

# Non-intrusive adaptive surrogate modeling of parametric frequency-response problems

DAVIDE PRADOVERA<sup>1</sup> & Fabio Nobile<sup>2</sup>

<sup>1</sup>University of Vienna [davide.pradovera@univie.ac.at | pradovera.github.io] — <sup>2</sup>EPF Lausanne

## TARGET PROBLEM

Parametric frequency-domain LTI system of size  $\gg 1$ :

$$\omega \in \mathbb{C}, \theta \in \mathbb{R}^d \rightsquigarrow \text{find } \mathbf{x}(\omega, \theta) : \omega \mathbf{E}(\theta) \mathbf{x}(\omega, \theta) = \mathbf{A}(\theta) \mathbf{x}(\omega, \theta) + \mathbf{b}(\omega, \theta)$$

Objectives:

- **Non-parametric MOR:** approximate  $\omega \mapsto \mathbf{x}(\omega, \theta)$  for a fixed  $\theta$ . This is often done with *rational functions*, i.e., ratios of polynomials.
- **Parametric MOR:** approximate  $(\omega, \theta) \mapsto \mathbf{x}(\omega, \theta)$ . This is much more complicated, since poles and residues (wrt  $\omega$ ) will depend on  $\theta$ .

## STRUCTURE OF SURROGATE MODEL

We seek an approximation in **parametric rational pole-residue format**:

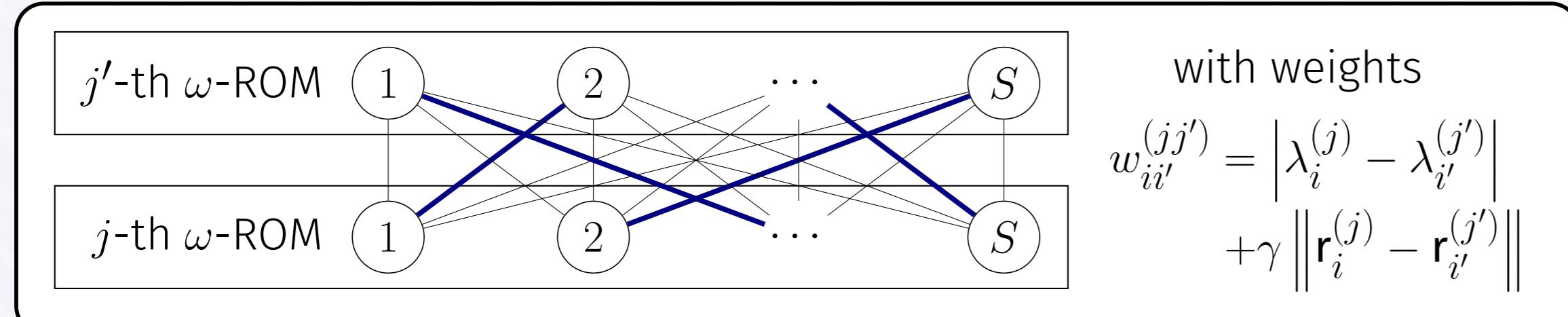
$$\mathbf{x}(\omega, \theta) \approx \sum_i \frac{\mathbf{r}_i(\theta)}{\omega - \lambda_i(\theta)} = \sum_i \frac{\sum_j \mathbf{r}_{ij} \phi_j(\theta)}{\omega - \sum_j \lambda_{ij} \phi_j(\theta)}$$

The functions  $\phi_j$  are a given scalar-valued basis, e.g., hat functions, polynomials, RBFs, ... so we only need to find the expansion coefficients  $\{\mathbf{r}_{ij}\}_{ij}$  and  $\{\lambda_{ij}\}_{ij}$ . To this aim, we first gather **data: univariate  $\omega$ -ROMs in pole-residue form**

$$\text{given } \{\theta_j\}_j \subset \mathbb{R}^d, \text{ build ROMs } \left\{ \tilde{\mathbf{x}}_j(\omega) = \sum_i \frac{\mathbf{r}_i^{(j)}}{\omega - \lambda_i^{(j)}} \approx \mathbf{x}(\omega, \theta_j) \right\}_j$$

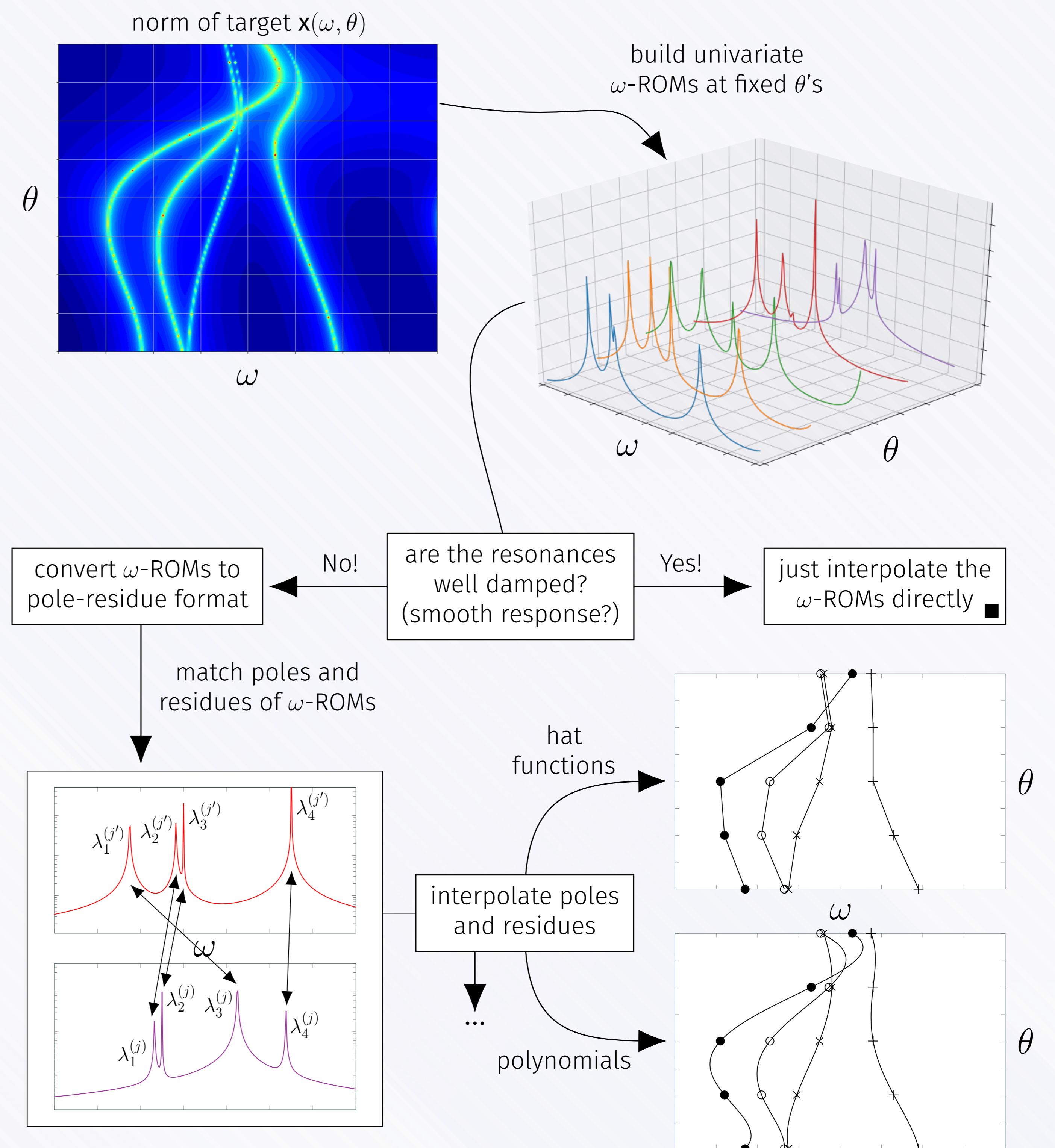
## MATCHING STRATEGY

Before we can use  $\{\lambda_i^{(j)}\}_{ij}$  to find  $\{\lambda_{ij}\}_{ij}$  (and the same for the  $\mathbf{r}$ 's) we need to match the poles for different  $j$ 's, otherwise we might be combining information pertaining to different resonating modes! For this, we look for *optimal permutations* of the terms in the pole-residue expansions: we build a weighted graph



and we find a “matching” set of edges that minimizes the total sum of weights.

## SAMPLE WORKFLOW



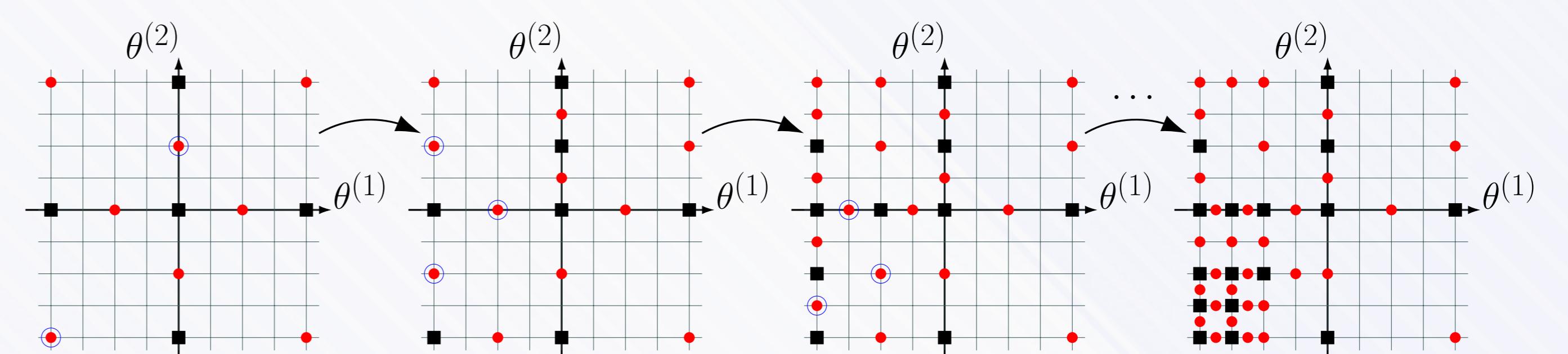
## NON-INTRUSIVE ADAPTIVE SAMPLING VIA LOCALLY ADAPTED SPARSE GRIDS

Sparse grids allow for structured localized refinements in arbitrary  $\theta$ -dimension  $d$ : given a set of SG points, we can define a discrete hierarchical SG neighborhood.

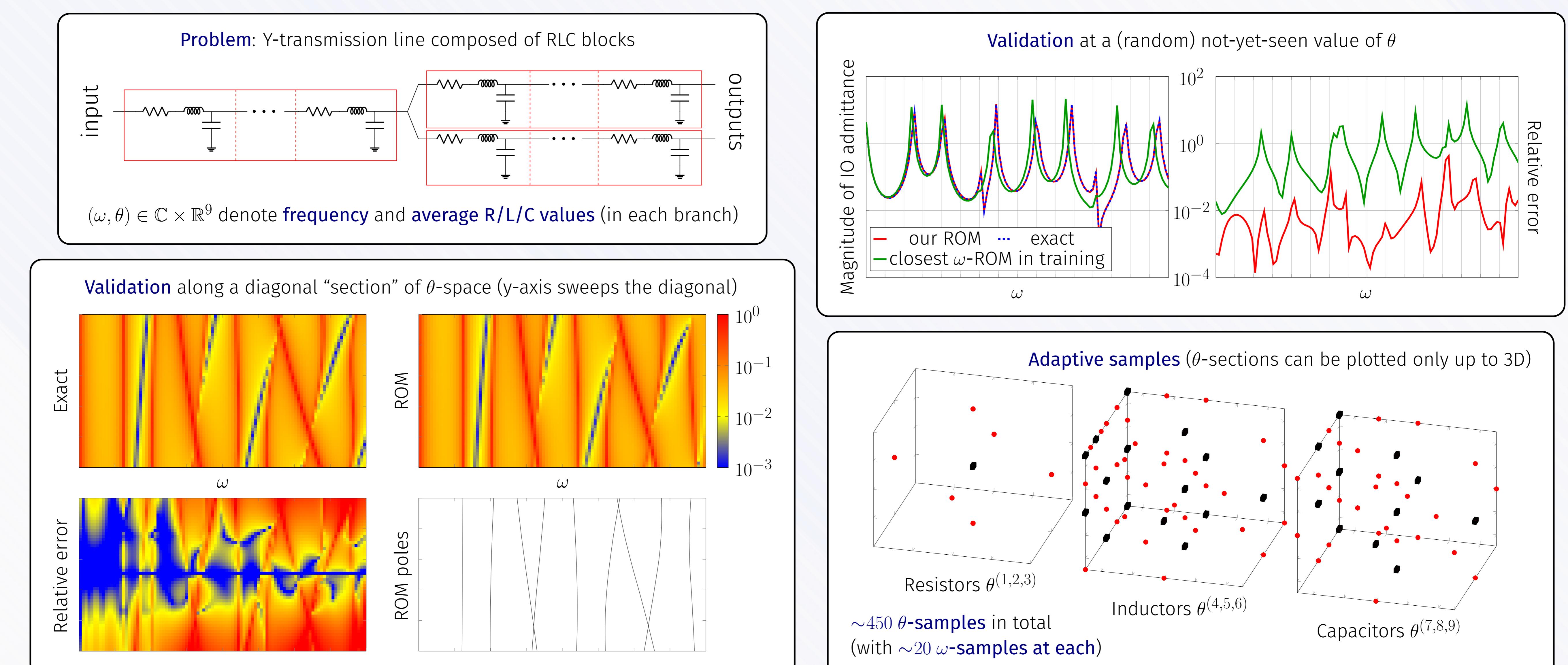
We can use this for non-intrusive adaptive sampling over  $\theta$ :

- We use a collection of SG points (**not necessarily an SG in the usual sense**) as training set. These are the black squares.
- We use their discrete neighborhood as test set. These are the red dots. **If a point of the test set is badly approximated, we move it to the training set** (blue circles).

This requires expensive computations at all points of the training and test sets.



## NUMERICAL RESULTS: IMPEDANCE OF PARAMETRIC TRANSMISSION LINE



## REFERENCES

- DP, “Interpolatory minimal rational model order reduction of parametric problems lacking uniform inf-sup stability”, SIAM J. Numer. Anal. 58, 2020.
- F. Nobile & DP, “Non-intrusive double-greedy parametric model reduction by interpolation of frequency-domain rational surrogates”, ESAIM:M2AN 55, 2021. ⇒
- DP, “Model order reduction based on functional rational approximants for parametric PDEs with meromorphic structure”, PhD thesis, 2021.
- DP & F. Nobile, “Frequency-domain non-intrusive greedy Model Order Reduction based on minimal rational approximation”, Sci. Comput. Electr. Eng. 36, 2021.
- F. Bonizzoni & DP, “Shape optimization for a noise reduction problem by non-intrusive parametric reduced modeling”, Proc. WCCM-ECCOMAS2020, 2021.

