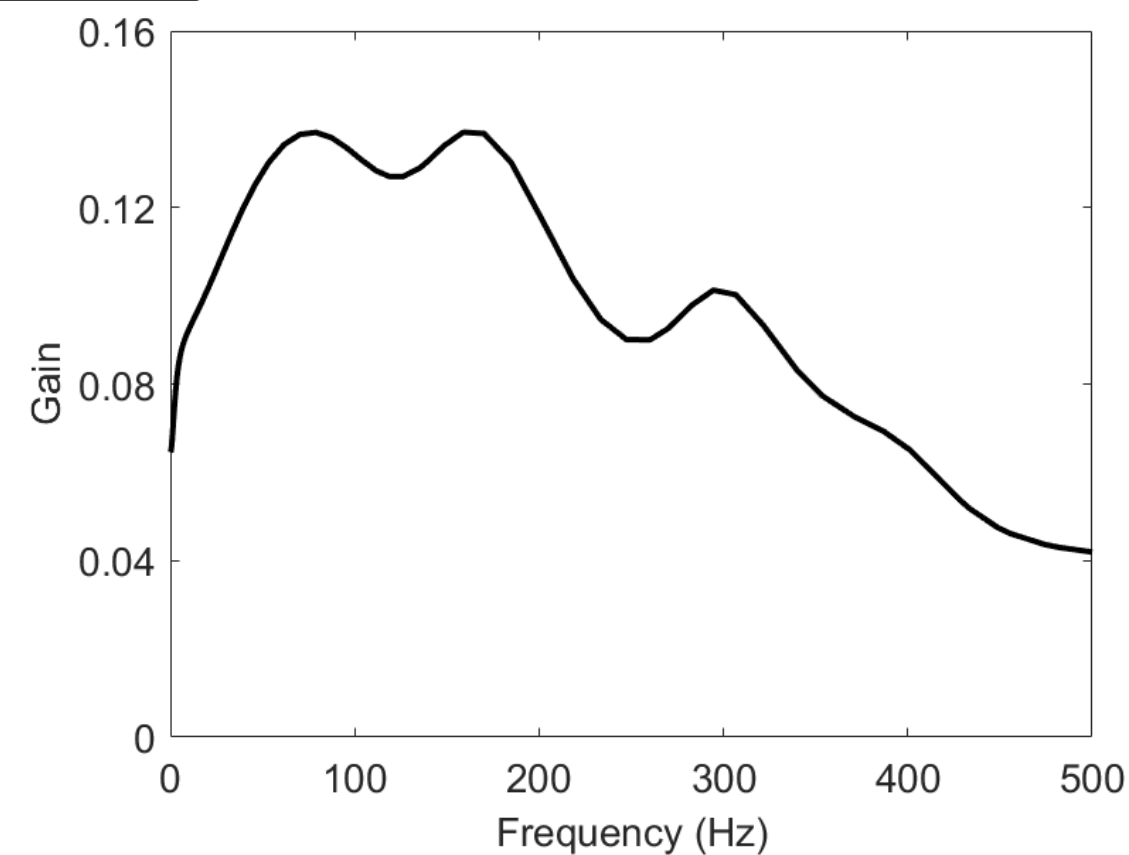
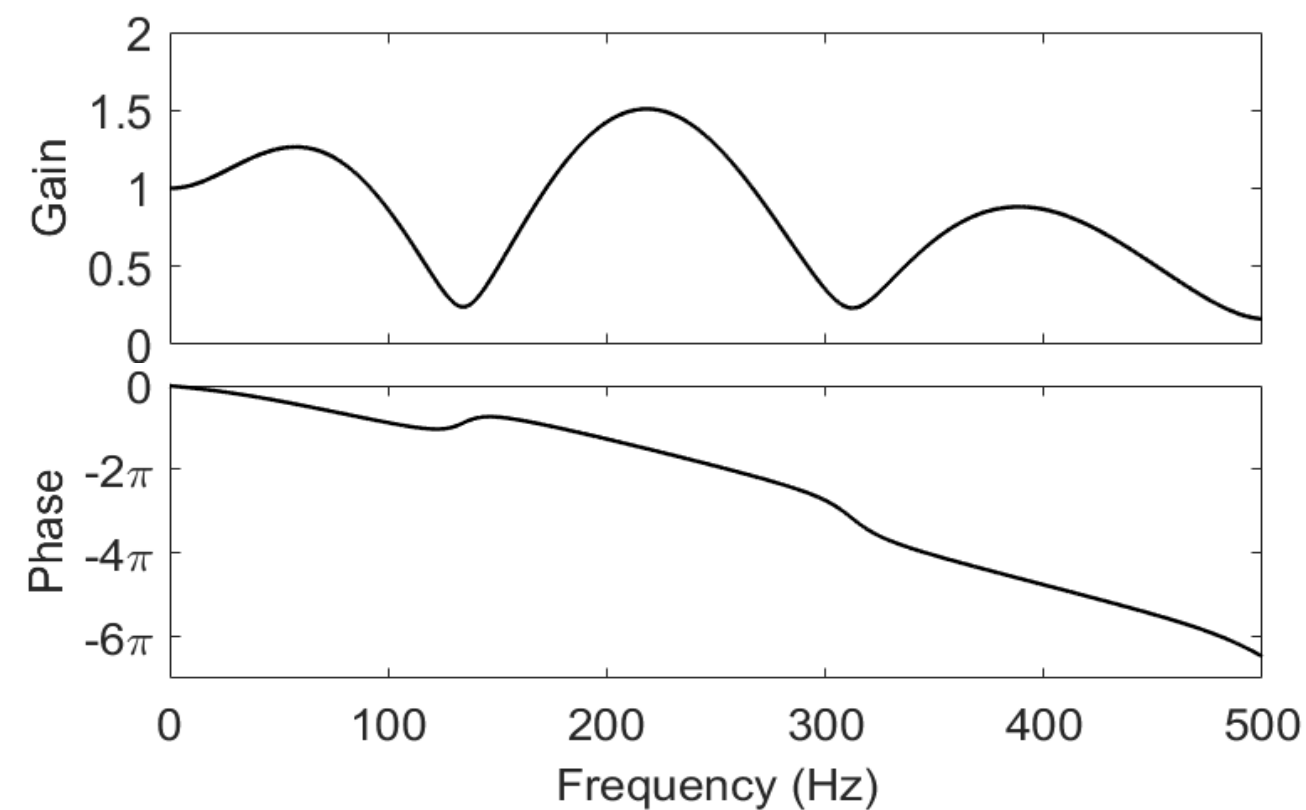
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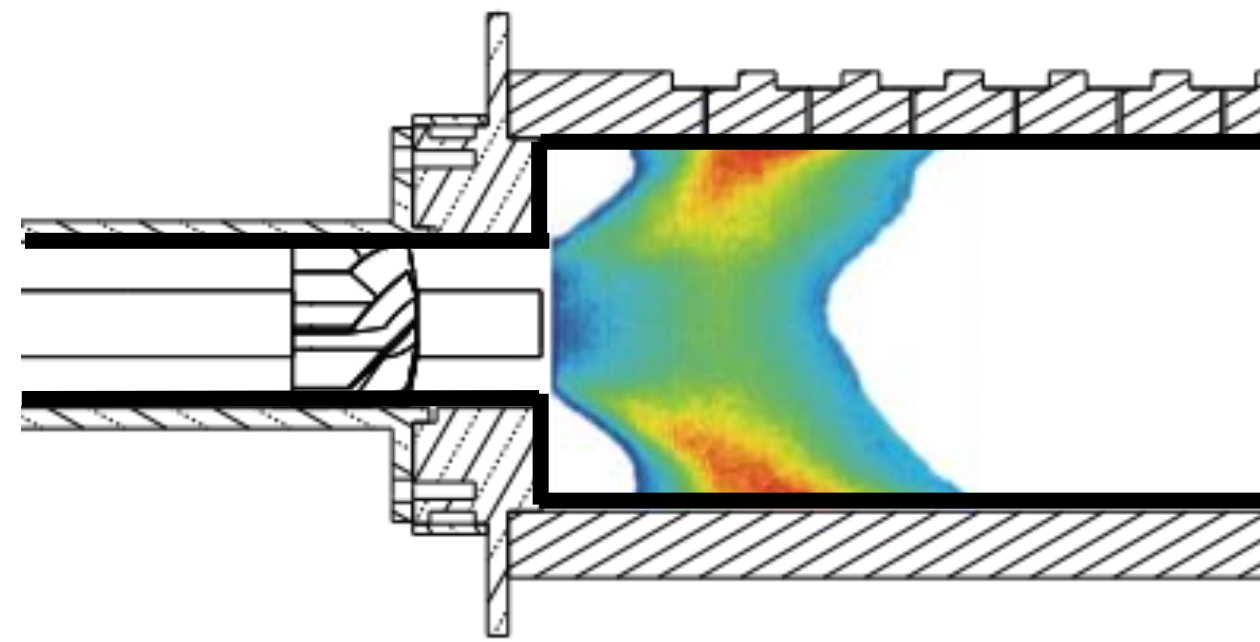
Premixed swirl burner



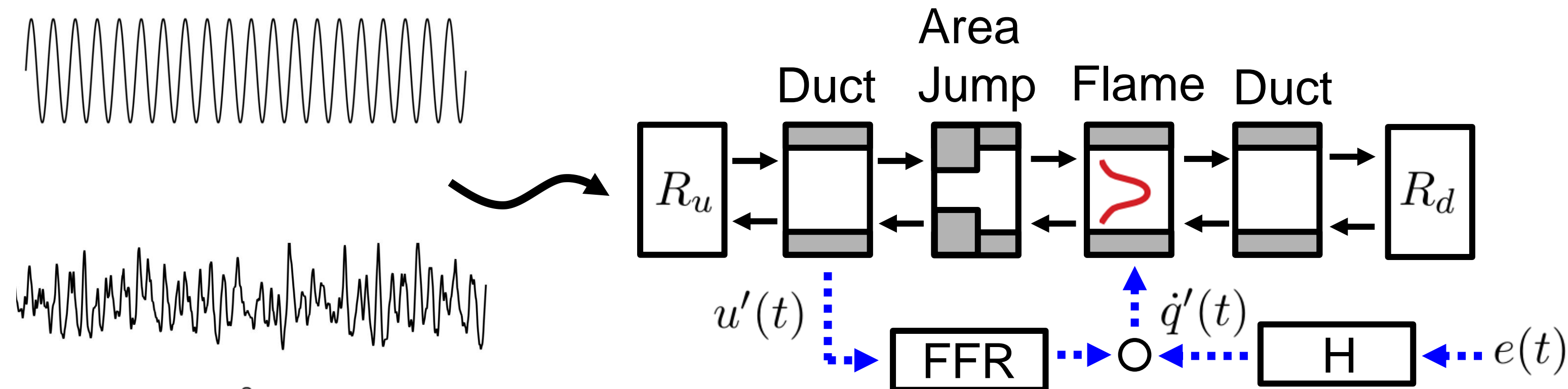
Network model



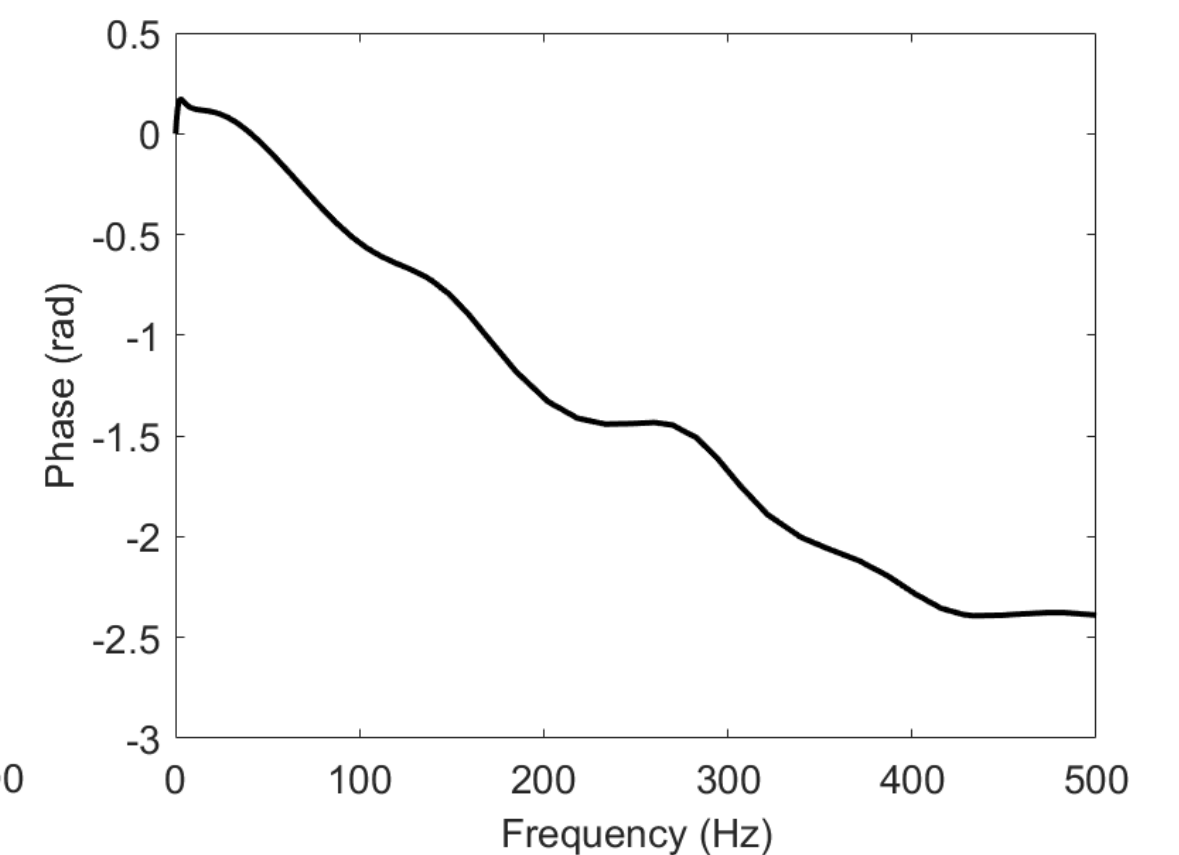
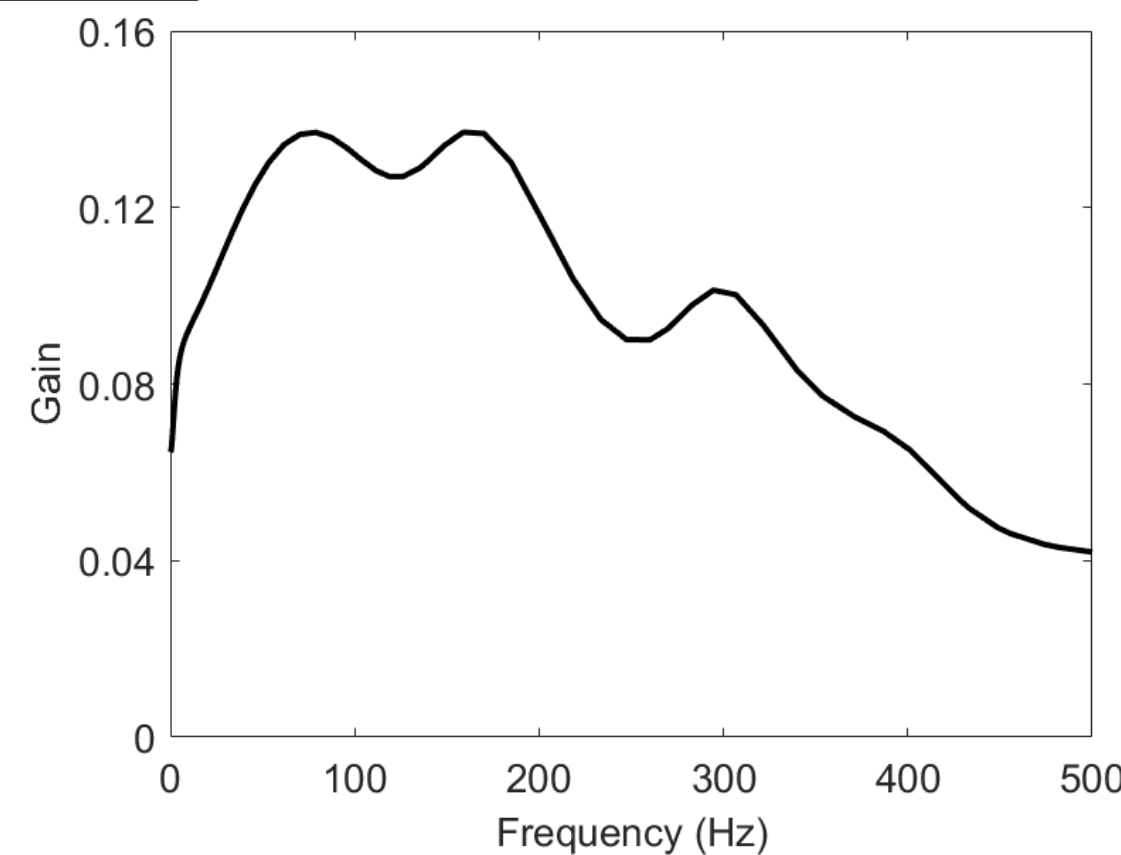
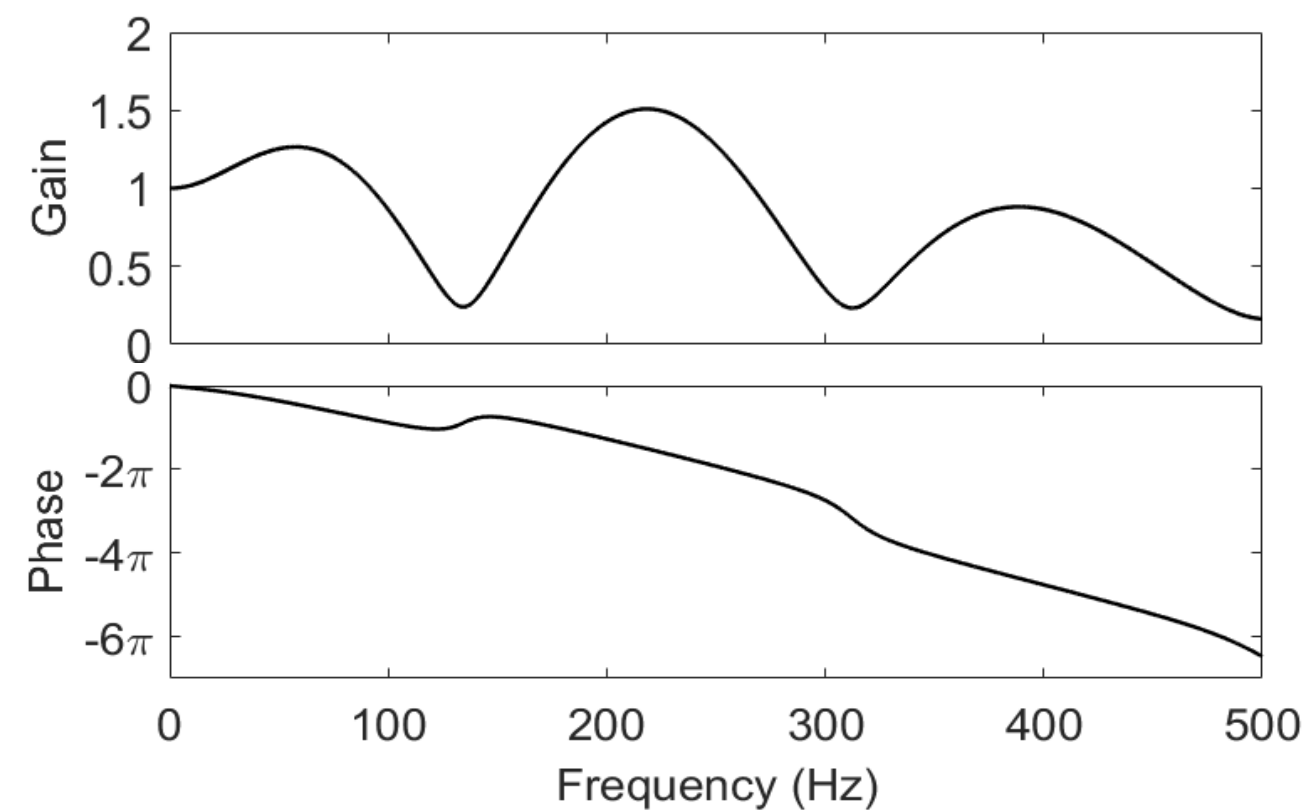
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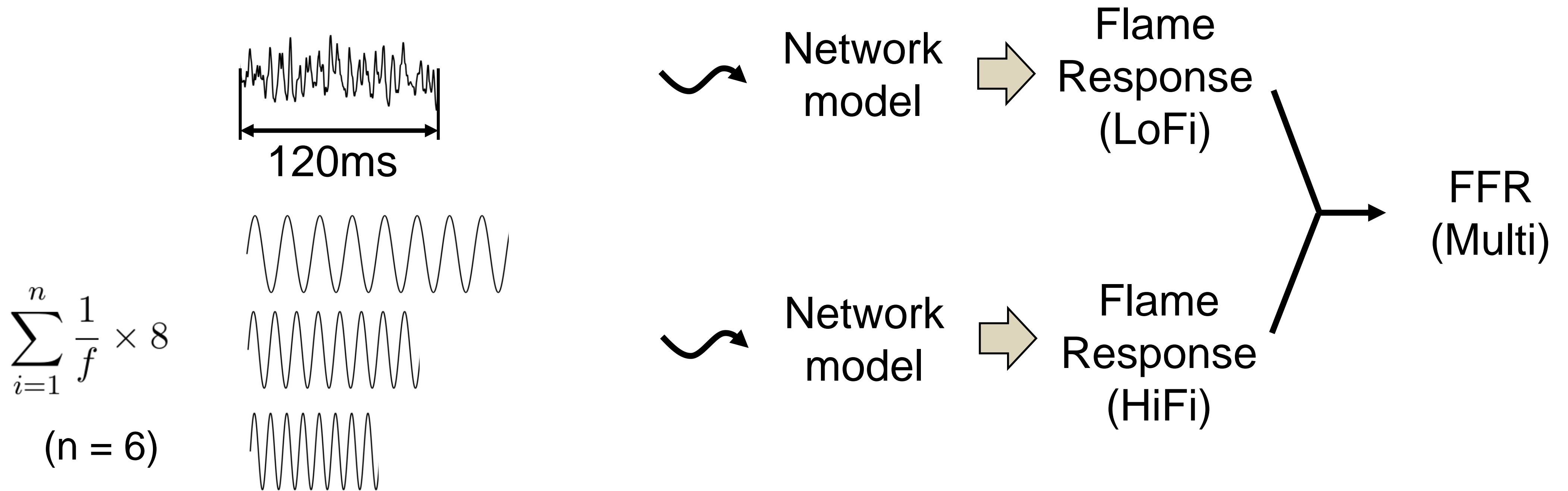
Premixed swirl burner



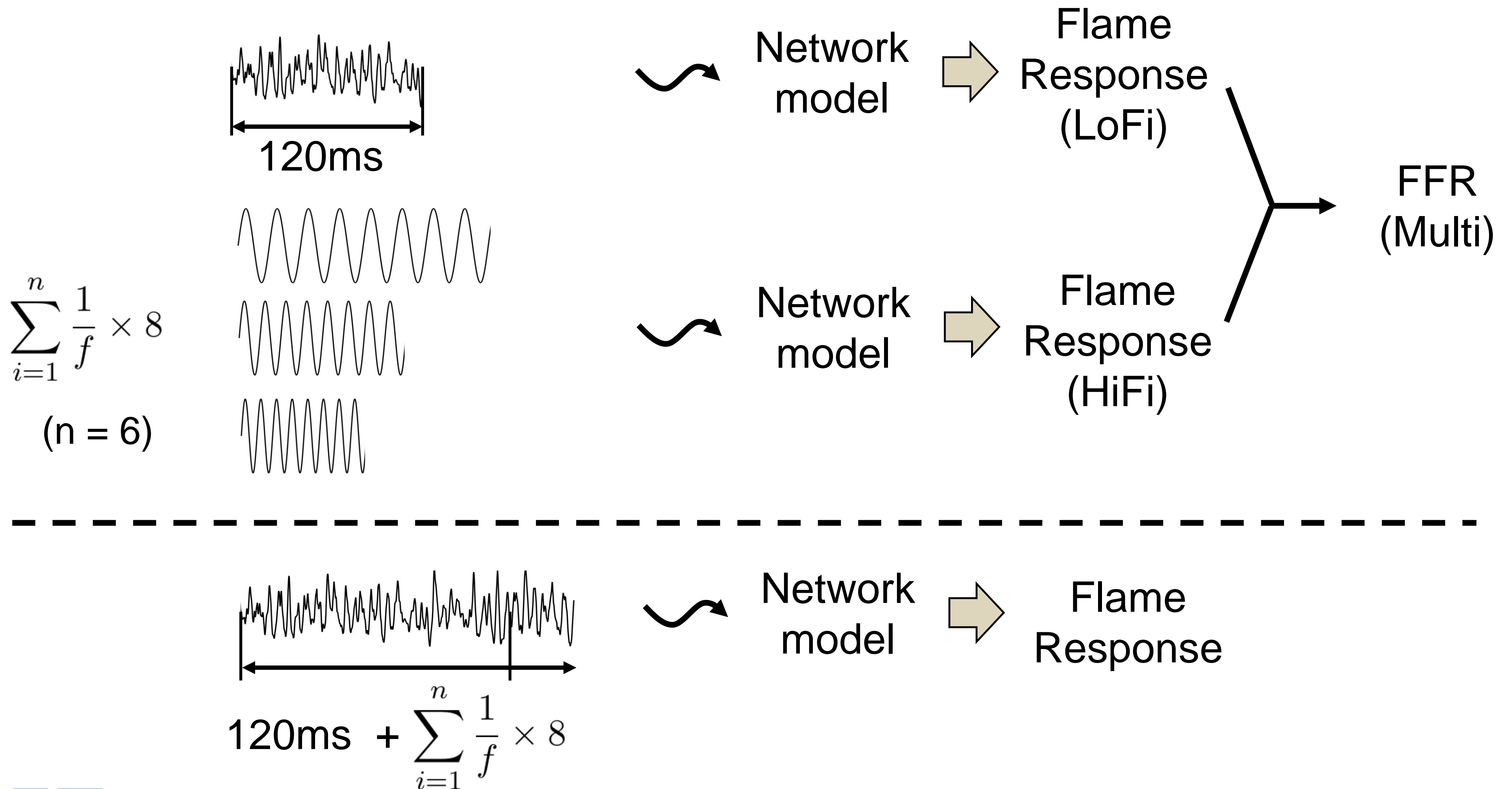
Network model



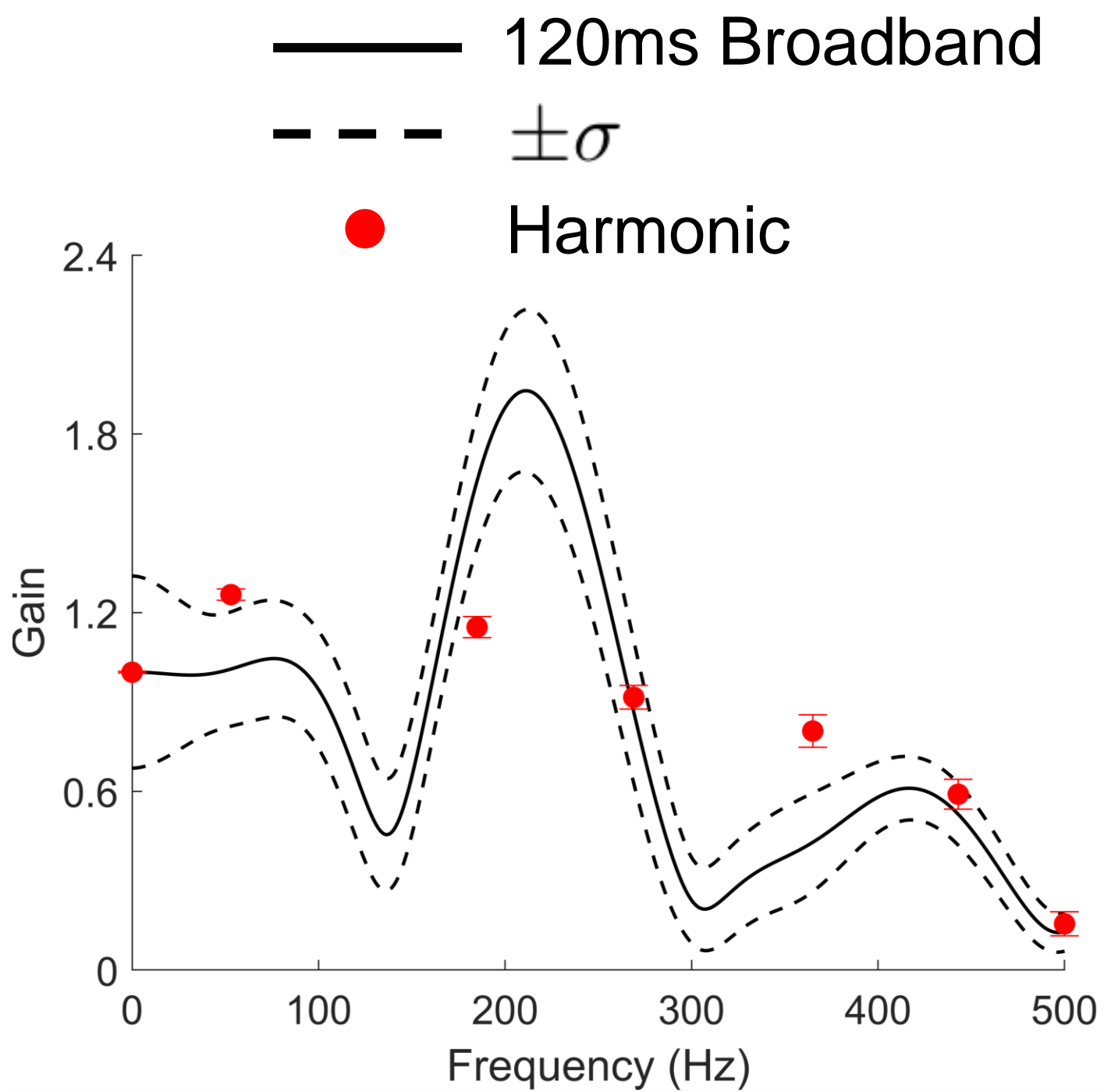
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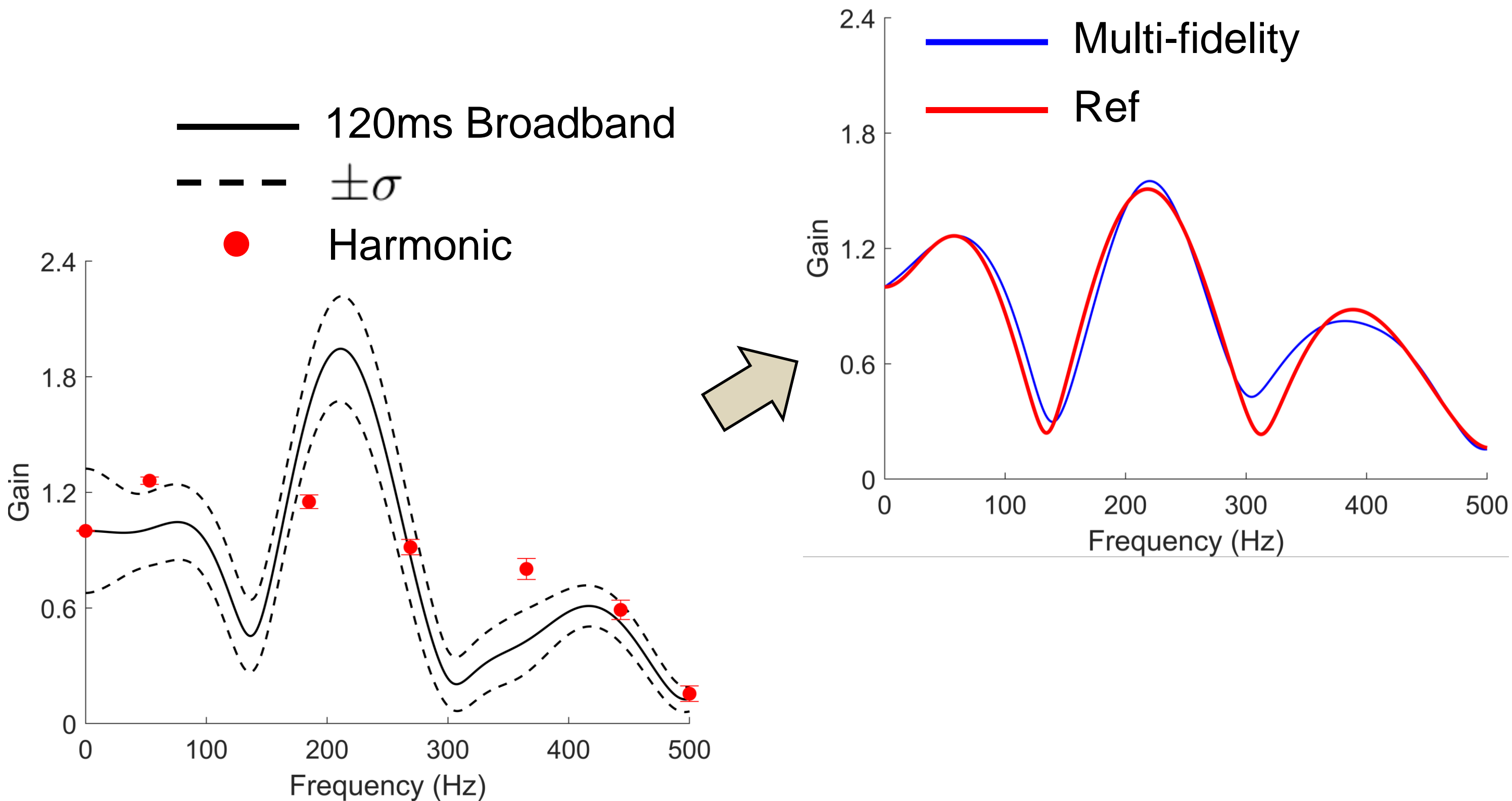
We force a combustor network model to identify flame frequency response



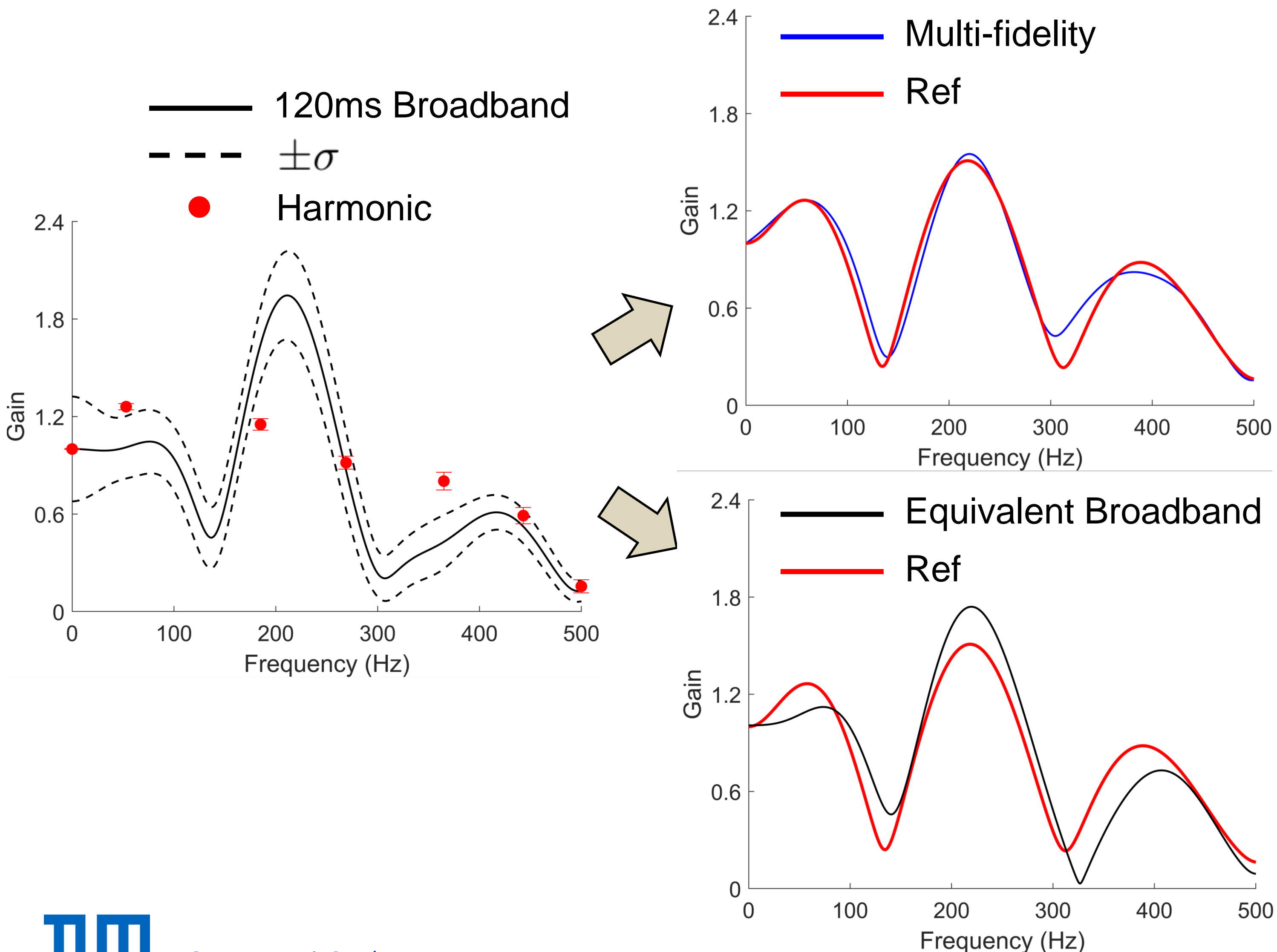
We start with a short broadband results and harmonic results at several frequencies



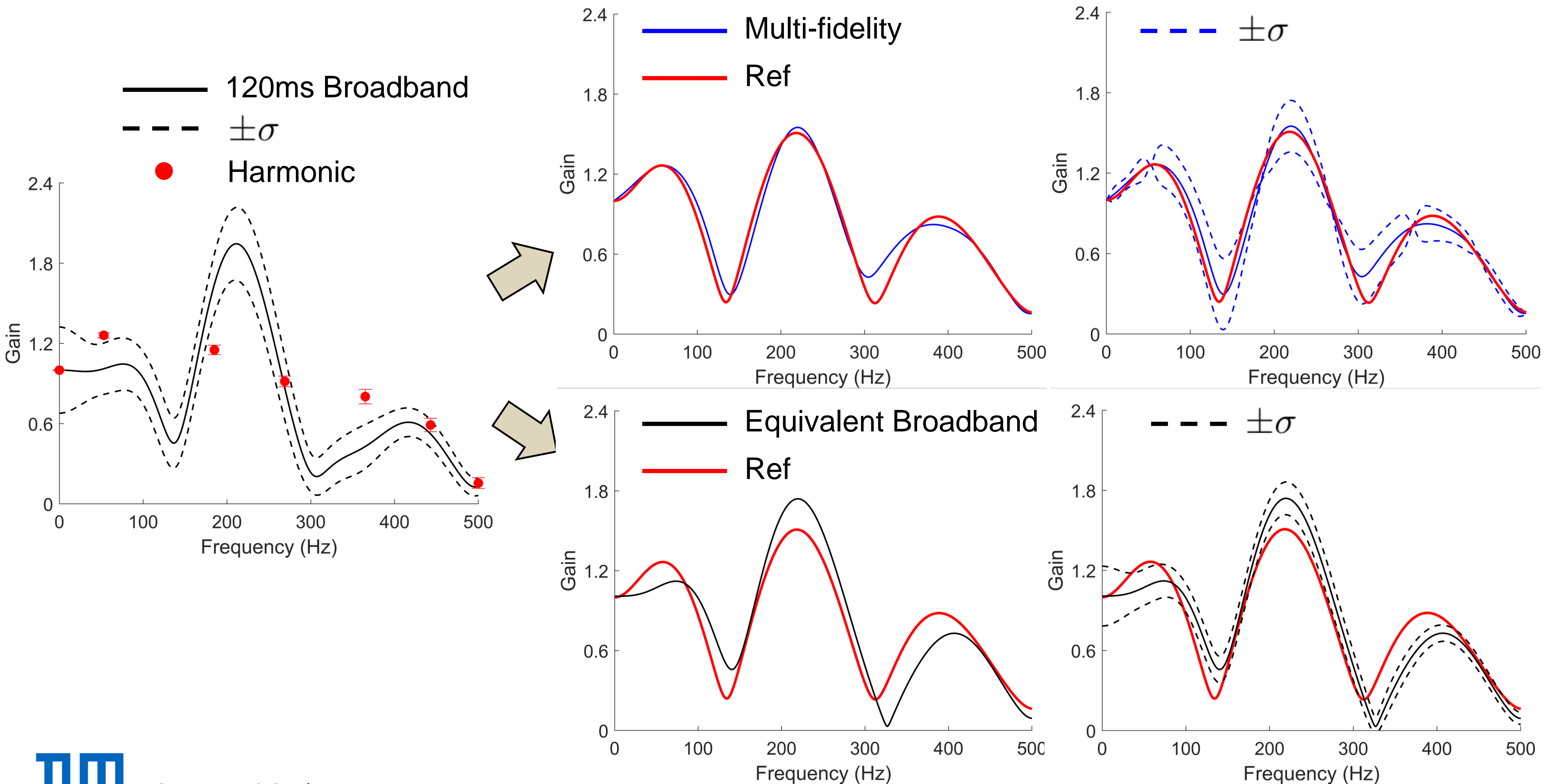
For gain, multi-fidelity approach yields a more globally accurate prediction



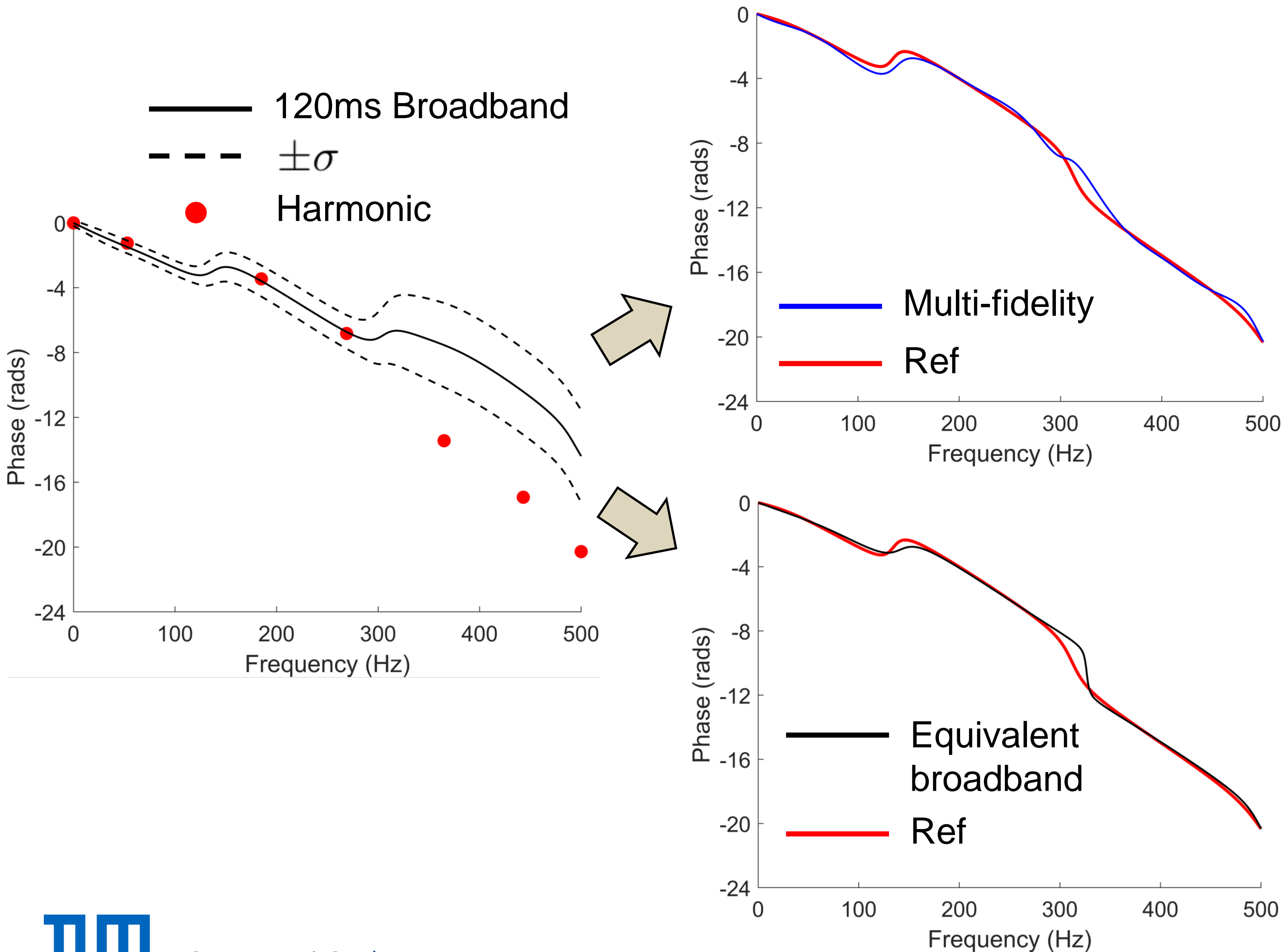
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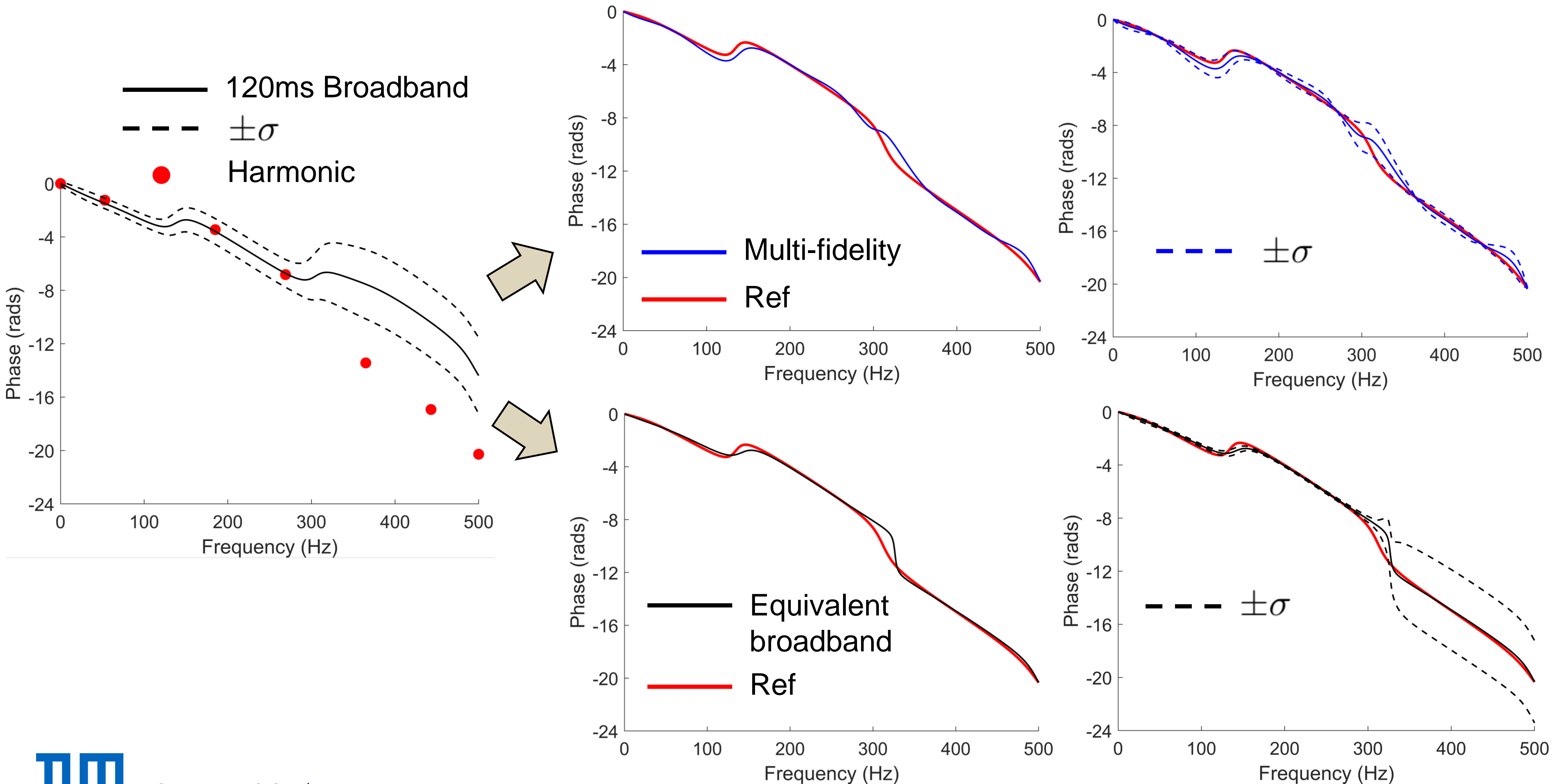
For gain, multi-fidelity approach yields more robust uncertainty estimation



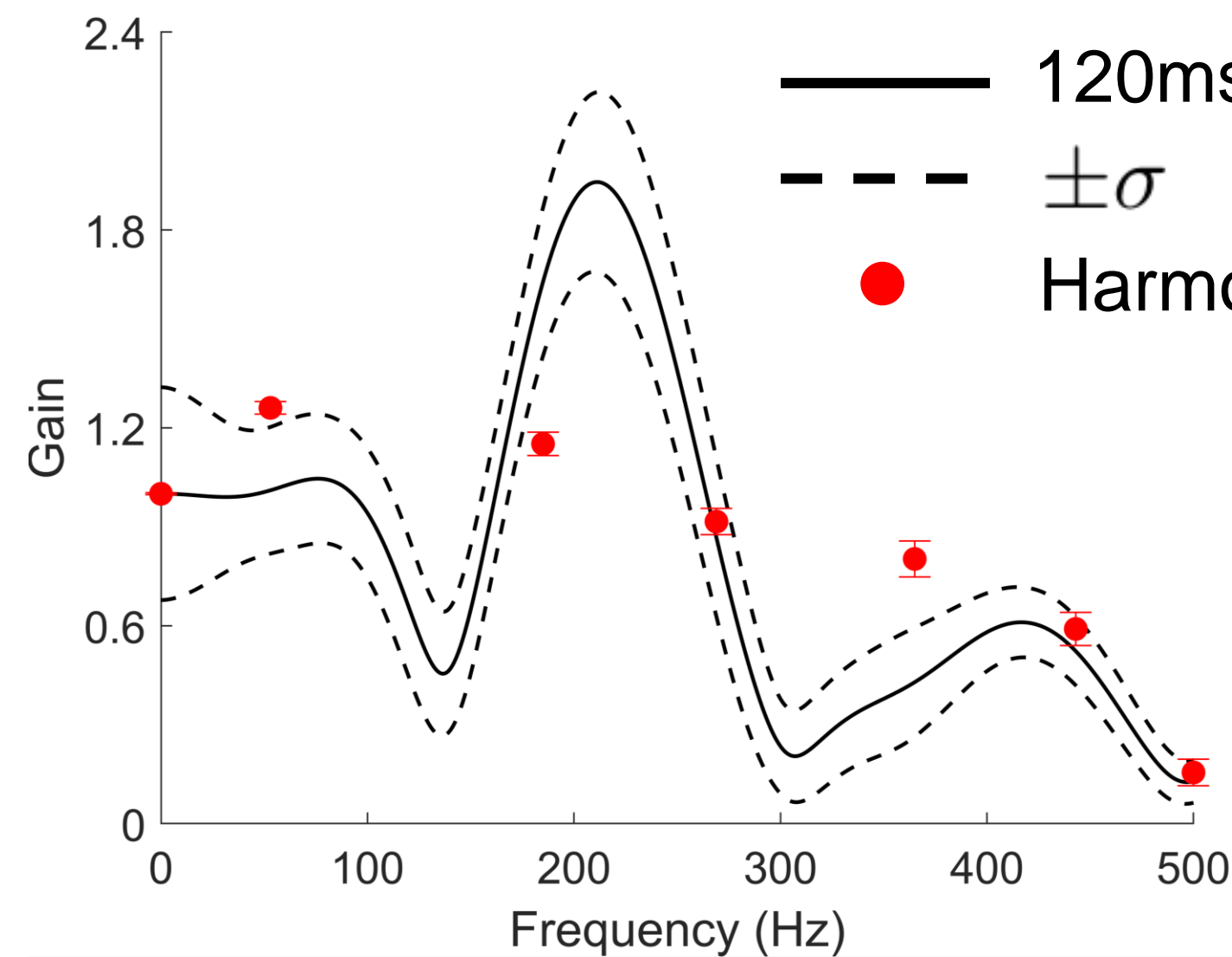
For phase, predictions made by both methods have similar accuracy



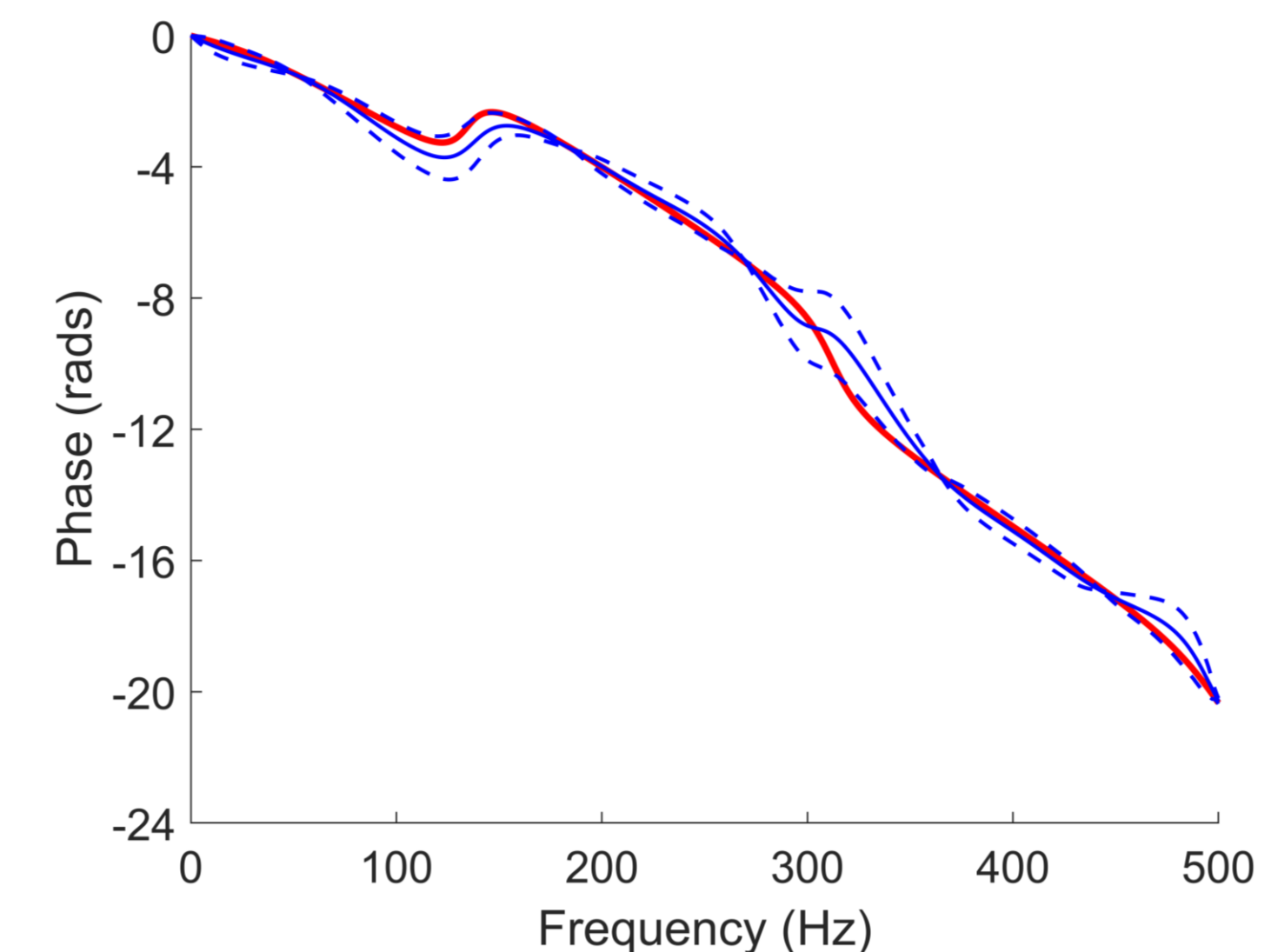
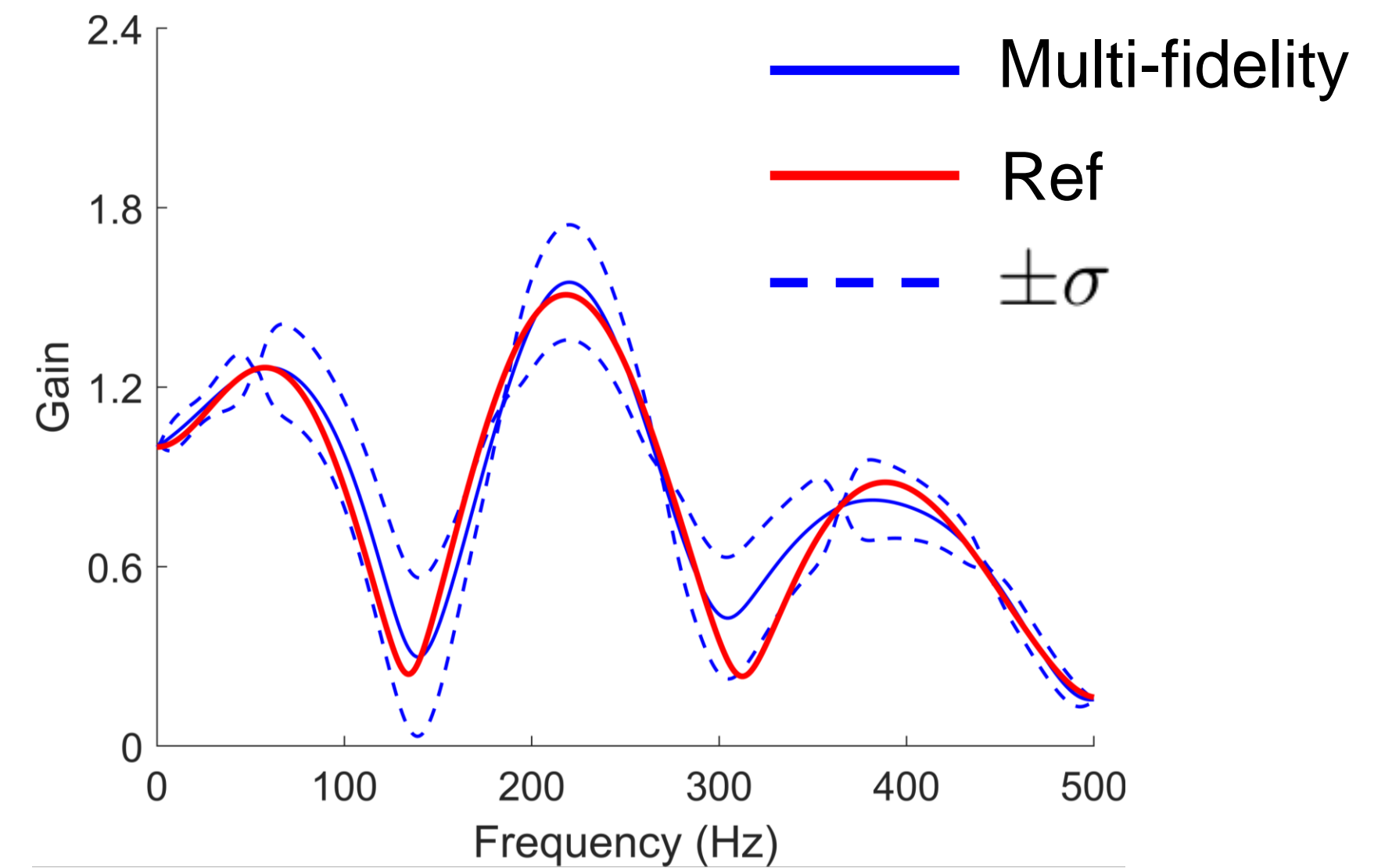
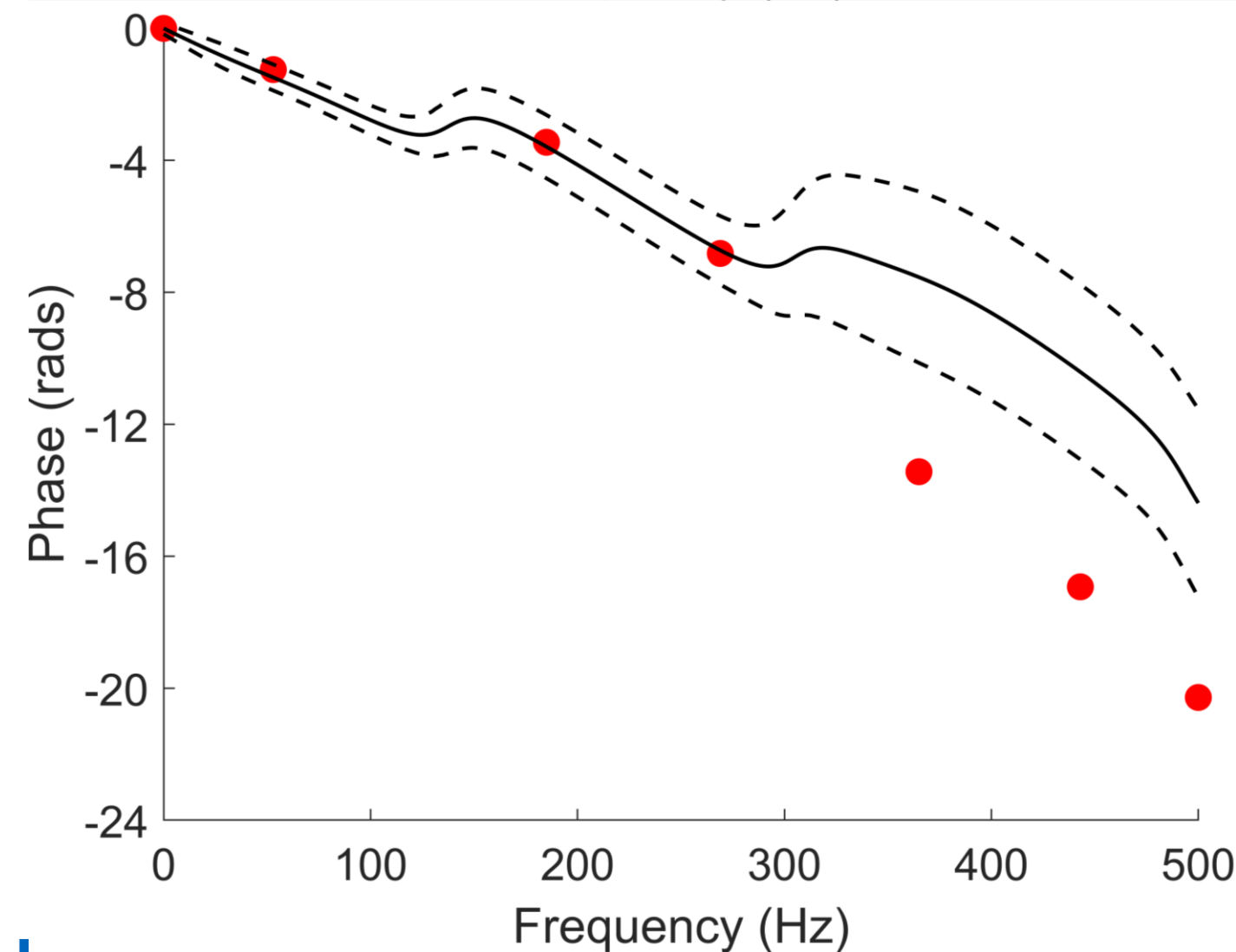
For phase, predictions made by multi-fidelity approach has less uncertainty



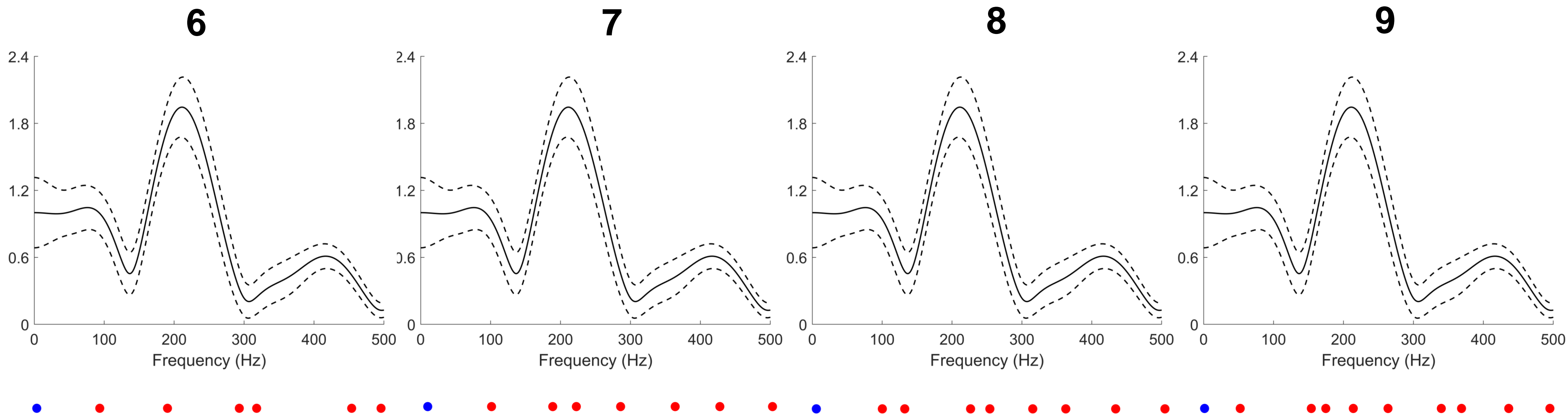
Overall, multi-fidelity approach yields globally more accurate and robust flame frequency response identification



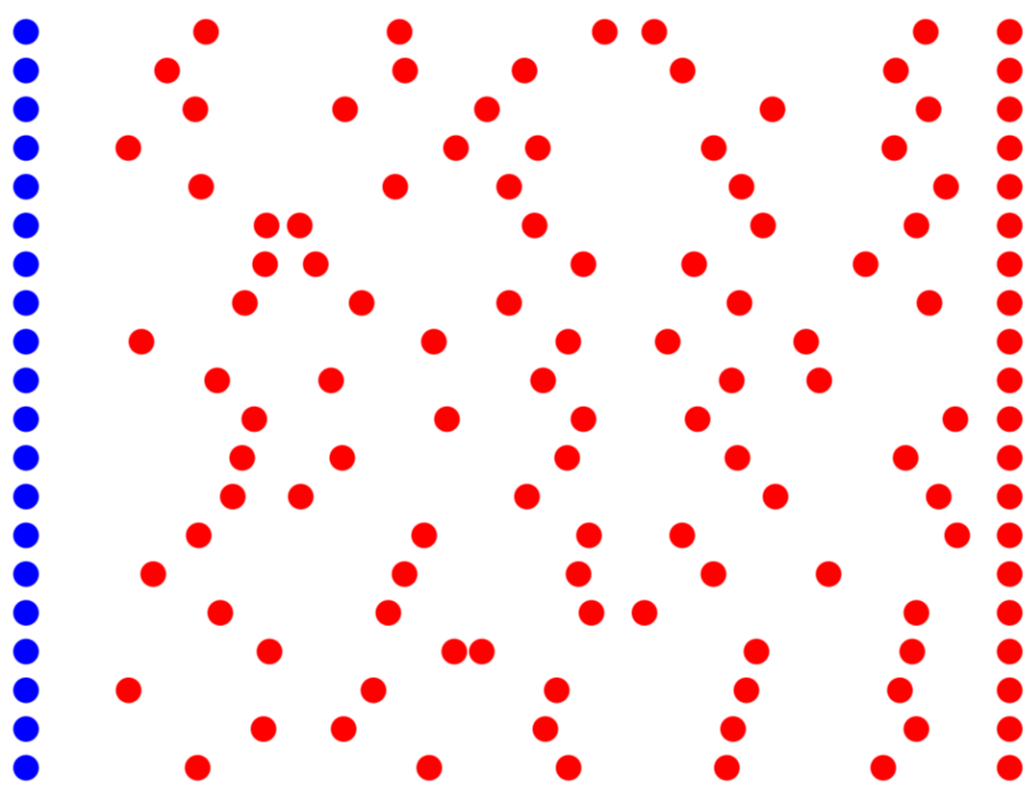
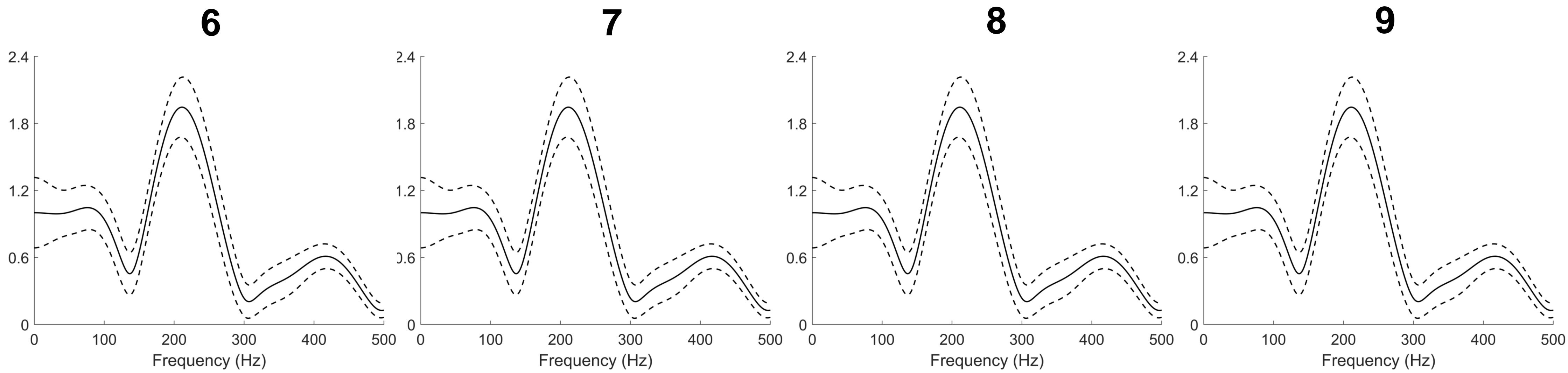
Multi-fidelity



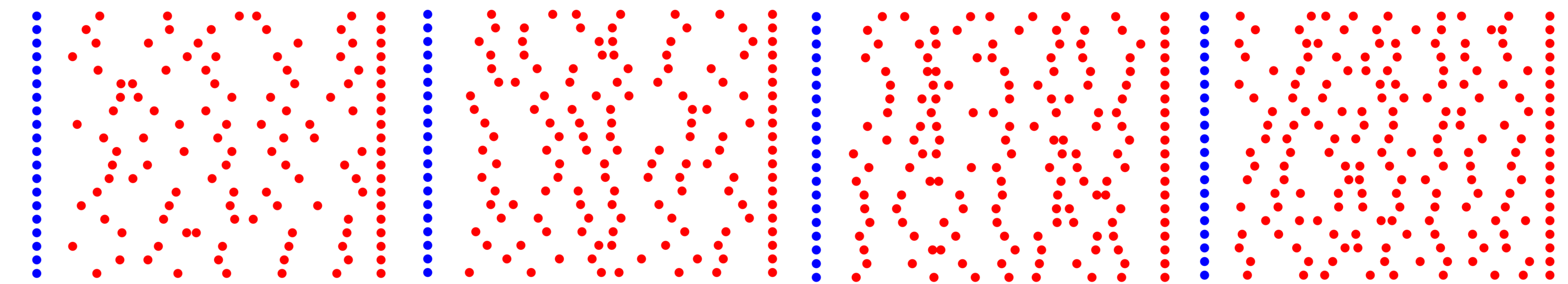
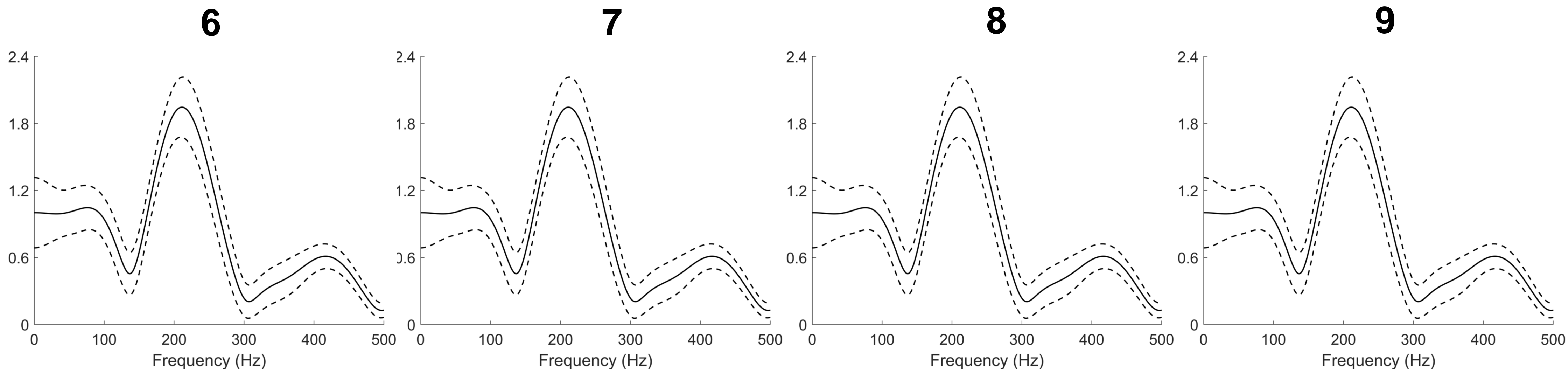
We investigated the impact of harmonic sample numbers and locations on multi-fidelity performance



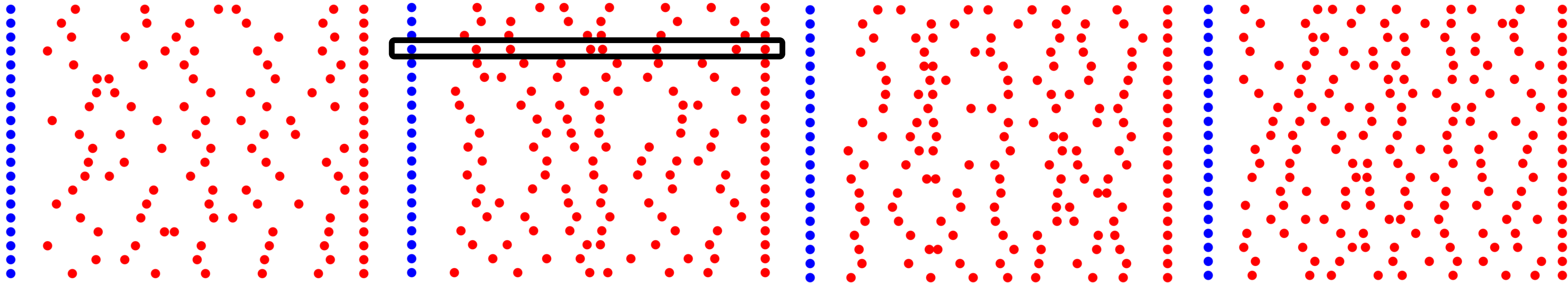
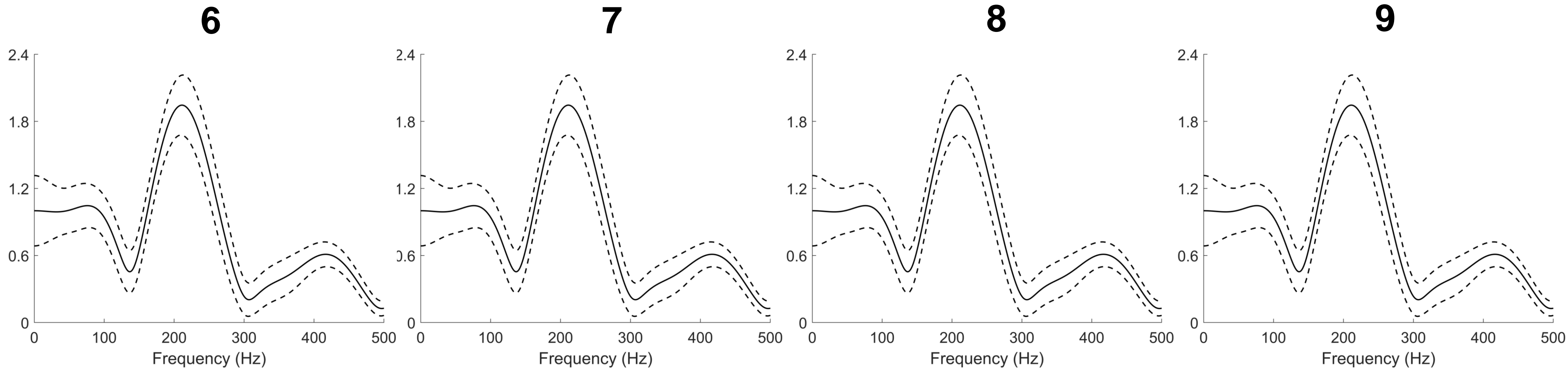
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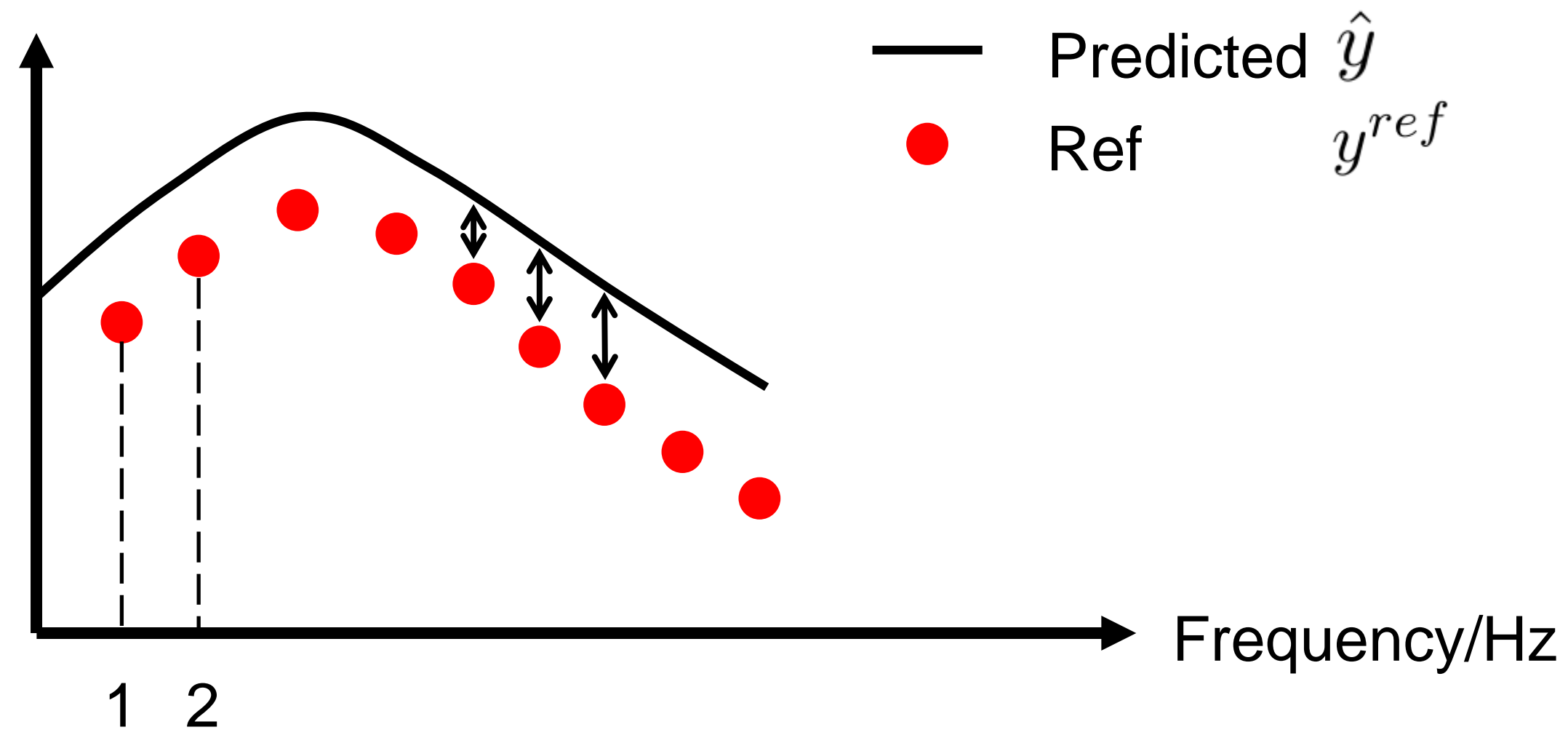
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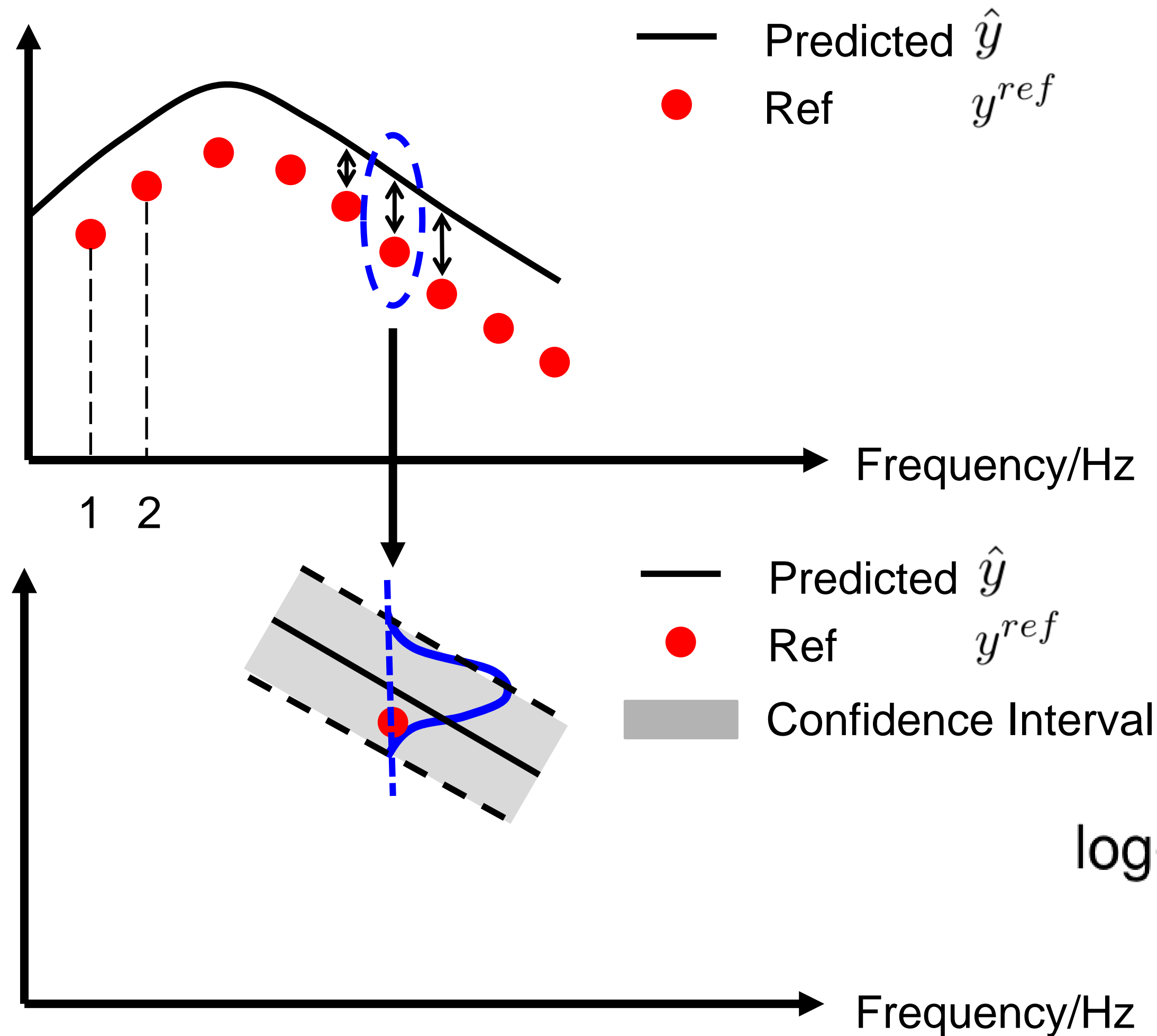


Root mean square error is used to assess the prediction accuracy



$$\text{RMSE} = \frac{\sqrt{\frac{1}{500} \sum_{i=1}^{500} (\hat{y}_i - y_i^{ref})^2}}{\text{range}(y^{ref})}$$

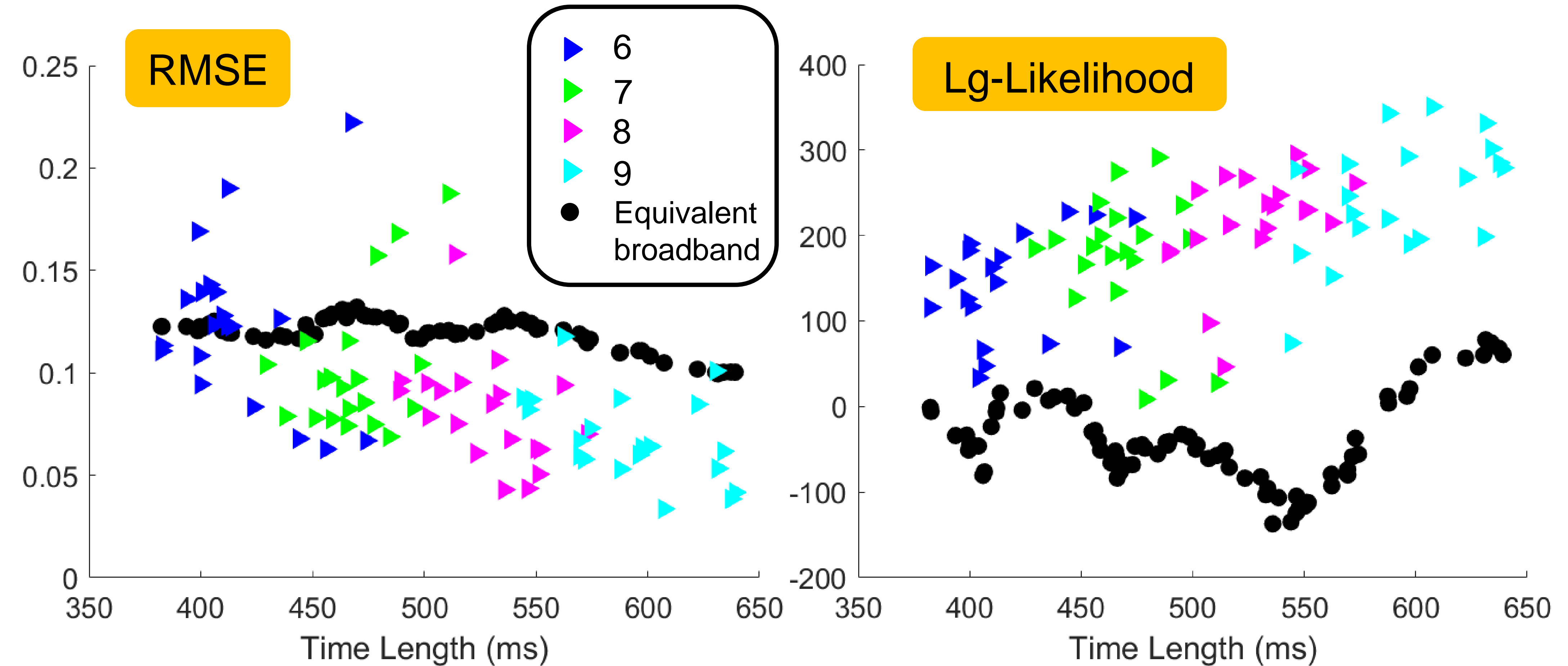
Lg-Likelihood is used to assess the prediction robustness



$$\text{RMSE} = \frac{\sqrt{\frac{1}{500} \sum_{i=1}^{500} (\hat{y}_i - y_i^{ref})^2}}{\text{range}(y^{ref})}$$

$$\text{log-likelihood} = \sum_{i=1}^{500} \log_{10} \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(\hat{y}_i - y_i^{ref})^2}{2\sigma_i^2}}$$

Number and location of harmonic excitations have direct impact on the performance of multi-fidelity approach

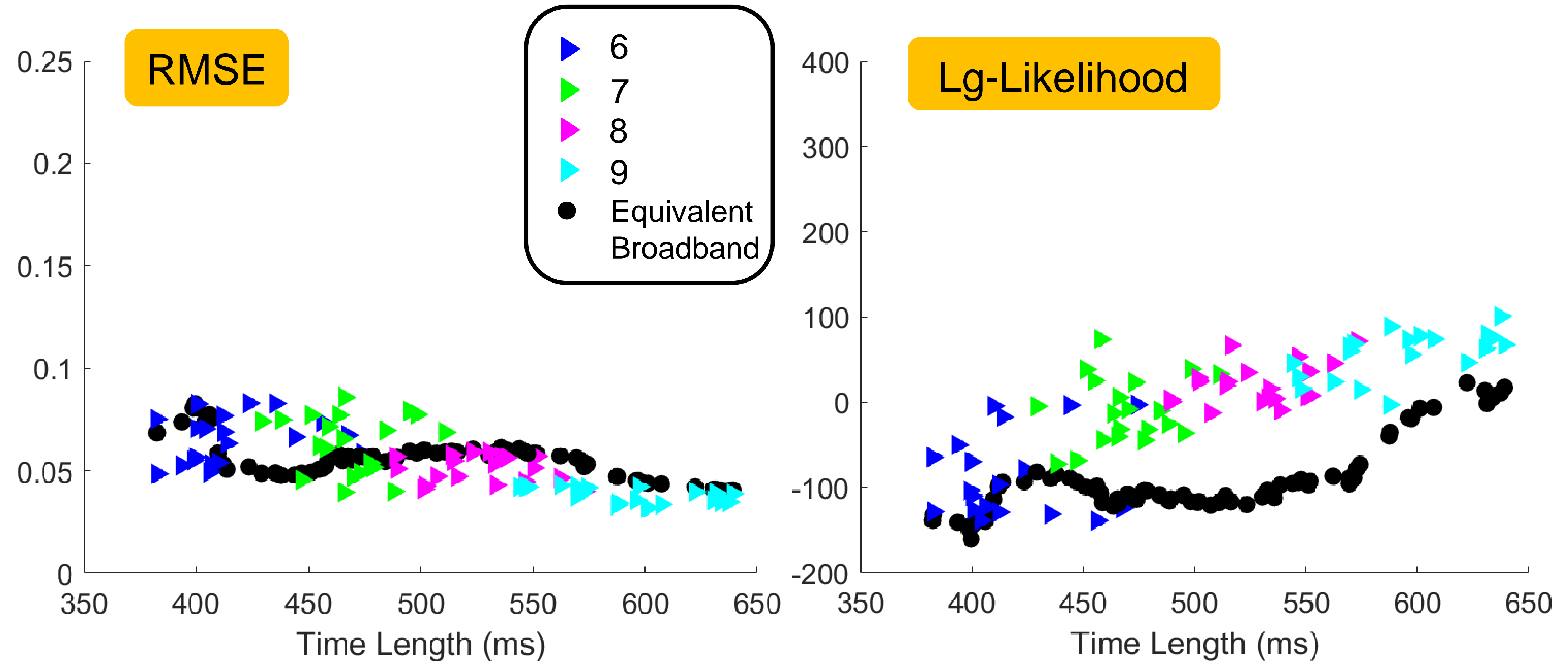


Gain

$$\text{RMSE} = \frac{\sqrt{\frac{1}{500} \sum_{i=1}^{500} (\hat{y}_i - y_i^{ref})^2}}{\text{range}(y^{ref})}$$

$$\text{Lg-Likelihood} = \sum_{i=1}^{500} \log_{10} \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(\hat{y}_i - y_i^{ref})^2}{2\sigma_i^2}}$$

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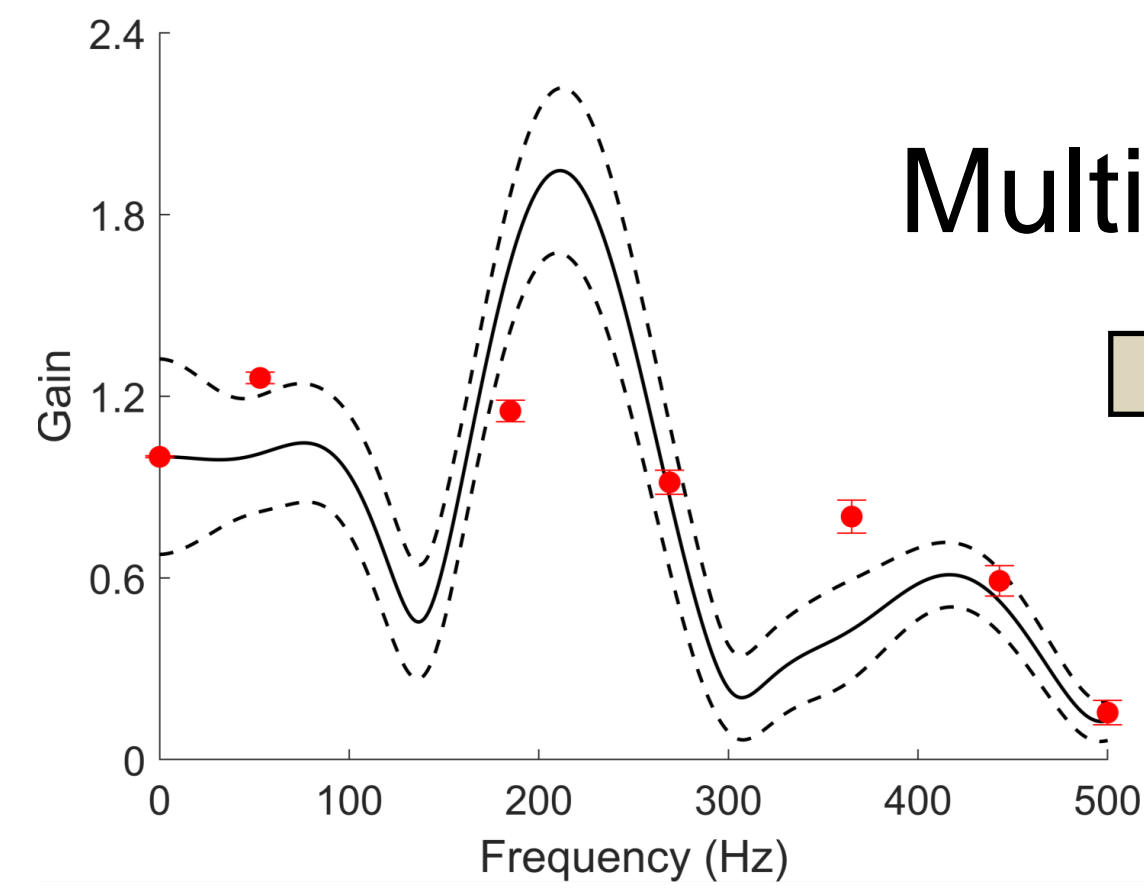
$$\text{RMSE} = \frac{\sqrt{\frac{1}{500} \sum_{i=1}^{500} (\hat{y}_i - y_i^{ref})^2}}{\text{range}(y^{ref})}$$

Phase

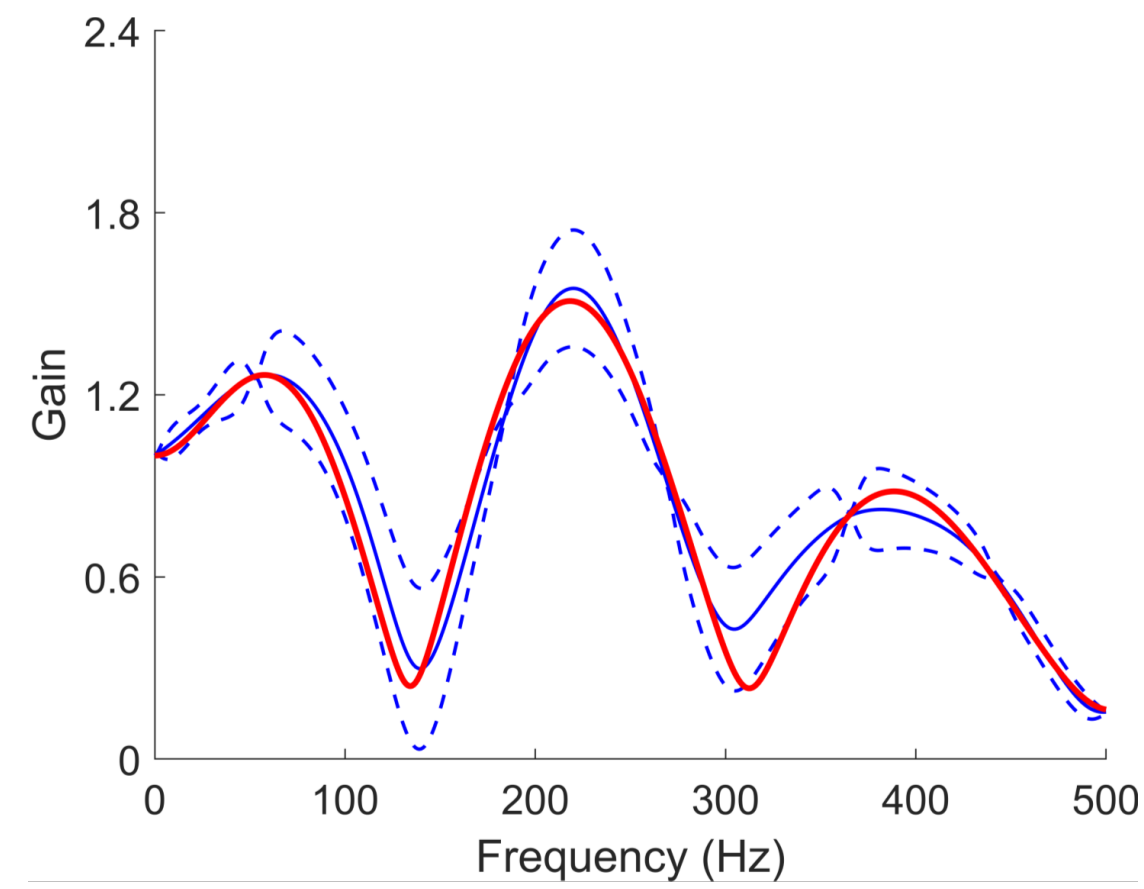
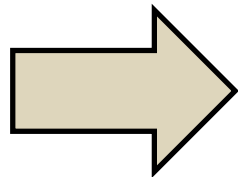
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Conclusion & Outlook

1

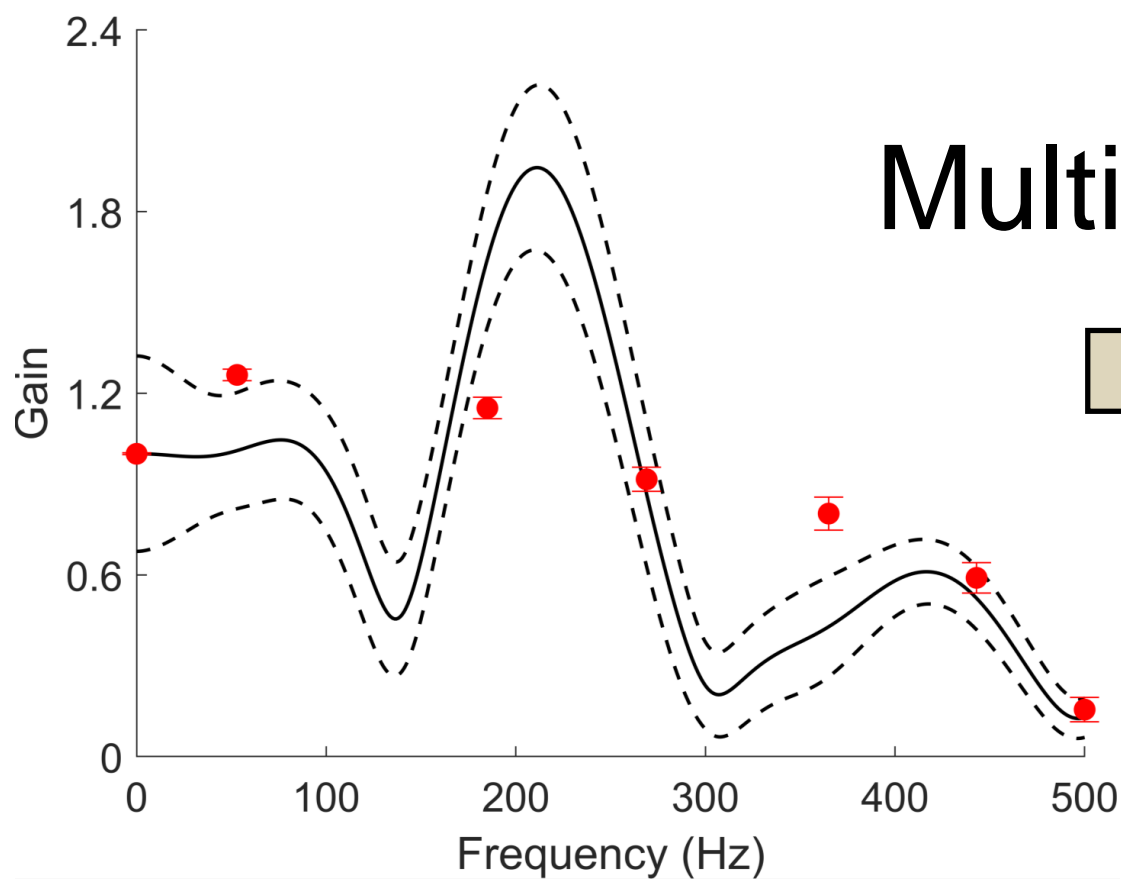


Multi-fidelity

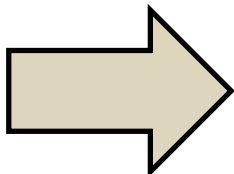


Conclusion & Outlook

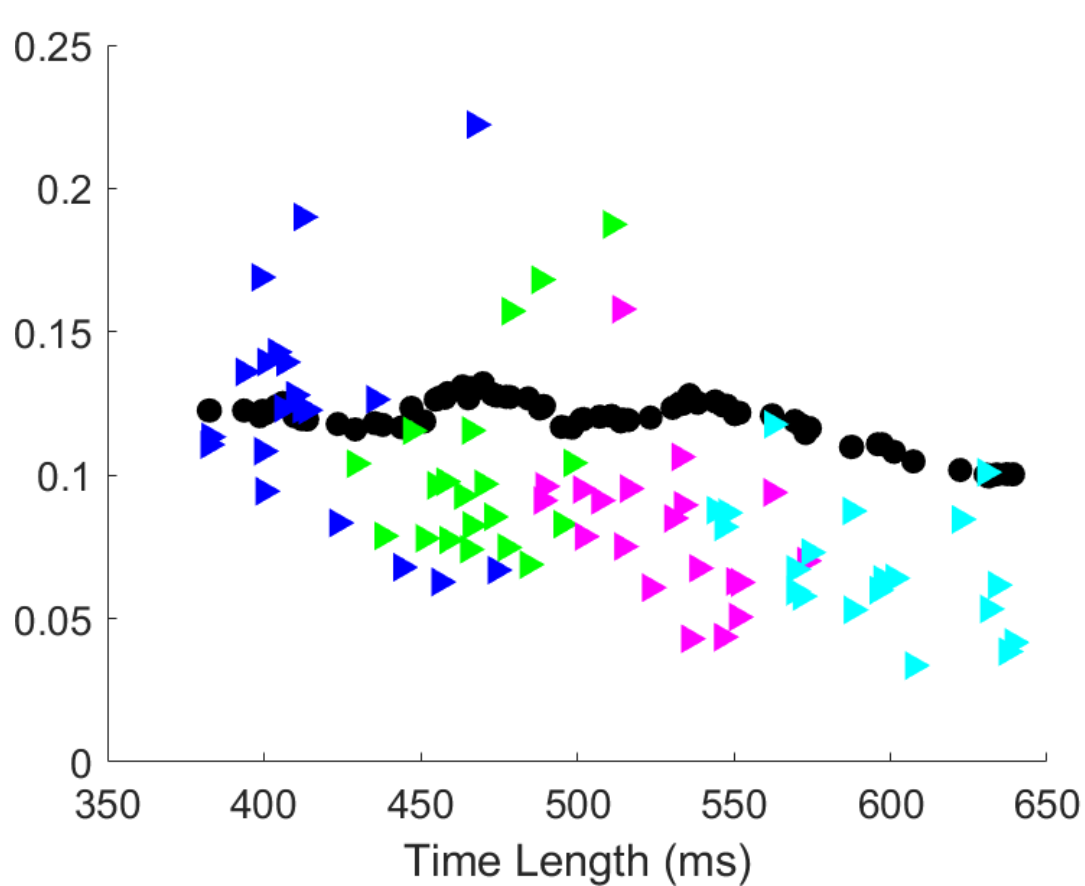
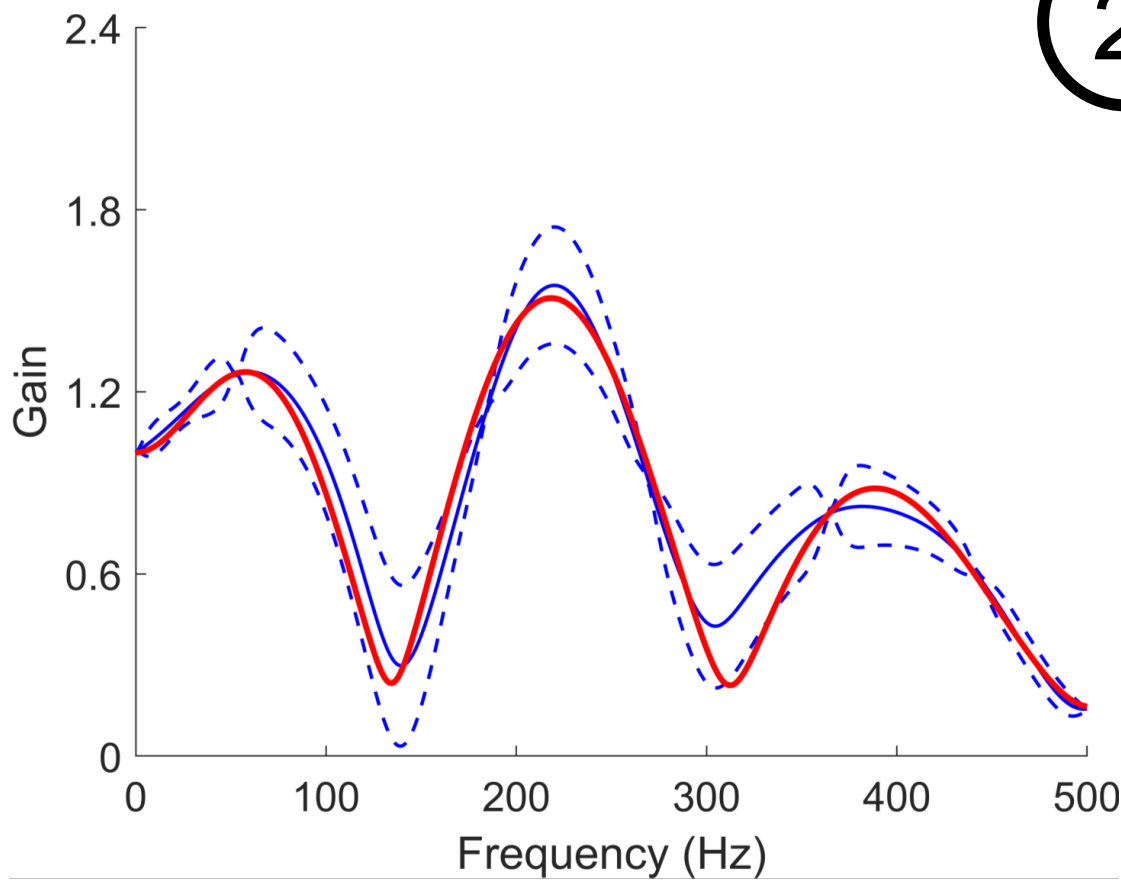
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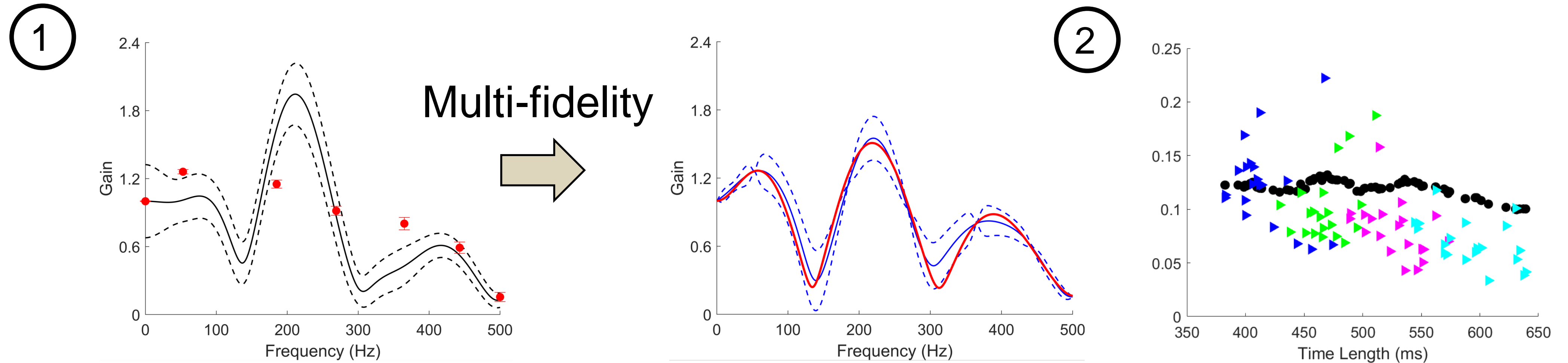
Multi-fidelity



2



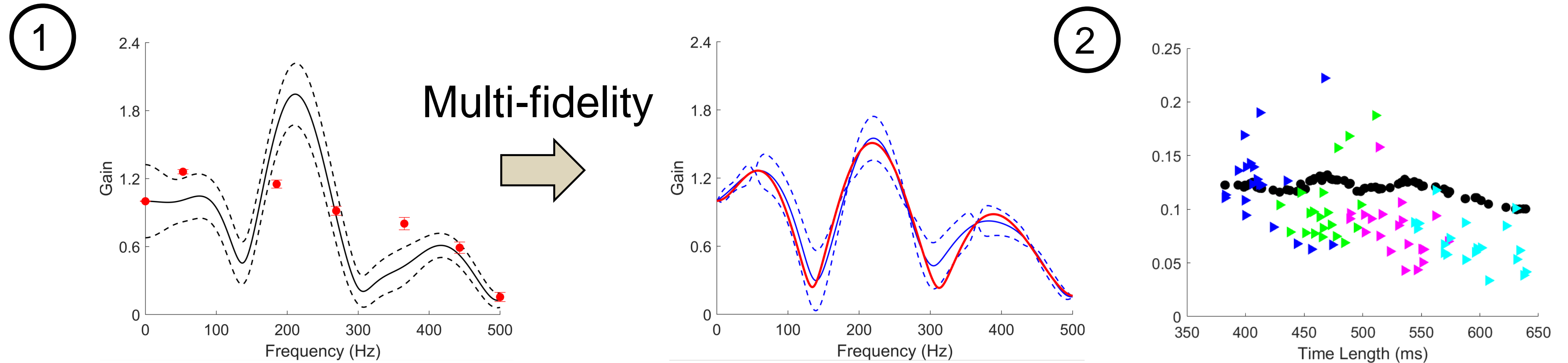
Conclusion & Outlook



In future study:

a. Impact of noise level?

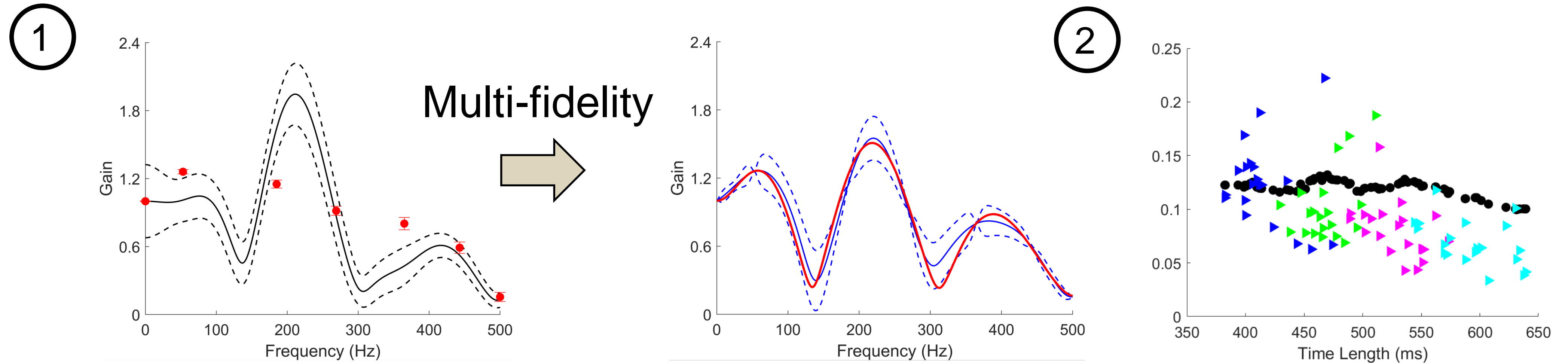
Conclusion & Outlook



In future study:

- Impact of noise level?
- Intelligent frequency selection for harmonic excitations?

Conclusion & Outlook



In future study:

- Impact of noise level?
- Intelligent frequency selection for harmonic excitations?
- Extend to identify frequency response of other dynamic systems?