

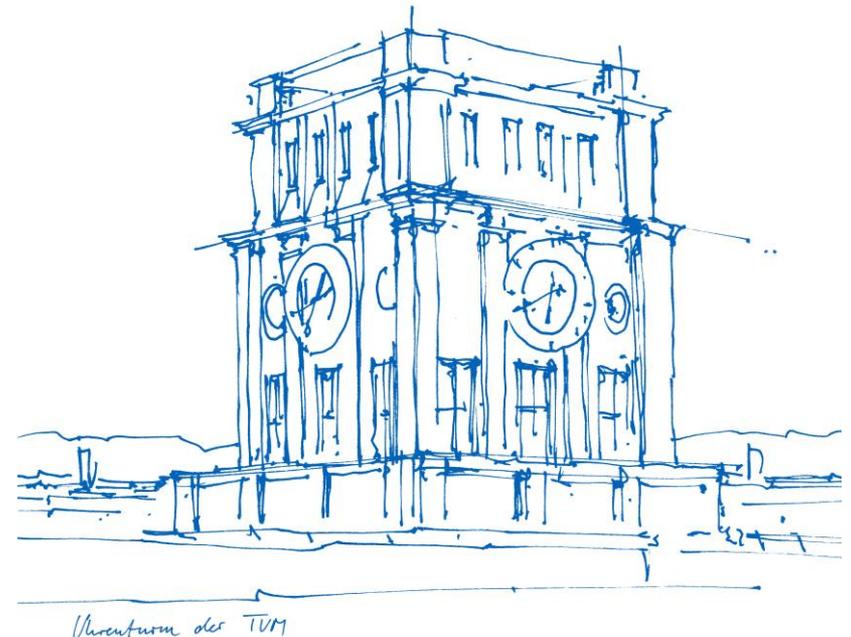
Automatic Adaptive Sampling in Parametric Model Order Reduction by Matrix Interpolation

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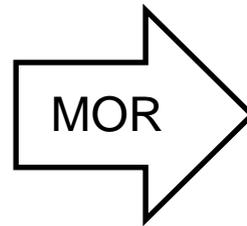
July 4th, AIM 2017



Motivation

Large-scale full order model (FOM)

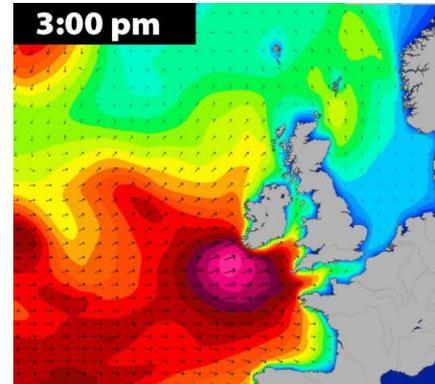
$$\begin{aligned} \mathbf{E} \dot{\mathbf{x}} &= \mathbf{A} \mathbf{x} + \mathbf{B} \mathbf{u} \\ \mathbf{y} &= \mathbf{C} \mathbf{x} \end{aligned} \quad \det(\mathbf{E}) \neq 0$$



Reduced order model (ROM)

$$\begin{aligned} \mathbf{E}_r \dot{\mathbf{x}}_r &= \mathbf{A}_r \mathbf{x}_r + \mathbf{B}_r \mathbf{u} \\ \mathbf{y}_r &= \mathbf{C}_r \mathbf{x}_r \end{aligned}$$

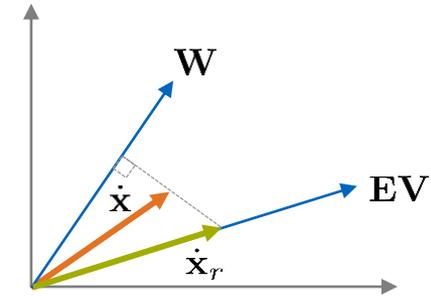
$$\mathbf{x}_r \in \mathbb{R}^r, \quad r \ll n$$



Projective Model Order Reduction

Approximation of the state vector:

$$\mathbf{x} = \mathbf{V} \mathbf{x}_r + \mathbf{e}, \quad \mathbf{V} \in \mathbb{R}^{n \times r}$$



Petrov-Galerkin projection:

$$\overbrace{\mathbf{W}^T \mathbf{E} \mathbf{V}}^{\mathbf{E}_r} \dot{\mathbf{x}}_r = \overbrace{\mathbf{W}^T \mathbf{A} \mathbf{V}}^{\mathbf{A}_r} \mathbf{x}_r + \overbrace{\mathbf{W}^T \mathbf{B}}^{\mathbf{B}_r} \mathbf{u}$$

$$\mathbf{y} \approx \mathbf{y}_r = \underbrace{\mathbf{C} \mathbf{V}}_{\mathbf{C}_r} \mathbf{x}_r$$

Rational Interpolation by Krylov subspace methods

Moments of a transfer function

$$\begin{aligned} \mathbf{G}(s) &= \mathbf{C}(s\mathbf{E} - \mathbf{A})^{-1}\mathbf{B} \\ &= \mathbf{G}(\Delta s + s_0) = - \sum_{i=0}^{\infty} \mathbf{M}_i(s_0)(s - s_0)^i \end{aligned}$$

$\mathbf{M}_i(s_0)$: i -th moment around s_0

Krylov subspace:

$$\mathcal{K}_r(\mathbf{M}, \mathbf{v}) = [\mathbf{v}, \mathbf{M}\mathbf{v}, \mathbf{M}^2\mathbf{v}, \dots, \mathbf{M}^{r-1}\mathbf{v}]$$

Moment Matching by Rational Krylov (RK) subspaces

Bases for input and output Krylov-subspaces:

$$\text{Im}(\mathbf{V}) = [\mathbf{A}_{s_0}^{-1}\mathbf{B}, \quad \mathbf{A}_{s_0}^{-1}\mathbf{E}\mathbf{A}_{s_0}^{-1}\mathbf{B}, \quad \dots, \quad (\mathbf{A}_{s_0}^{-1}\mathbf{E})^{r-1}\mathbf{A}_{s_0}^{-1}\mathbf{B}]$$

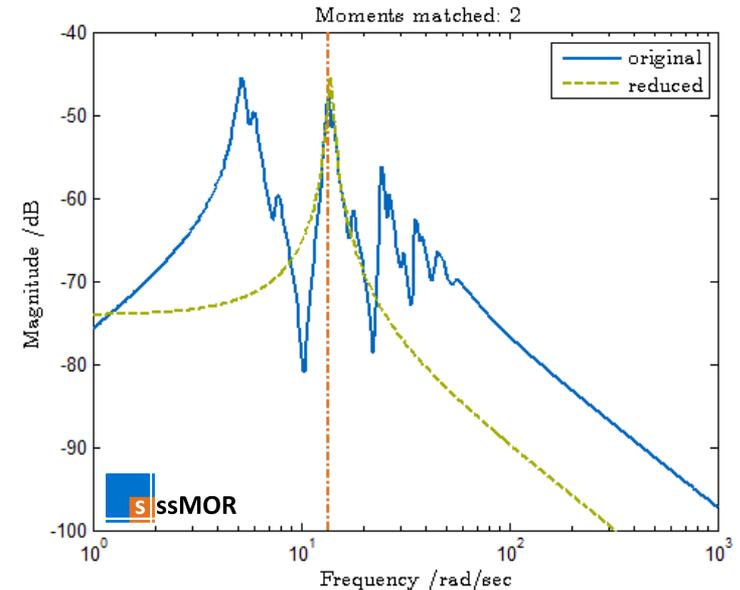
$$\text{Im}(\mathbf{W}) = [\mathbf{A}_{s_0}^{-T}\mathbf{C}^T, \quad \mathbf{A}_{s_0}^{-T}\mathbf{E}^T\mathbf{A}_{s_0}^{-T}\mathbf{C}^T, \quad \dots, \quad (\mathbf{A}_{s_0}^{-T}\mathbf{E}^T)^{r-1}\mathbf{A}_{s_0}^{-T}\mathbf{C}^T]$$



$$\mathbf{M}_i(s_0) = \mathbf{M}_{r,i}(s_0)$$

for $i = 0, \dots, 2r$

Moments from full and reduced order model around certain **shifts match!**



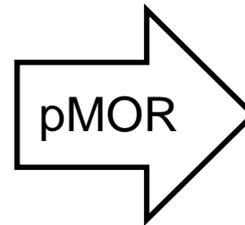
Parametric Model Order Reduction (pMOR)

Large-scale parametric model

$$\mathbf{E}(\mathbf{p}) \dot{\mathbf{x}} = \mathbf{A}(\mathbf{p}) \mathbf{x} + \mathbf{B}(\mathbf{p}) \mathbf{u}$$

$$\mathbf{y} = \mathbf{C}(\mathbf{p}) \mathbf{x}$$

$$\mathbf{p} \in \mathcal{D} \subset \mathbb{R}^d$$



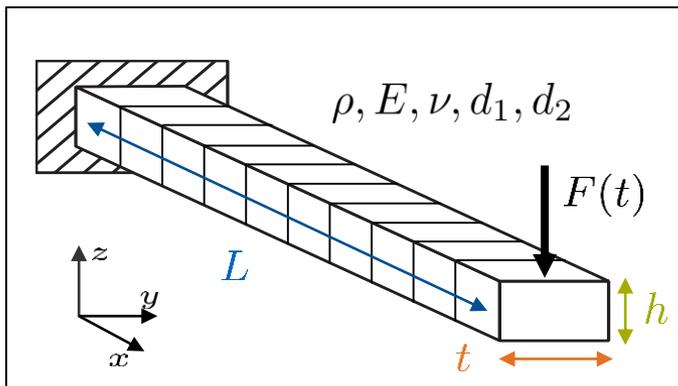
Reduced order parametric model

$$\mathbf{E}_r(\mathbf{p}) \dot{\mathbf{x}}_r = \mathbf{A}_r(\mathbf{p}) \mathbf{x}_r + \mathbf{B}_r(\mathbf{p}) \mathbf{u}$$

$$\mathbf{y}_r = \mathbf{C}_r(\mathbf{p}) \mathbf{x}_r$$

$$\mathbf{x}_r \in \mathbb{R}^r, r \ll n$$

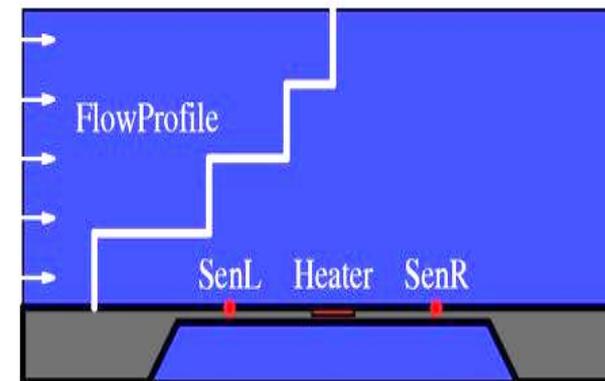
- Linear dynamic systems with **design parameters** (e.g. material / geometry parameters,...)
- **Goal:** numerically efficient reduction with **preservation of the parameter dependency**



Timoshenko beam

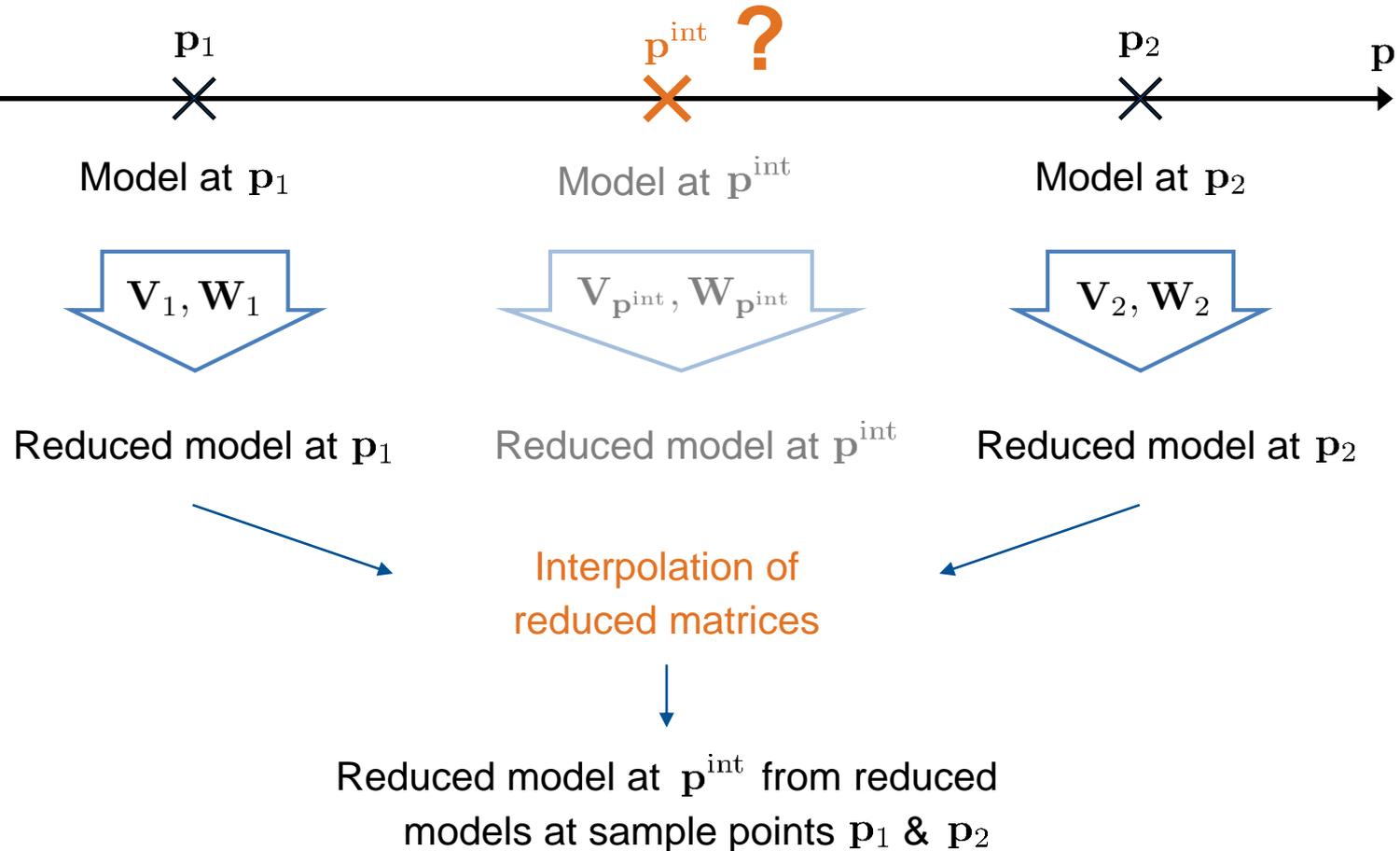


Solar panels



Flow sensing anemometer

pMOR by Matrix Interpolation – Main Idea



pMOR by Matrix Interpolation – Procedure

[Panzer et al. '10]

1.) Individual reduction

$$\begin{aligned} \mathbf{E}_{r,i} \dot{\mathbf{x}}_{r,i}(t) &= \mathbf{A}_{r,i} \mathbf{x}_{r,i}(t) + \mathbf{B}_{r,i} \mathbf{u}(t) & \mathbf{E}_{r,i} &= \mathbf{W}_i^T \mathbf{E}_i \mathbf{V}_i, & \mathbf{A}_{r,i} &= \mathbf{W}_i^T \mathbf{A}_i \mathbf{V}_i \\ \mathbf{y}_{r,i}(t) &= \mathbf{C}_{r,i} \mathbf{x}_{r,i}(t) & \mathbf{B}_{r,i} &= \mathbf{W}_i^T \mathbf{B}_i, & \mathbf{C}_{r,i} &= \mathbf{C}_i \mathbf{V}_i \end{aligned}$$

$$\begin{aligned} \mathbf{p}_i, \quad i &= 1, \dots, K \\ \mathbf{V}_i &:= \mathbf{V}(\mathbf{p}_i) \\ \mathbf{W}_i &:= \mathbf{W}(\mathbf{p}_i) \end{aligned}$$

2.) Transformation to generalized coordinates

$$\begin{aligned} \underbrace{\mathbf{E}_{r,i}^*}_{\mathbf{M}_i^T \mathbf{E}_{r,i} \mathbf{T}_i} \dot{\mathbf{x}}_{r,i}^*(t) &= \underbrace{\mathbf{A}_{r,i}^*}_{\mathbf{M}_i^T \mathbf{A}_{r,i} \mathbf{T}_i} \mathbf{x}_{r,i}^*(t) + \underbrace{\mathbf{B}_{r,i}^*}_{\mathbf{M}_i^T \mathbf{B}_{r,i}} \mathbf{u}(t) \\ \mathbf{y}_{r,i}(t) &= \underbrace{\mathbf{C}_{r,i} \mathbf{T}_i}_{\mathbf{C}_{r,i}^*} \mathbf{x}_{r,i}^*(t) \end{aligned}$$

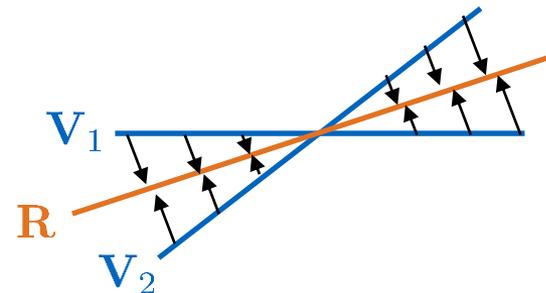
$$\begin{aligned} \mathbf{T}_i &= (\mathbf{R}^T \mathbf{V}_i)^{-1} \\ \mathbf{M}_i &= (\mathbf{R}^T \mathbf{W}_i)^{-1} \end{aligned}$$

$$\mathbf{x}_{r,i} = \mathbf{T}_i \mathbf{x}_{r,i}^*$$

$$\begin{aligned} \mathbf{V}_{\text{all}} &= [\mathbf{V}_1, \dots, \mathbf{V}_K] \\ \mathbf{V}_{\text{all}} &\stackrel{\text{SVD}}{=} \mathbf{U} \mathbf{\Sigma} \mathbf{N}^T \\ \mathbf{R} &= \mathbf{U}(:, 1:r) \end{aligned}$$

How to choose \mathbf{T}_i and \mathbf{M}_i ?

Goal: Adjustment of the local bases \mathbf{V}_i to $\mathbf{V}_i^* = \mathbf{V}_i \mathbf{T}_i$, in order to make the gen. coordinates $\mathbf{x}_{r,i}^*$ compatible w.r.t. a reference subspace \mathbf{R} .



$$\begin{aligned} &\text{High correlation} \\ \mathbf{V}_i^* &\longleftrightarrow \mathbf{R}: \\ \mathbf{T}_i^T \mathbf{V}_i^T \mathbf{R} &\stackrel{!}{=} \mathbf{I} \end{aligned}$$

Dual procedure for the local bases \mathbf{W}_i

pMOR by Matrix Interpolation – Procedure

[Panzer et al. '10]

1.) Individual reduction

$$\begin{aligned} \mathbf{E}_{r,i} \dot{\mathbf{x}}_{r,i}(t) &= \mathbf{A}_{r,i} \mathbf{x}_{r,i}(t) + \mathbf{B}_{r,i} \mathbf{u}(t) & \mathbf{E}_{r,i} &= \mathbf{W}_i^T \mathbf{E}_i \mathbf{V}_i, & \mathbf{A}_{r,i} &= \mathbf{W}_i^T \mathbf{A}_i \mathbf{V}_i \\ \mathbf{y}_{r,i}(t) &= \mathbf{C}_{r,i} \mathbf{x}_{r,i}(t) & \mathbf{B}_{r,i} &= \mathbf{W}_i^T \mathbf{B}_i, & \mathbf{C}_{r,i} &= \mathbf{C}_i \mathbf{V}_i \end{aligned}$$

$$\begin{aligned} \mathbf{p}_i, \quad i &= 1, \dots, K \\ \mathbf{V}_i &:= \mathbf{V}(\mathbf{p}_i) \\ \mathbf{W}_i &:= \mathbf{W}(\mathbf{p}_i) \end{aligned}$$

2.) Transformation to generalized coordinates

$$\begin{aligned} \underbrace{\mathbf{E}_{r,i}^*}_{\mathbf{M}_i^T \mathbf{E}_{r,i} \mathbf{T}_i} \dot{\mathbf{x}}_{r,i}^*(t) &= \underbrace{\mathbf{A}_{r,i}^*}_{\mathbf{M}_i^T \mathbf{A}_{r,i} \mathbf{T}_i} \mathbf{x}_{r,i}^*(t) + \underbrace{\mathbf{B}_{r,i}^*}_{\mathbf{M}_i^T \mathbf{B}_{r,i}} \mathbf{u}(t) \\ \mathbf{y}_{r,i}(t) &= \underbrace{\mathbf{C}_{r,i} \mathbf{T}_i}_{\mathbf{C}_{r,i}^*} \mathbf{x}_{r,i}^*(t) \end{aligned}$$

$$\begin{aligned} \mathbf{T}_i &= (\mathbf{R}^T \mathbf{V}_i)^{-1} \\ \mathbf{M}_i &= (\mathbf{R}^T \mathbf{W}_i)^{-1} \end{aligned}$$

$$\mathbf{x}_{r,i} = \mathbf{T}_i \mathbf{x}_{r,i}^*$$

$$\begin{aligned} \mathbf{V}_{\text{all}} &= [\mathbf{V}_1, \dots, \mathbf{V}_K] \\ \mathbf{V}_{\text{all}} &\stackrel{\text{SVD}}{=} \mathbf{U} \mathbf{\Sigma} \mathbf{N}^T \\ \mathbf{R} &= \mathbf{U}(:, 1:r) \end{aligned}$$

3.) Interpolation

$$\begin{aligned} \mathbf{E}_r^*(\mathbf{p}^{\text{int}}) &= \sum_{i=1}^K \omega_i(\mathbf{p}) \mathbf{E}_{r,i}^*, & \mathbf{A}_r^*(\mathbf{p}^{\text{int}}) &= \sum_{i=1}^K \omega_i(\mathbf{p}^{\text{int}}) \mathbf{A}_{r,i}^* \\ \mathbf{B}_r^*(\mathbf{p}^{\text{int}}) &= \sum_{i=1}^K \omega_i(\mathbf{p}) \mathbf{B}_{r,i}^*, & \mathbf{C}_r^*(\mathbf{p}^{\text{int}}) &= \sum_{i=1}^K \omega_i(\mathbf{p}^{\text{int}}) \mathbf{C}_{r,i}^* \end{aligned}$$

$$\sum_{i=1}^K \omega_i(\mathbf{p}^{\text{int}}) = 1$$

But: how to choose the **sample points**??

Adaptive Sampling

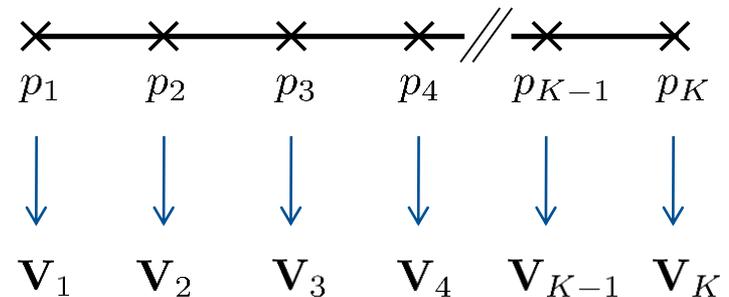
Requirements:

- Parametric space should be adequately sampled
- Avoid undersampling and oversampling
- More parameter samples should be placed in **highly sensitive zones**

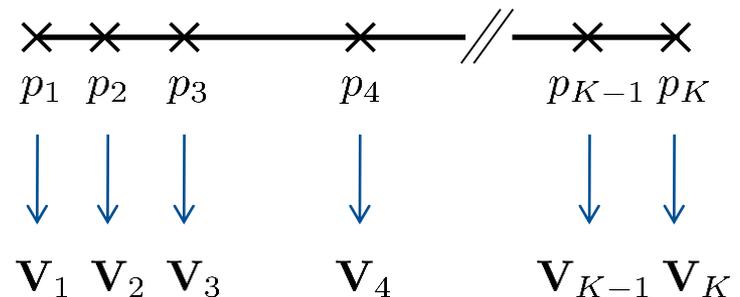
Quantification of parametric sensitivity:

- System-theoretic measure that quantifies the **parametric sensitivity** is needed in order to guide the adaptive refinement
- Adaptive sampling using **angle between subspaces**

Uniform Sampling:

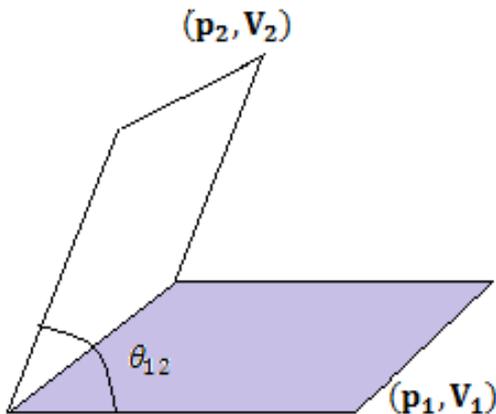


Adaptive Sampling:



Adaptive Sampling via subspace angles

Concept of subspace angles:



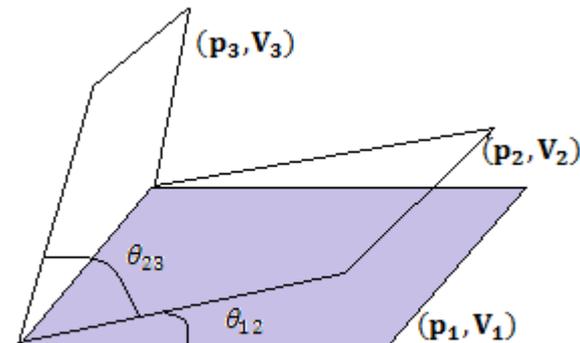
- V_1 and V_2 are orthonormal bases for the subspaces \mathcal{V}_1 and \mathcal{V}_2
- The largest angle between the subspaces can be determined by

$$\theta_{12} = \arcsin\left(\sqrt{1 - \sigma_r^2}\right) = \arccos(\sigma_r)$$

σ_r : smallest singular value of $V_1^T V_2$

Usage for adaptive grid refinement:

- The larger the subspace angle, the more different are the projection matrices, and thus:
 - the higher the parametric sensitivity
 - and the more sample points can be introduced in the respective sub-span



Automatic Adaptive Sampling: Pseudo-Code

- 1) Input θ_{\max}
 - 2) Divide the entire parameter range into a uniform grid, calling it p_1, p_2, \dots, p_K
 - 3) **While** all $l_{i,i+1} > 1$ **do**
 - a) Calculate the projection matrices $\mathbf{V}_1, \mathbf{V}_2, \dots, \mathbf{V}_K$ corresponding to each of these values p_1, p_2, \dots, p_K
 - b) Compute subspace angles $\theta_{12}, \theta_{23}, \dots, \theta_{K-1,K}$ between these \mathbf{V}_i 's, each taken pairwise
 - c) Calculate
$$l_{12} = \left\lceil \frac{\theta_{12}}{\theta_{\max}} \right\rceil, l_{23} = \left\lceil \frac{\theta_{23}}{\theta_{\max}} \right\rceil, \dots, l_{K-1,K} = \left\lceil \frac{\theta_{K-1,K}}{\theta_{\max}} \right\rceil$$
 - d) Divide the interval between p_1 and p_2 into l_{12} further intervals. Likewise, do the same for all the other intervals.
 - e) Obtain new grid points p_1, p_2, \dots, p_N , whereas $N > K$
- End While**

Local reduction at sample points possible using any preferred MOR technique

```
theta(i) =  
subspace(Vp{i}, Vp{i+1})
```

Quantitative indicator of how many pieces each parameter interval is to be further broken

Stopping criterion:

1. All ratios are equal to 1
2. Specified maximum number of samples points reached

Next iteration: local reduction, etc. only at points that got added in the last while-loop iteration (efficient!)

Numerical example: Timoshenko Beam

- Finite element 3D model of a Timoshenko beam
- Parameter is the length of the beam: $p \equiv L$
- One-sided Krylov reduction with shifts at $s_0 = 0$
- $\theta_{\max} = 10^\circ$ chosen

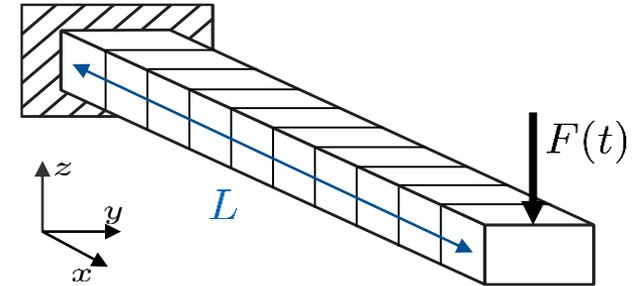


Table 1: Sample points p_i , subspace angles $\theta_{i,i+1}$ and ratios $l_{i,i+1}$

	p_i [m]		0.5			1.5	2.5	3.5	4.5	5.5	
iter 1	$\theta_{i,i+1}$ [$^\circ$]				25.79	14.20	8.61	7.06	5.73		
	$l_{i,i+1}$				3	2	1	1	1		
	p_i [m]	0.5	0.833	1.167	1.5	2	2.5	3.5	4.5	5.5	
iter 2	$\theta_{i,i+1}$ [$^\circ$]		10.15	8.59	7.05	8.18	6.03	8.61	7.06	5.73	
	$l_{i,i+1}$		2	1	1	1	1	1	1	1	
	p_i [m]	0.5	0.667	0.833	1.167	1.5	2	2.5	3.5	4.5	5.5
iter 3	$\theta_{i,i+1}$ [$^\circ$]		5.26	4.89	8.59	7.05	8.18	6.03	8.61	7.06	5.73
	$l_{i,i+1}$		1	1	1	1	1	1	1	1	1

Numerical example: Timoshenko Beam

Initial uniform grid with $K = 6$

Table 1: Sample points p_i , subspace angles $\theta_{i,i+1}$ and ratios $l_{i,i+1}$

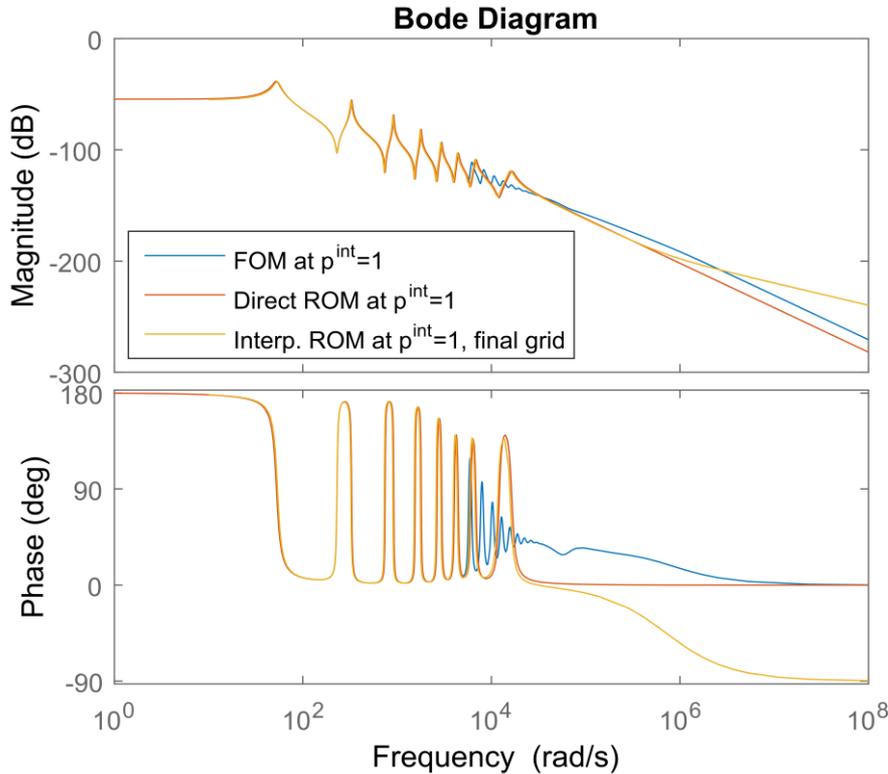
iter 1	p_i [m]	0.5			1.5		2.5		3.5		4.5		5.5
	$\theta_{i,i+1}$ [°]				25.79		14.20		8.61		7.06		5.73
	$l_{i,i+1}$				3		2		1		1		1
iter 2	p_i [m]	0.5	0.833	1.167	1.5	2	2.5	3.5	4.5	5.5			
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	$l_{i,i+1}$		2	1	1	1	1	1	1	1	1		
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	$\theta_{i,i+1}$ [°]		5.26	4.89	8.59	7.05	8.18	6.03	8.61	7.06	5.73		
	$l_{i,i+1}$		1	1	1	1	1	1	1	1	1		

Adaptive Sampling Scheme

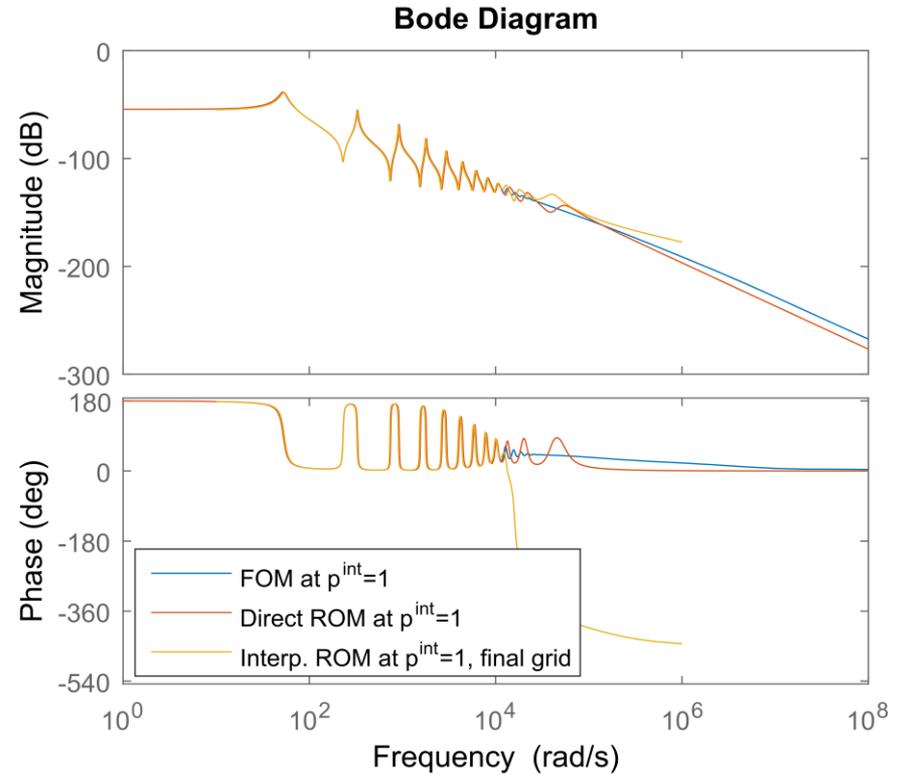
Interpolation point $p^{\text{int}} = 1.0$
 between ROM 3 & ROM 4

Final refined grid with $N = 10$

Numerical results – Direct vs. Interpolated ROM



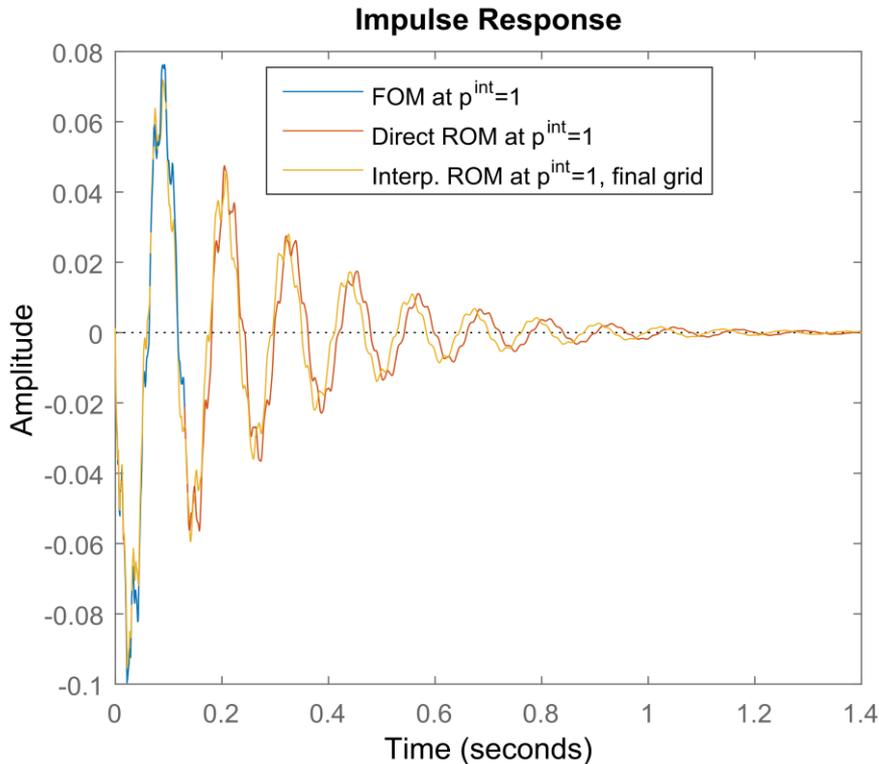
FOM size $n = 240$, ROMs size $r = 17$



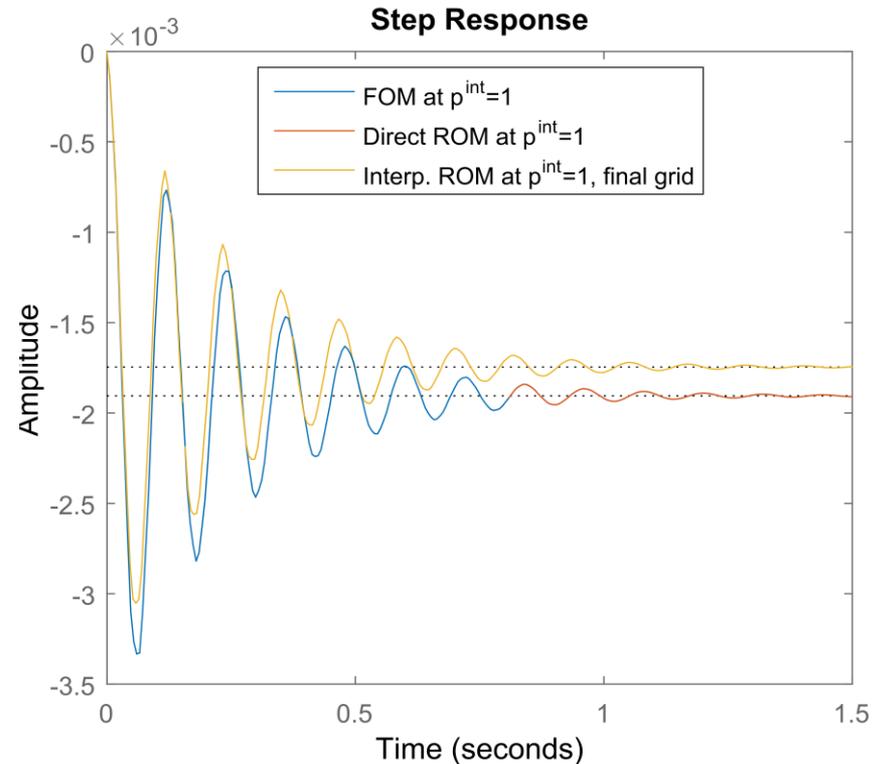
FOM size $n = 2400$, ROMs size $r = 25$

Two errors: model reduction error + interpolation error

Numerical results – Direct vs. Interpolated ROM



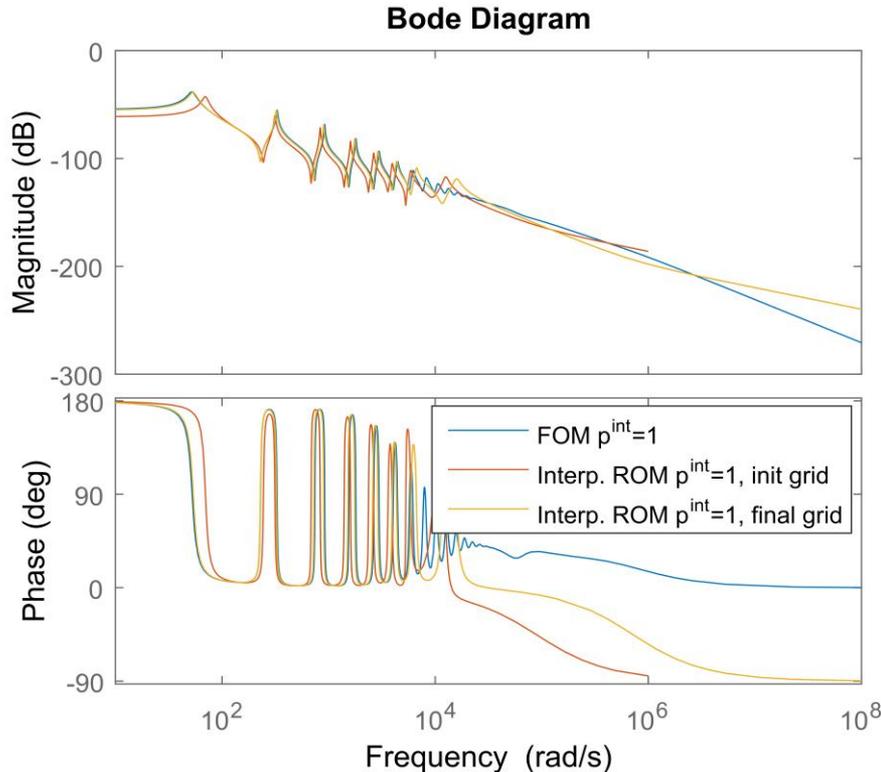
FOM size $n = 2400$, ROMs size $r = 25$



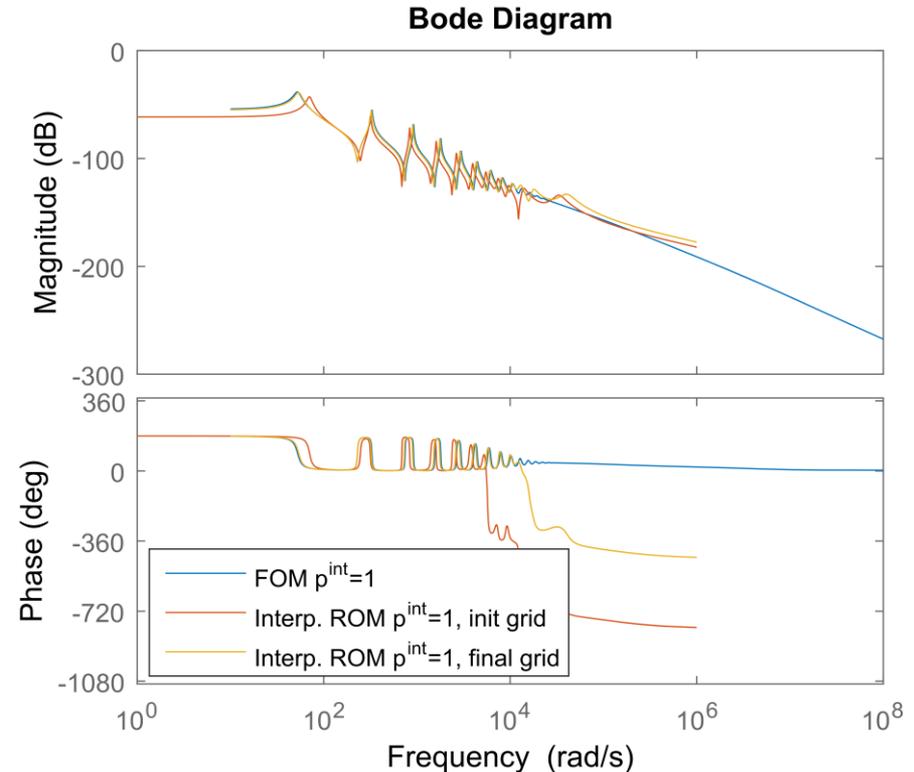
FOM size $n = 2400$, ROMs size $r = 25$

With MatrInterp: no need to reduce the model for every new parameter value

Numerical results – Initial vs. Final Grid



FOM size $n = 240$, ROMs size $r = 17$

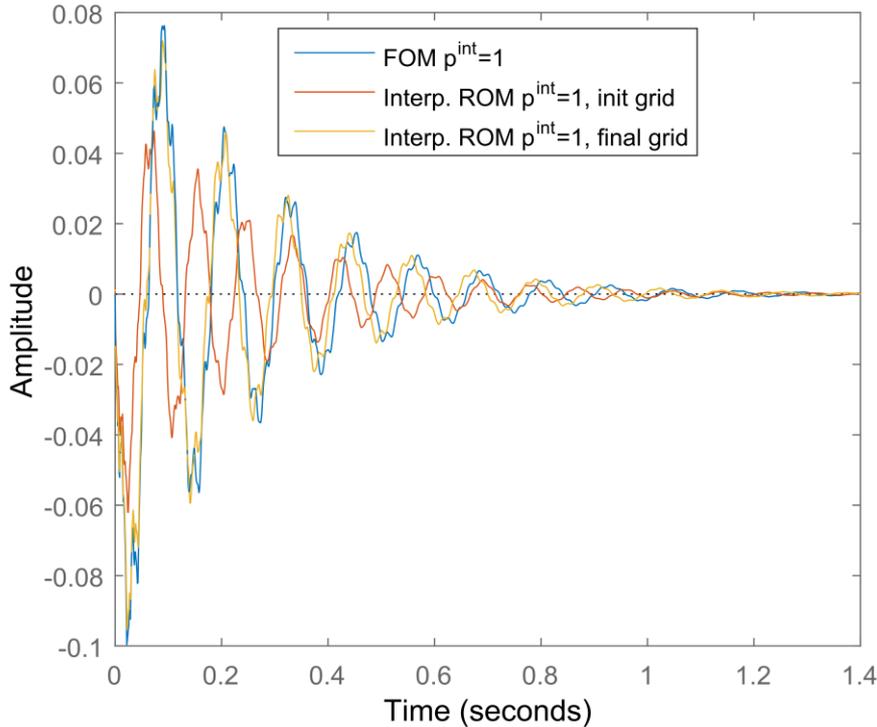


FOM size $n = 2400$, ROMs size $r = 25$

ROMs calculated with the final grid yield better approximations

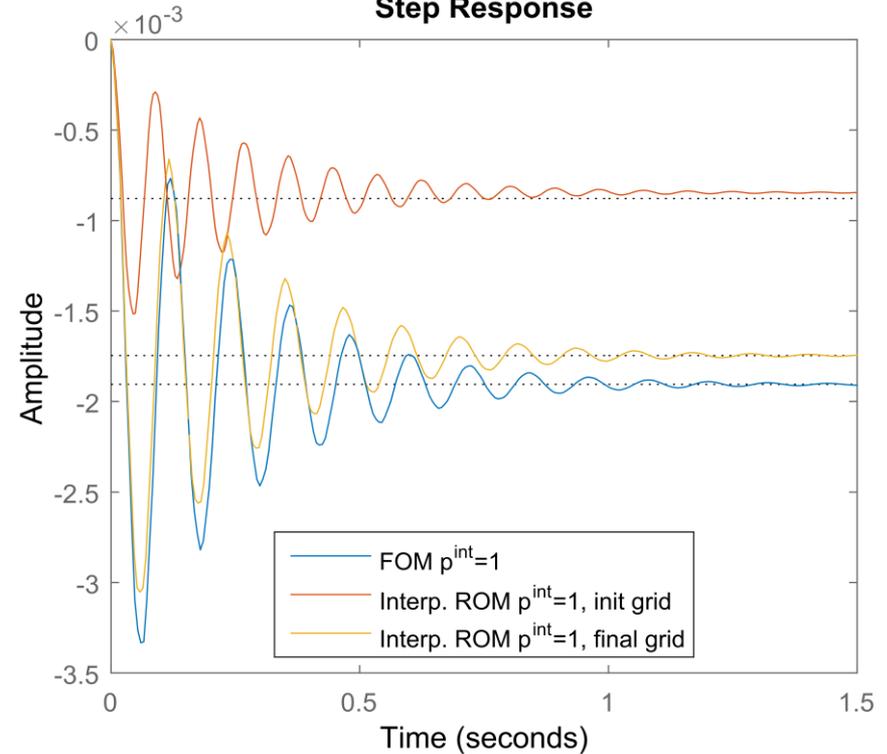
Numerical results – Initial vs. Final Grid

Impulse Response



FOM size $n = 2400$, ROMs size $r = 25$

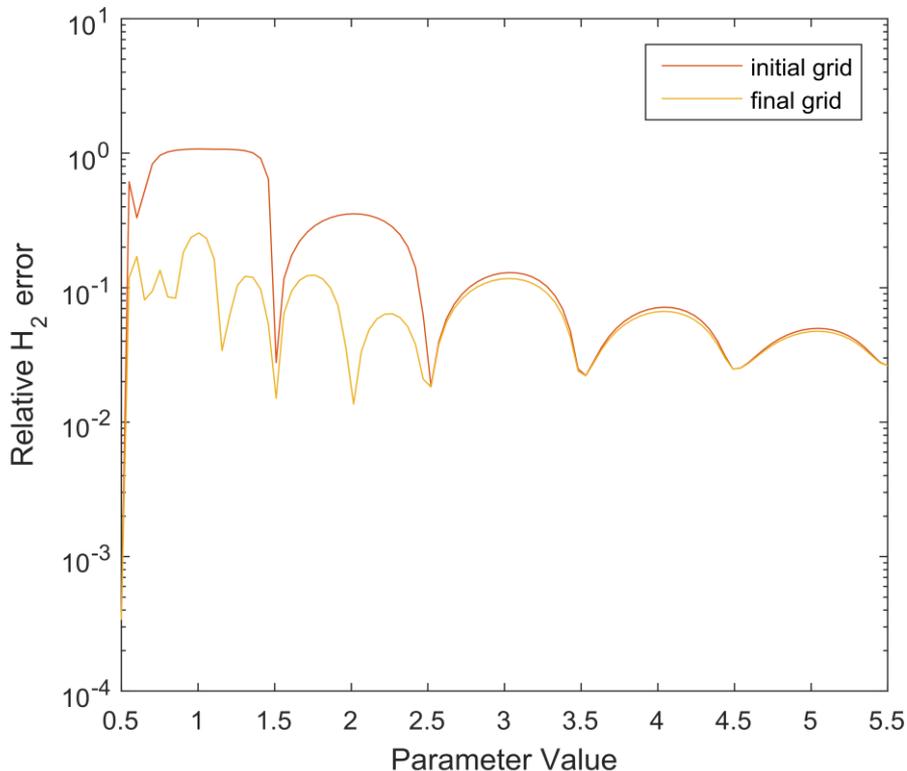
Step Response



FOM size $n = 2400$, ROMs size $r = 25$

ROMs calculated with the final grid yield better approximations

Numerical results – Initial vs. Final Grid



- **Quantitative evaluation of the approximation**
- **Relative H₂ error for $n_P=100$ different query points p^{int}**
- **Errors particularly small in the proximity of the sample points**
- **Final grid yields smaller errors for smaller beam lengths due to the adaptive refinement in this region**

Relative H₂ error between FOMs and interpolated ROMs for different parameter values and grids: FOM size $n = 240$, ROM size $r = 17$

ssMOR Toolbox – Analysis and Reduction of Parametric Models in

- ✓ Definition of **parametric sparse state-space models**

```
psys = loadFemBeam3D(Opts)  
psys = loadAnemometer3parameter
```

- ✓ Manipulation of **psss-class objects**

```
psys = fixParameter(psys, 2, 1.7)  
psys = unfixParameter(psys, 3)
```

- ✓ **Compatible** with the **sss** & **sssMOR** toolboxes

```
param = [p1, p2, p3, p4]  
sys = psys(param)
```

```
bode(psys, param); step(sys);
```

- ✓ Different **parametric reduction methods** available (offline- & online-phase)

```
psysr = matrInterpOffline  
(psys, param, r, Opts);
```

```
psysr = globalPmorOffline  
(psys, param, r, Opts)
```

```
sysr = psysr(pInterp)
```

- ✓ **localReduction** & **adaptiveSampling** as **core functions**



www.rt.mw.tum.de/?morlab



Summary & Outlook

Takehome Messages:

- A simple automatic sampling strategy is presented for **adaptively choosing sample points** in parametric model order reduction
- Scheme uses concept of **subspace angles** to measure need of further sampling points
- Adaptive approach is **fully automated** and **embedded in the matrix interpolation framework**
- Algorithm is applied to a **Timoshenko beam model**, achieving satisfactory results.

Future Extensions / Ongoing Work:

- **Extension** of proposed adaptive sampling scheme to **2D and 3D parametric case**
- Higher dimensional case ($d > 3$) with **adaptive sparse grids** is topic of future research
- **psssMOR toolbox** is being actively developed and will be **available open-source very soon!!**

Thank you for your attention!

Backup

References

[Amsallem '10]

Interpolation on manifolds of CFD-based fluid and finite element-based structural reduced-order models for on-line....

[Bazaz et al. '15]

Adaptive Parameter Space Sampling in Matrix Interpolatory pMOR.

[Benner et al. '15]

A survey of projection-based model reduction methods for parametric dynamical systems.

[Baur et al. '15]

Comparison of methods for parametric model order reduction of instationary problems.

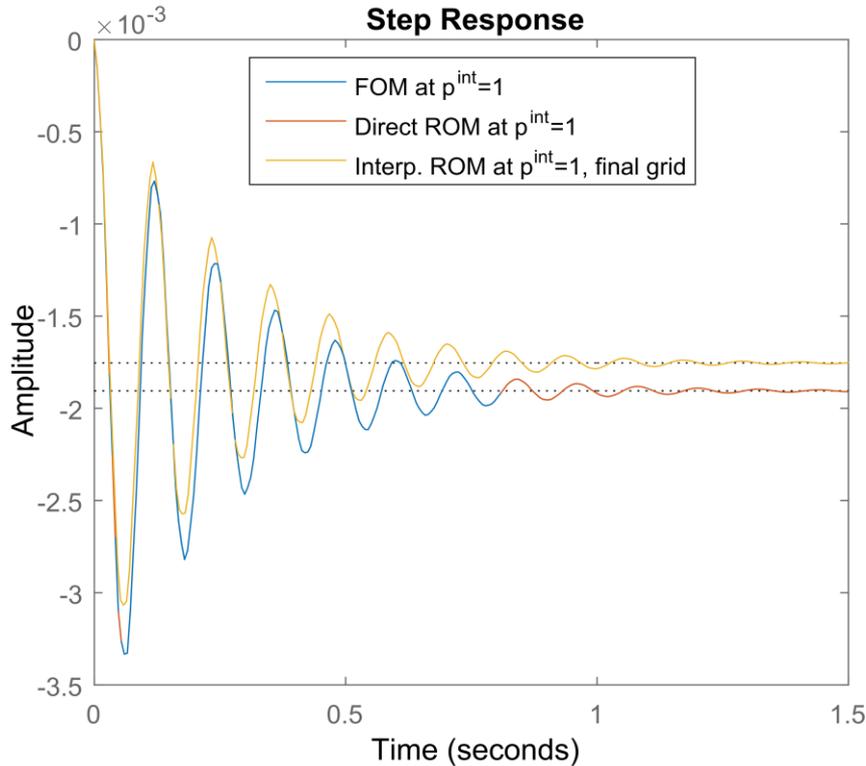
[Geuss et al. '08]

On Parametric Model Order Reduction by Matrix Interpolation.

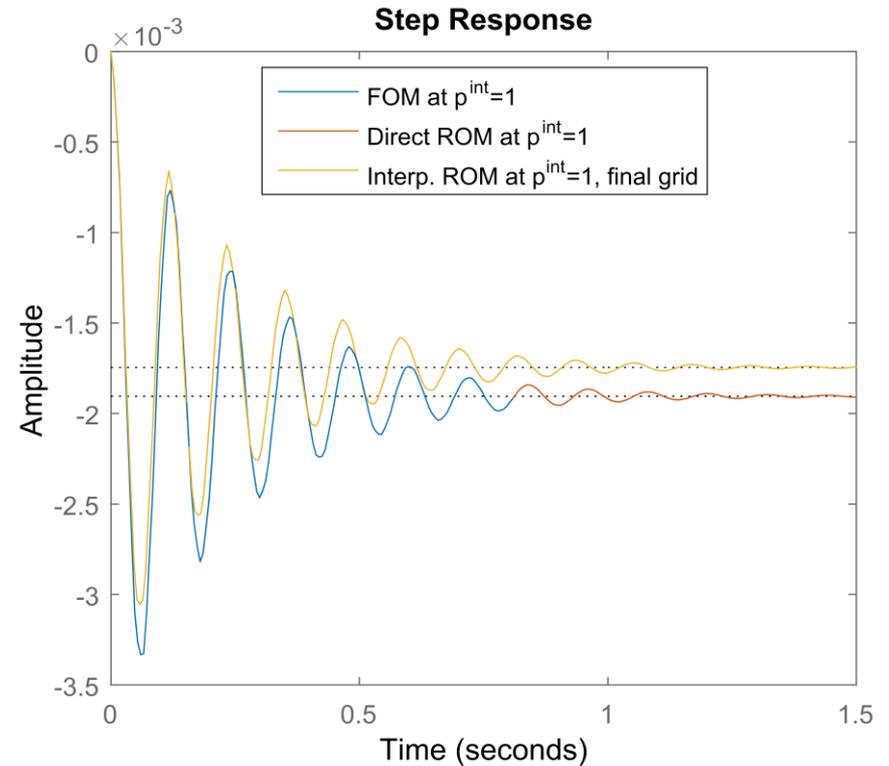
[Panzer et al. '10]

Parametric Model Order Reduction by Matrix Interpolation.

Numerical results – Direct vs. Interpolated ROM

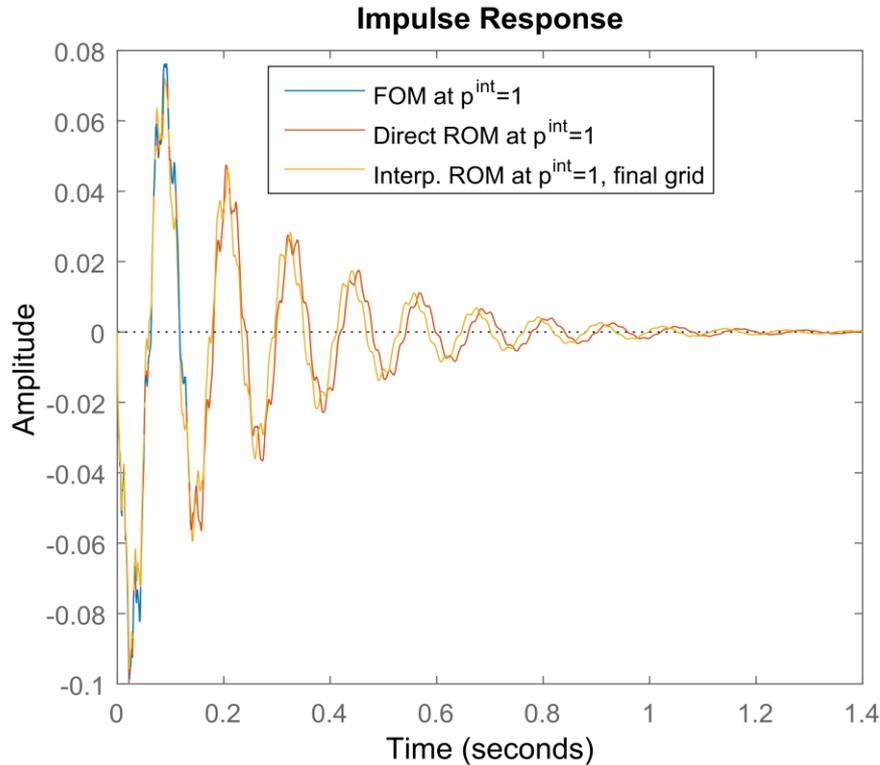


FOM size $n = 240$, ROMs size $r = 17$

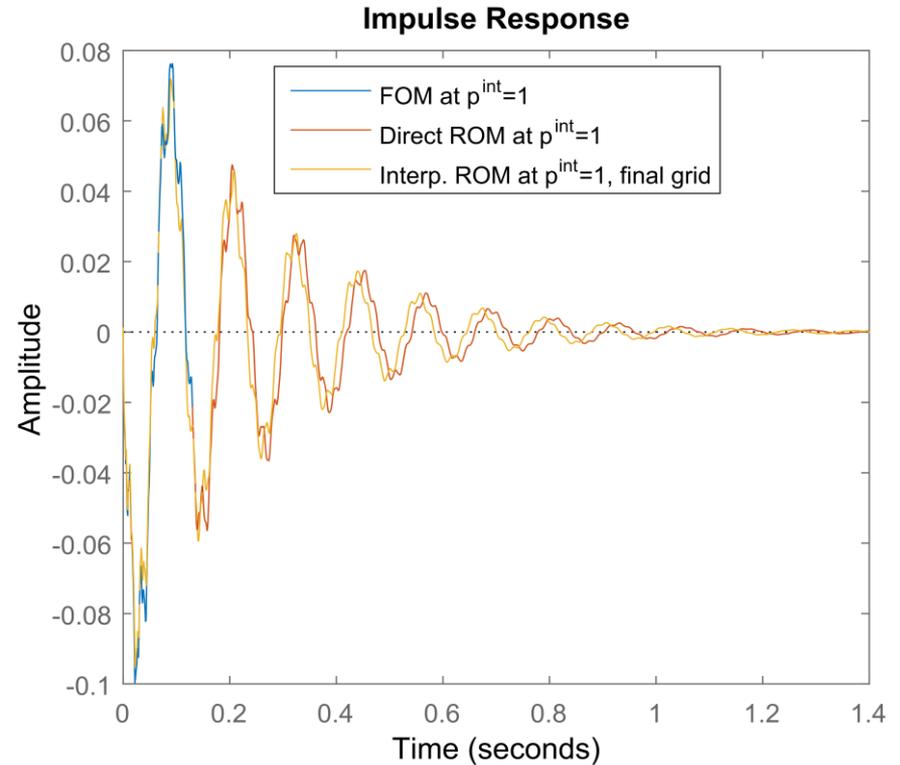


FOM size $n = 2400$, ROMs size $r = 25$

Numerical results – Direct vs. Interpolated ROM

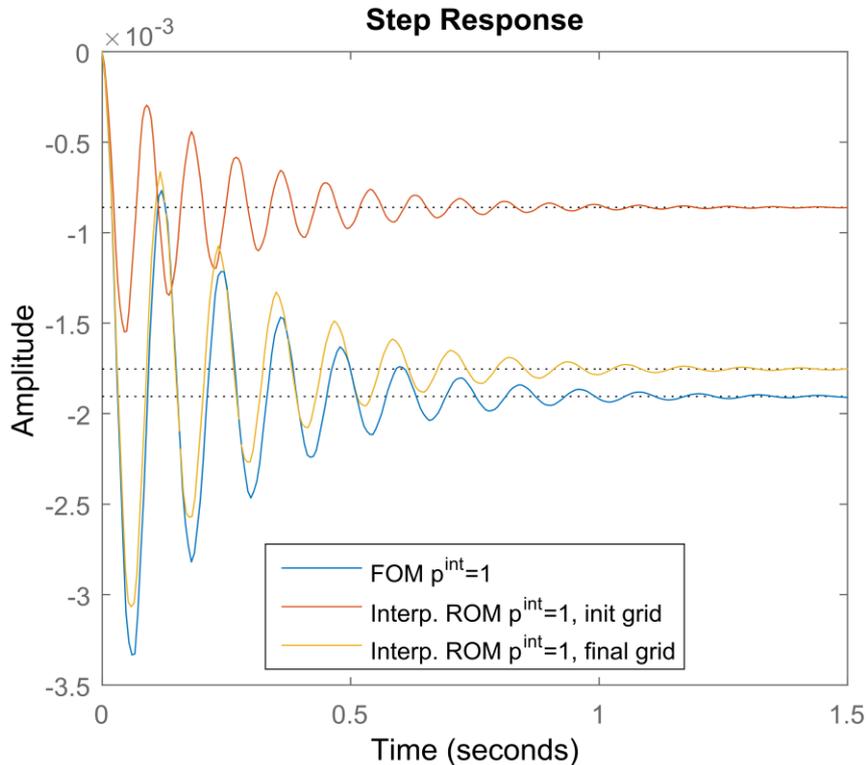


FOM size $n = 240$, ROMs size $r = 17$

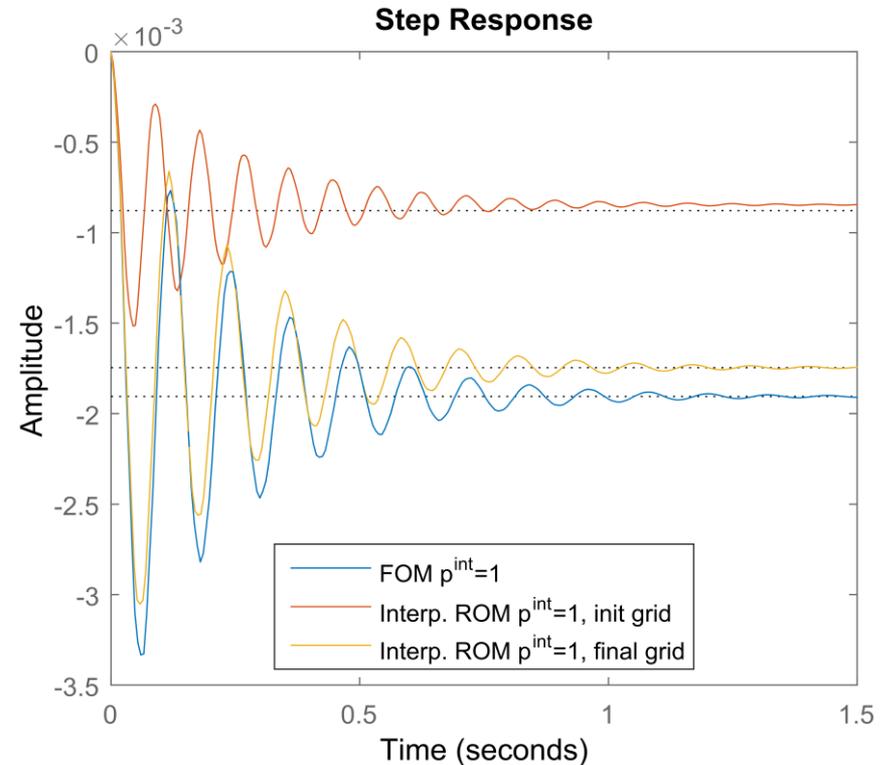


FOM size $n = 2400$, ROMs size $r = 25$

Numerical results – Initial vs. Final Grid

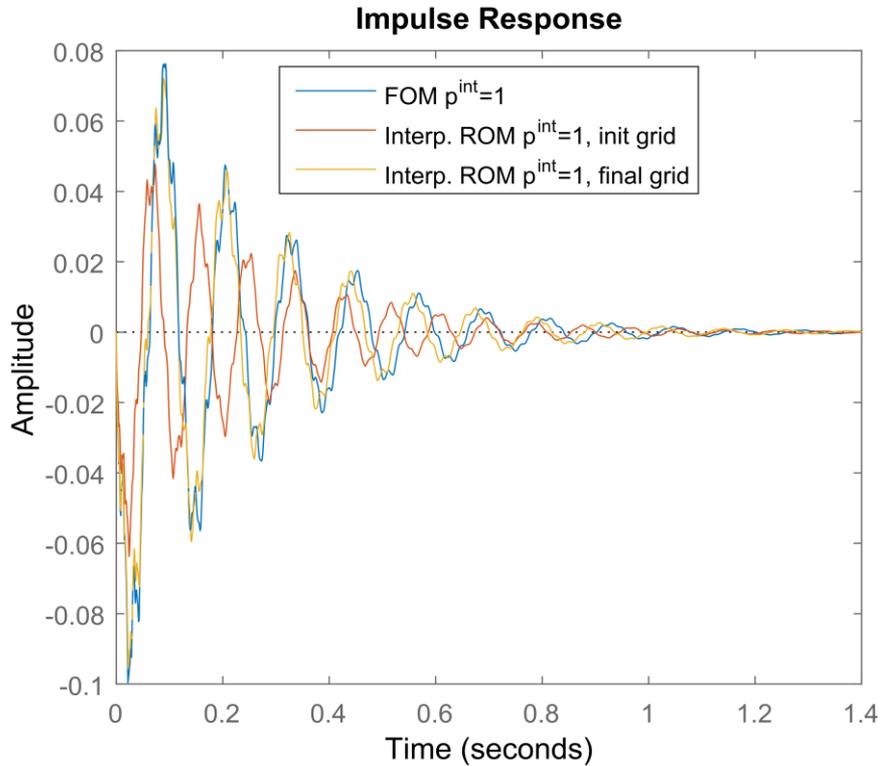


FOM size $n = 240$, ROMs size $r = 17$

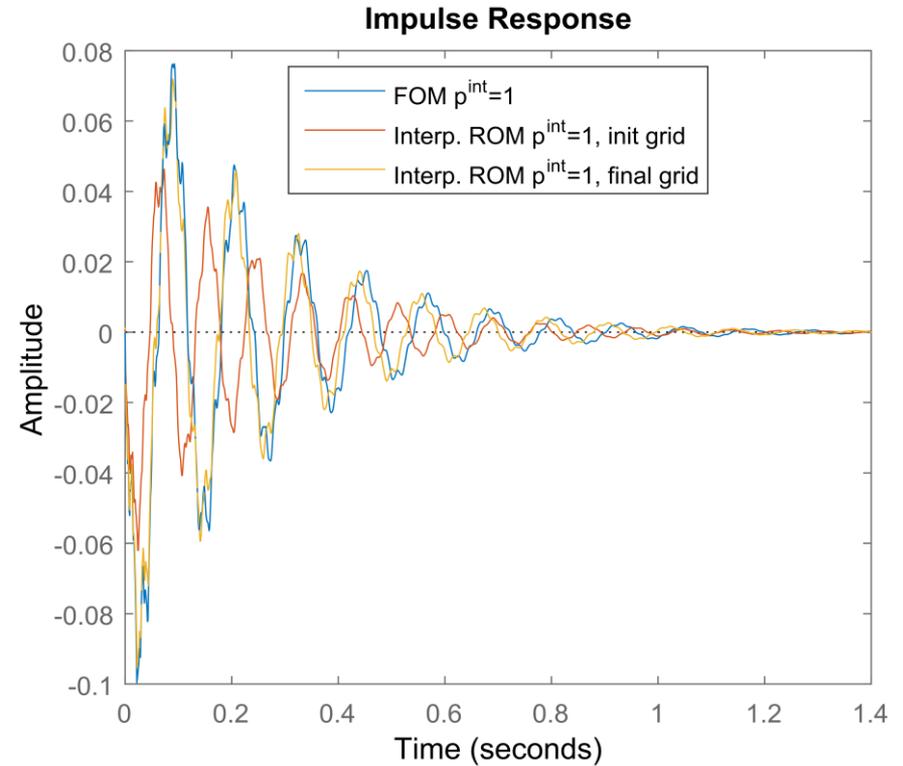


FOM size $n = 2400$, ROMs size $r = 25$

Numerical results – Initial vs. Final Grid

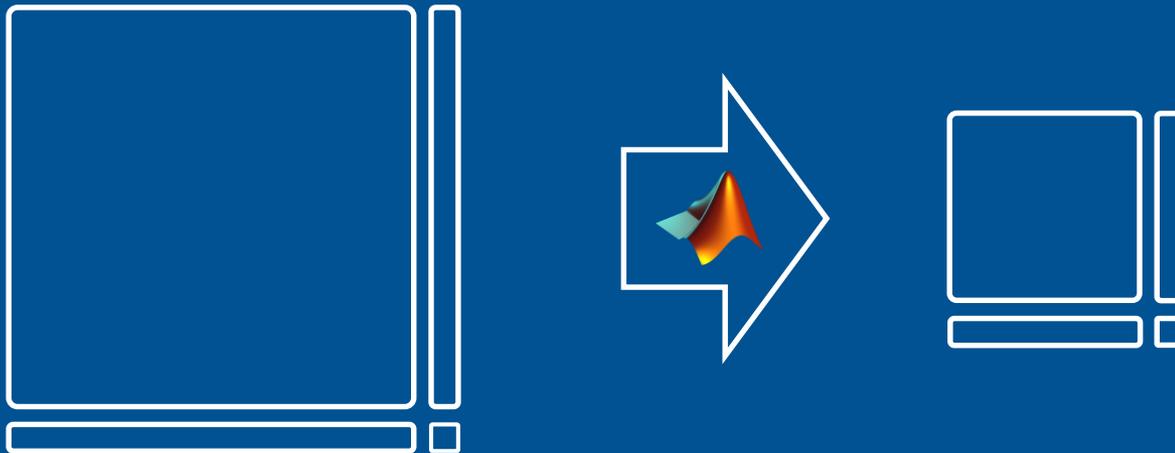


FOM size $n = 240$, ROMs size $r = 17$



FOM size $n = 2400$, ROMs size $r = 25$

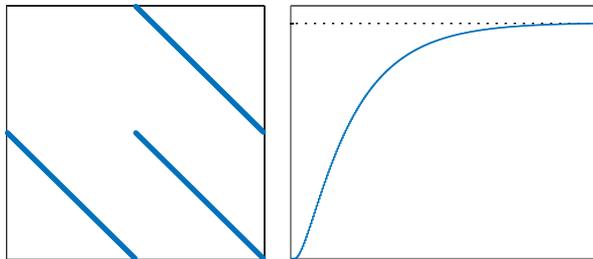
sss & sssMOR – MATLAB Toolboxes



Toolboxes for sparse, large-scale models in



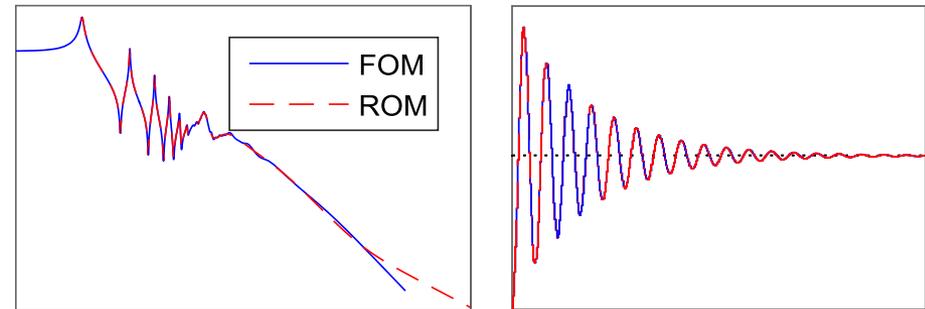
```
sys = sss (A, B, C, D, E);
```



```
bode(sys), sigma(sys)  
step(sys), impulse(sys)  
norm(sys,2), norm(sys,inf)  
  
c2d, lsim, eigs, connect,...
```



```
sysr = tbr (sys, r)  
sysr = rk (sys, s0)  
sysr = irka (sys, s0)  
sysr = cure(sys)  
sysr = cirka(sys, s0)  
⋮
```



Powered by: **M-M.E.S.S. toolbox** [Saak, Köhler, Benner] for Lyapunov equations

Available at www.rt.mw.tum.de/?sssMOR

[Castagnotto/Cruz Varona/Jeschek/Lohmann '17]: „**sss & sssMOR: Analysis and Reduction of Large-Scale Dynamic Systems in MATLAB**“, at-Automatisierungstechnik]



Main characteristics



- ✓ **State-space models** of very high order on a standard computer $\mathcal{O}(10^8)$
- ✓ Many Control System Toolbox functions, revisited to **exploit sparsity**
- ✓ Allows system analysis in **frequency** (`bode`, `sigma`, ...) and **time domain** (`step`, `norm`, `lsim`, ...), as well as **manipulations** (`connect`, `truncate`, ...)
- ✓ Is **compatible** with the built-in syntax
- ✓ **New functionality:** `eigs`, `residue`, `pzmap`, ...



- ✓ **Classical** (`modalMor`, `tbr`, `rk`, ...) and **state-of-the-art** (`isrk`, `irka`, `cirka`, `cure`, ...) reduction methods
- ✓ Both **highly-automatized**

```
sysr = irka(sys,n)
```


and highly-customizable

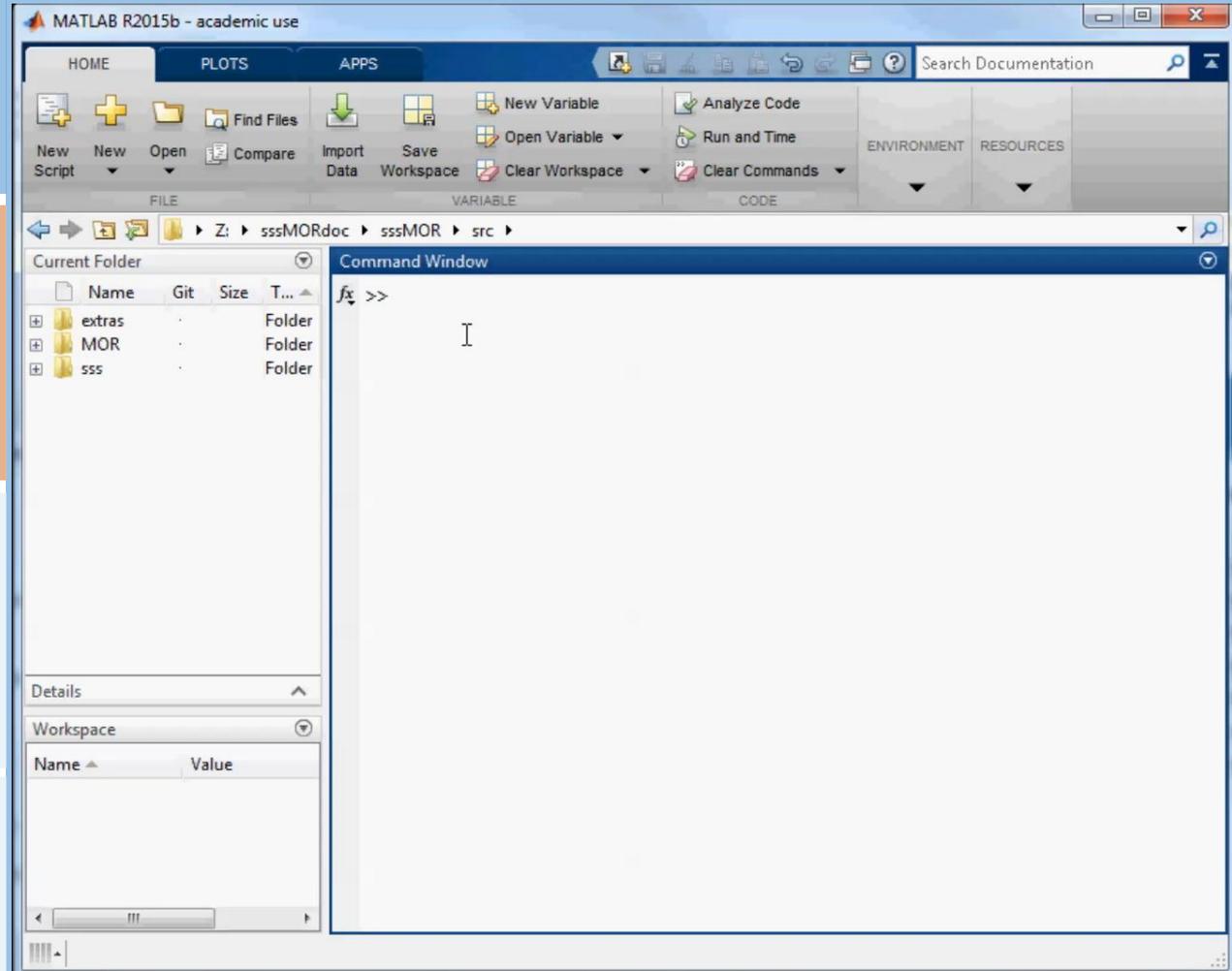
```
Opts.maxiter = 100  
Opts.tol = 1e-6  
Opts.stopcrit = 'combAll'  
Opts.verbose = true  
sysr = irka(sys,n,Opts)
```
- ✓ `solveLse` and `lyapchol` as **core functions**



Comprehensive
documentation with
examples and references

ssMOR App
graphical user interface

completely **free**
and **open source**
(contributions welcome)

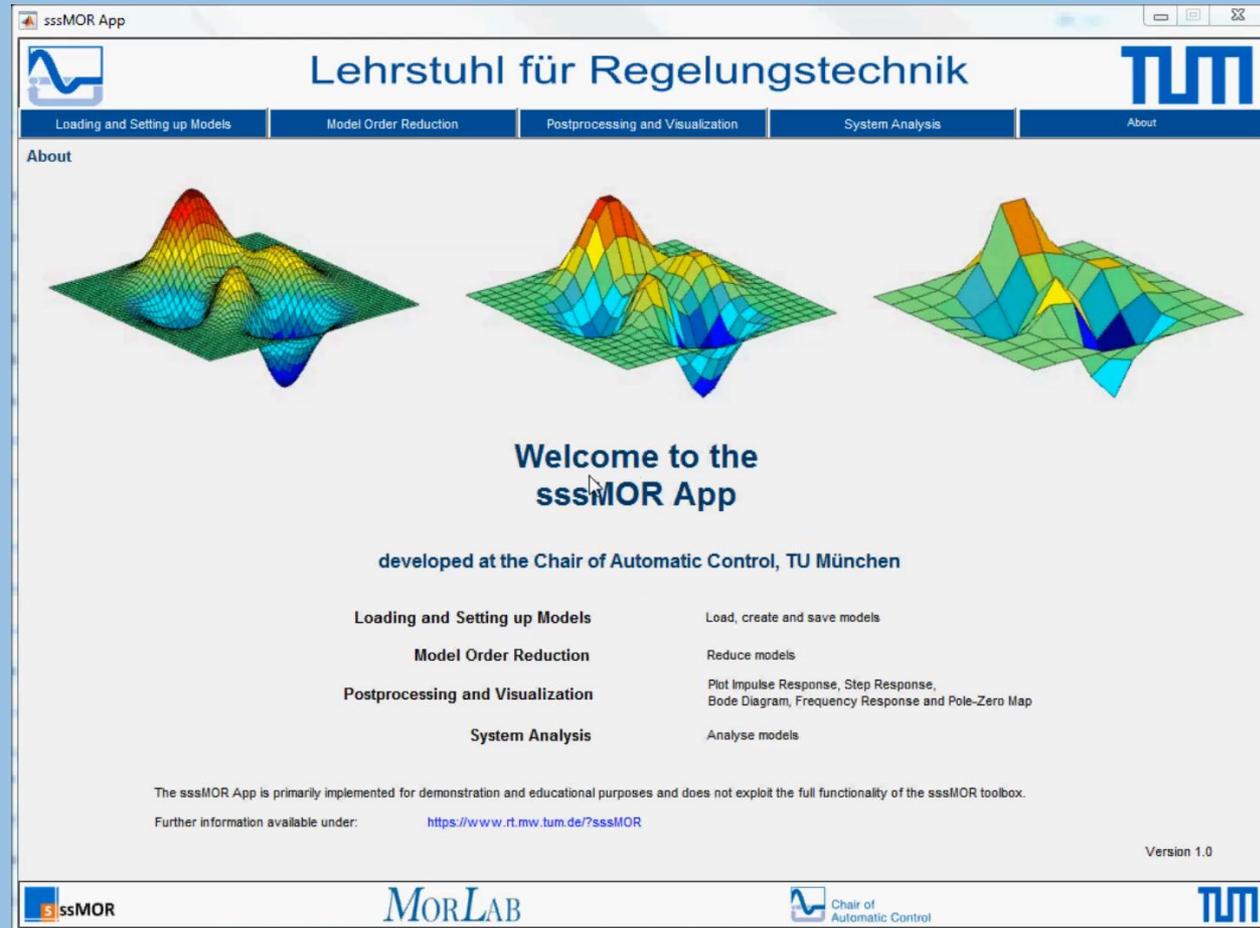




Comprehensive
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sssMOR App

Lehrstuhl für Regelungstechnik

Loading and Setting up Models | Model Order Reduction | Postprocessing and Visualization | System Analysis | About

About

Three 3D surface plots showing a function with multiple peaks and valleys, colored with a gradient from blue to red.

Welcome to the sssMOR App

developed at the Chair of Automatic Control, TU München

Loading and Setting up Models	Load, create and save models
Model Order Reduction	Reduce models
Postprocessing and Visualization	Plot Impulse Response, Step Response, Bode Diagram, Frequency Response and Pole-Zero Map
System Analysis	Analyse models

The sssMOR App is primarily implemented for demonstration and educational purposes and does not exploit the full functionality of the sssMOR toolbox.

Further information available under: <https://www.rt.mw.tum.de/?sssMOR>

Version 1.0

sssMOR MORLAB Chair of Automatic Control TUM



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