

Finding the Characteristics: Radial Basis Function Interpolation for Parametric Model Order Reduction

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Definition and stability

Let

- ▶ $A \in \mathbb{R}^{d \times d}$
- ▶ $B \in \mathbb{R}^d$
- ▶ $C \in \mathbb{R}^{1 \times d}$

A *linear time-invariant* (LTI) system

$$\Sigma : \begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad (1)$$

is called *stable* if A has eigenvalues only in the left half plane.

Model order reduction

Model order reduction methods try to find a *reduced LTI system*

$$\hat{\Sigma} : \begin{cases} \dot{x}(t) = \hat{A}x(t) + \hat{B}u(t) \\ \hat{y}(t) = \hat{C}x(t) \end{cases} \quad (2)$$

where

- ▶ $r \ll d$
- ▶ $\hat{A} \in \mathbb{R}^{r \times r}$, $\hat{B} \in \mathbb{R}^r$, $\hat{C} \in \mathbb{C}^{1 \times r}$

and \hat{A} has eigenvalues only in the left half plane.

Transfer function

The input-output map $y(u)$ of (1) is characterized by the *transfer function*

$$H : \mathbb{C} \rightarrow \mathbb{C}, \quad H(\omega) = C(\omega I - A)^{-1}B$$

in frequency space. \hat{H} is defined accordingly for (2).

Error estimate

Let $y(t)$ and $\hat{y}(t)$ be the output of (1) and (2). Then the *error of $y(t)$* is bounded by

$$\max_{t>0} |y(t) - \hat{y}(t)| \leq \|H - \hat{H}\|_{\mathcal{H}_2} \|u\|_{\mathcal{L}_2},$$

where the \mathcal{H}_2 -norm is defined as

$$\|H - \hat{H}\|_{\mathcal{H}_2}^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} |H(i\omega) - \hat{H}(i\omega)|^2 d\omega$$

\mathcal{H}_2 optimality

Given

- ▶ a stable dynamical system (1),
- ▶ a reduced order system (2).

If the reduced system (2) *minimizes* $\|H - \hat{H}\|_{\mathcal{H}_2}$, it Hermite interpolates (1) at its mirror poles $\sigma_1, \dots, \sigma_r$.

Petrov-Galerkin projection

Let

- ▶ r fixed, $\sigma_1, \dots, \sigma_r$ given
- ▶ V, W such that

$$\begin{aligned}(\sigma_i I - A)^{-1} B &\in \text{span}(V) \\ (\sigma_i I - A)^{-T} C^T &\in \text{span}(W) \\ V^T W &= I\end{aligned}$$

Then the reduced order model by *Petrov-Galerkin projection*

$$\hat{A} = V^T A W, \quad \hat{B} = V^T B, \quad \hat{C} = C W$$

Hermite interpolates (1) at $\sigma_1, \dots, \sigma_r$.

Remark

- ▶ \hat{A} is unique up to matrix similarity

Iterative Rational Krylov Algorithm (IRKA)

- ▶ **Problem:** Find $\sigma_1, \dots, \sigma_r$ for (1)
- ▶ **Solution by IRKA:** Local optimum
 - ▶ Initial $\sigma_1, \dots, \sigma_r$ given
 - ▶ Fixed-point iteration
 - ▶ Locally convergent if local optimum is attractive (e. g. for state-space-symmetric systems)

Parametric LTI system

Given a compact domain $\Omega \subset \mathbb{R}^n$. Let

- ▶ A, B and C as in (1)
- ▶ A, B and C depend (smoothly) on some $p \in \Omega$

Then

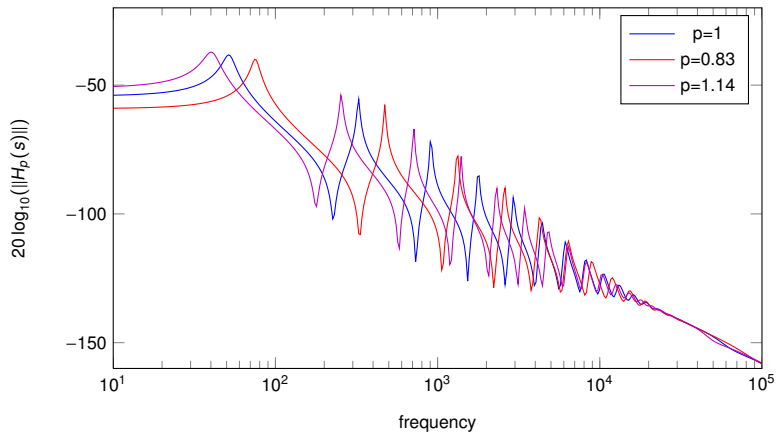
- ▶ $A(p), B(p)$ and $C(p)$ define a *parametric LTI system*

$$\Sigma : \begin{cases} \dot{x}(t) = A(p)x(t) + B(p)u(t), \\ y(t) = C(p)x(t). \end{cases}$$

- ▶ Each value of p defines an LTI system, which can be reduced as before

Parametric LTI system

Transfer function of a parametrized LTI system for different choices of p (elastic beam):



Parametric model order reduction

- ▶ *Goal*: Fast computation of $\hat{A}(p), \hat{B}(p), \hat{C}(p) \forall p$
- ▶ *General ideas*:
 - ▶ Relax \mathcal{H}_2 -optimality slightly
 - ▶ Apply well-established approximation methods
...such as radial basis function interpolation
- ▶ to be effective, *smoothness* is absolutely essential!

Approximation of parametric dependency

Candidates for approximation are

- ▶ $\hat{A}(p), \hat{B}(p), \hat{C}(p)$

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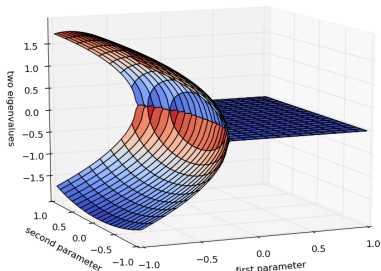
- ▶ $\hat{A}(p), \hat{B}(p), \hat{C}(p) \rightsquigarrow$ non-unique, matrix similarity!
- ▶ $\sigma_1(p), \dots, \sigma_r(p)$

Approximation of parametric dependency

Candidates for approximation are

- ▶ $\hat{A}(p), \hat{B}(p), \hat{C}(p) \rightsquigarrow$ non-unique, matrix similarity!
- ▶ $\sigma_1(p), \dots, \sigma_r(p) \rightsquigarrow$ eigenvalue crossings and splittings, non-smooth!

Imaginary parts of two eigenvalues of a matrix depending on two parameters:

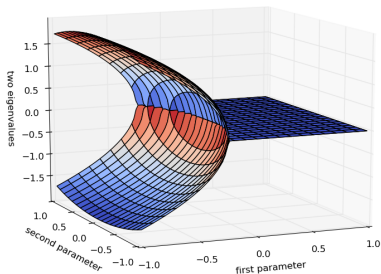


Approximation of parametric dependency

Candidates for approximation are

- ▶ $\hat{A}(p), \hat{B}(p), \hat{C}(p) \rightsquigarrow$ non-unique, matrix similarity!
- ▶ $\sigma_1(p), \dots, \sigma_r(p) \rightsquigarrow$ eigenvalue crossings and splittings, non-smooth!

Imaginary parts of two eigenvalues of a matrix depending on two parameters:



- ▶ Coefficients of the *characteristic polynomial* $\prod_{i=1}^r (s - \sigma_i(p))$
 \rightsquigarrow smooth enough?

Smoothness of the characteristic polynomial

Let

- ▶ π map a matrix to its characteristic polynomial
- ▶ Q map a polynomial to its coefficients
- ▶ λ map a matrix to its eigenvalues

Then

▶

$$\hat{A}(\cdot) \in C^\infty(\mathbb{R}^n; \mathbb{R}^{r \times r}) \Rightarrow Q(\pi(\hat{A}(\cdot))) \in C^\infty(\mathbb{R}^n; \mathbb{R}^{r+1})$$

▶

$$\hat{A} \text{ stable} \Rightarrow \begin{cases} Q(\pi(\hat{A}(p))) \geq 0 \\ \Re \lambda(\hat{A}(p)) \leq 0 \end{cases}$$

$$\forall P \in \mathbb{R}^{r \times r}, \det P \neq 0 : \begin{cases} \pi(\hat{A}(p)) = \pi(P\hat{A}(p)P^{-1}) \\ \lambda(\hat{A}(p)) = \lambda(P\hat{A}(p)P^{-1}) \end{cases}$$

Smoothness of the characteristic polynomial

Let

- ▶ ρ map a set of r roots to their polynomial
- ▶ Q map the resulting polynomial to its coefficients

Then

- ▶ Q is linear, hence Q^{-1} , too
- ▶ ρ^{-1} maps a polynomial to its roots
 - ▶ *closed form representations* for $r \leq 5$
 - ▶ computation unstable for $r > 5$

Smoothness of the characteristic polynomial

Let $r \leq 5$. Assume IRKA converges

- ▶ locally
- ▶ to a local optimum
- ▶ returns $\Sigma(p) = (\sigma_1(p), \dots, \sigma_r(p))$

Moreover, assume that *a perturbation of p* is small enough to not leave the region of

- ▶ convergence
- ▶ attraction to the local minimum

Then

- ▶ $f = Q \circ \rho \circ \Sigma(\cdot)$ is smooth
- ▶ standard *RBF interpolation* is applicable

Smoothness of the characteristic polynomial

Assume IRKA converges as before, $r \leq 5$. Moreover, assume again that a *perturbation of p* is small enough to not leave the region of

- ▶ convergence
- ▶ attraction to the local minimum

Let

- ▶ $\tilde{f} \approx f = Q \circ \rho \circ \Sigma(\cdot)$
- ▶ $\tilde{\Sigma} = \rho^{-1} \circ Q^{-1} \circ \tilde{f}$

Then $\tilde{\Sigma}$

- ▶ approximates the *results of IRKA*
- ▶ can be computed stably

↪ *find* those smooth regions!

Smoothness of the characteristic polynomial

Let $f = Q \circ \rho \circ \Sigma(\cdot)$.

- ▶ We are looking for *discontinuities* of $f(p)$
- ▶ Simple *criterion* for k -means or spectral clustering (Ng et al.): tuple $(p, f(p))$

~> How to determine the *number of clusters*?

Definition

Let

- ▶ $\Omega \subset \mathbb{R}^n$ a domain
- ▶ F a class of functions $f : \Omega \rightarrow \mathbb{C}$ that form a Hilbert space \mathcal{H} with inner product (\cdot, \cdot)

The function $\kappa : \Omega \times \Omega \rightarrow \mathbb{C}$ is called *reproducing kernel* if

$$\begin{aligned} \forall y \in \Omega : \quad & \kappa(\cdot, y) \in F, \\ \forall f \in F, y \in \Omega : \quad & f(y) = (f(\cdot), \kappa(\cdot, y)) \quad (\text{reproducing property}). \end{aligned}$$

Properties

Let $\xi_i \in \mathbb{C}$, $x_i, x, y, z \in \Omega$, $i, j = 1, \dots, N$, $N \in \mathbb{N}$ arbitrary

- ▶ *Positive definiteness*

$$\sum_{i,j} \xi_i \bar{\xi}_j \kappa(x_j, x_i) \geq 0$$

- ▶ $\kappa(y, z) = (\kappa(x, z), \kappa(x, y))$, $\kappa(x, y) = \overline{\kappa(y, x)}$, $\kappa(x, x) \geq 0$, ...

Given: $\mathcal{H}(\Omega)$ with inner product (\cdot, \cdot)

Existence

Necessary and sufficient condition: A *continuous evaluation functional*

$$\delta_x : \mathcal{H} \rightarrow \mathbb{C}, f \rightarrow f(x)$$

exists on \mathcal{H}

Uniqueness

- ▶ Assumption: A reproducing kernel κ exists for \mathcal{H}

Then the reproducing kernel κ of \mathcal{H} is *unique* and, therefore, characterizes \mathcal{H} .

Native space of κ

Given

- ▶ $\kappa : \Omega \times \Omega \rightarrow \mathbb{C}$, positive definite
- ▶ $F = \text{span} \{ \kappa(\cdot, x) : x \in \Omega \}$

Moreover, define

$$(f, g)_\kappa \equiv \sum_{i,j} \alpha_i \bar{\beta}_j \kappa(x_j, x_i)$$

for arbitrary $f, g \in F$ with

- ▶ $f = \sum_i \alpha_i \kappa(\cdot, x_i)$
- ▶ $g = \sum_j \beta_j \kappa(\cdot, x_j)$

Then

- ▶ $\mathcal{H} = \text{cl}F$ with respect to $\|f\|_\kappa^2 \equiv (f, f)_\kappa$ has reproducing kernel κ
- ▶ \mathcal{H} is called the *native space* of κ

Examples

Let $x, y \in \Omega = \mathbb{R}^n$.

- ▶ *Positive definite functions*

$$\kappa(x, y) = \phi(x - y), \quad \text{invariant to } T(n)$$

- ▶ *Radial basic functions* (RBF)

$$\kappa(x, y) = \phi(\|x - y\|_2), \quad \text{invariant to } SE(n)$$

RBF examples

Let $\epsilon > 0$, $\tau > n/2$. Denote by

- ▶ K_ν the modified Bessel function of 2nd kind,
- ▶ $\mathcal{F}f$ the Fourier transform of f .

Popular RBF choices are

Sobolev splines

$$\phi(x) = \frac{K_{\tau-n/2}(\|x\|_2) \|x\|_2^{\tau-n/2}}{2^{\tau-1} \Gamma(\tau)}, \quad \mathcal{H} = W_2^\tau(\mathbb{R}^n)$$

Gaussians

$$\phi(x) = e^{-\epsilon^2 \|x\|_2^2}, \quad \mathcal{H} = \left\{ f \in L_2(\mathbb{R}^n) \cap C^\infty(\mathbb{R}^n) : e^{\frac{\|x\|_2^2}{8\epsilon^2}} \mathcal{F}f \in L^2(\mathbb{R}^n) \right\}$$

RBF interpolation

Given a function $f \in \mathcal{H}$, select

- ▶ sampling $X = \{x_1, \dots, x_N\} \subset \Omega, N = |X| < \infty$
- ▶ *ansatz*

$$\tilde{f}(x) = \sum_{i=1}^N \xi_i k(x, x_i).$$

Then \tilde{f} is an *interpolant* to f on X if (ξ_1, \dots, ξ_N) is a solution of

$$\forall j = 1 \dots N : \tilde{f}(x_j) = f(x_j). \quad (3)$$

\leadsto *offline* phase (sampling, IRKA) \leftrightarrow *online* phase (metamodel, reduced model)

Given f, \tilde{f}, X as before.

Optimality of RBF interpolation

- ▶ $\forall \tilde{\mathbf{s}} \in \{\mathbf{s} \in \mathcal{H} : (3)\} : \|\tilde{f}\|_k \leq \|\tilde{\mathbf{s}}\|_k$
- ▶ $\forall \tilde{\mathbf{s}} \in \{\sum_i \xi_i \kappa(\cdot, x_i) : \xi_i \in \mathbb{C}\} : \|f - \mathbf{s}\|_k \leq \|f - \tilde{\mathbf{s}}\|_k$

Define the *fill-distance* of X as $h \equiv \sup_{y \in \Omega} \max_{x \in X} \|x - y\|_2$

Sampling inequalities

Let

- ▶ α a multi-index
- ▶ σ the sampling order

Then $\exists C_1 > 0 : \|D^\alpha f\|_{L_q(\Omega)} \leq C_1 (h^\sigma \|f\|_k + h^{-|\alpha|} \|f(X)\|_{\ell_\infty(\mathbb{R}^{|X|})})$

Error estimates

Assume a continuous embedding of \mathcal{H} into $W_2^p, 0 < p < \infty$.

Then $\exists C > 0 : \|f - \tilde{f}\|_{L_q(\Omega)} \leq Ch^{p-n} \max(0, \frac{1}{2} - \frac{1}{q}) \|f\|_k$

Remarks

- ▶ Gaussians, multi-quadrics: *spectral* approximation orders
 - ▶ *Sobolev* functions \leftrightarrow ansatz with Gaussians: polynomial approximation orders
 - ▶ *Conditionally* positive functions: polynomial detrending
 - ▶ Native space *norm*: indicator for problems (e. g. discontinuities)
- ~> employ *Gaussians* (or multiquadrics)
- ~> use low-order polynomial *detrending*
- ~> determine *number of clusters* by norm of the native space

Medium size model

- ▶ *Reuse results* from offline phase
- ▶ Galerkin projection for system matrices in *affine form* (medium size)
- ▶ Project *medium-size model* to $\tilde{\Sigma}$ in online phase

For details, see Sara Grundel's talks at MoRePas II, Nonlinear MOR Workshop, and Overton's "60th birthday" Workshop.

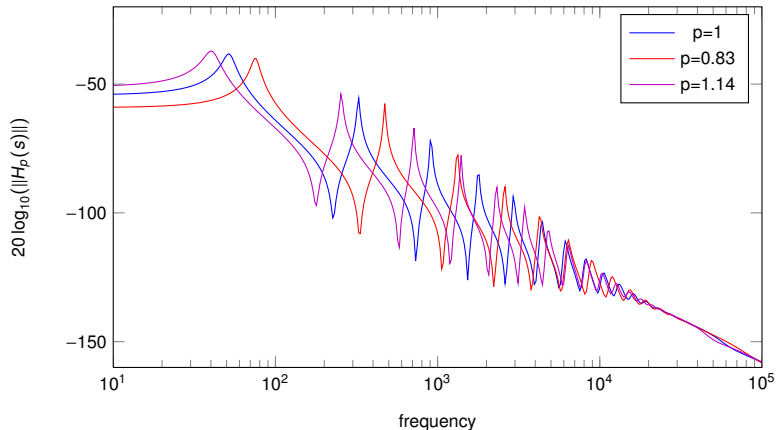
~> *speed-up* without additional cost

Examples

- ▶ Parametric beam model ($d = 240$)
- ▶ Anemometer ($d = 29,008$, $n = 1$ and $n = 3$)
- ▶ Synthetic model (to exhibit more challenging problems)

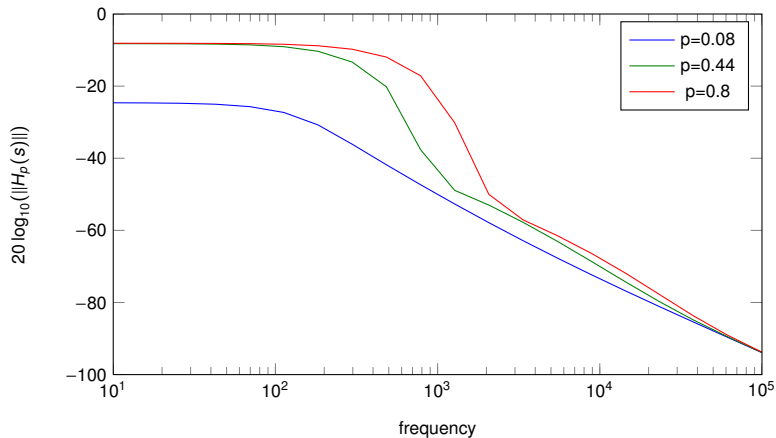
Timoshenko beam

Transfer function of a parametrized LTI system for different choices of p :



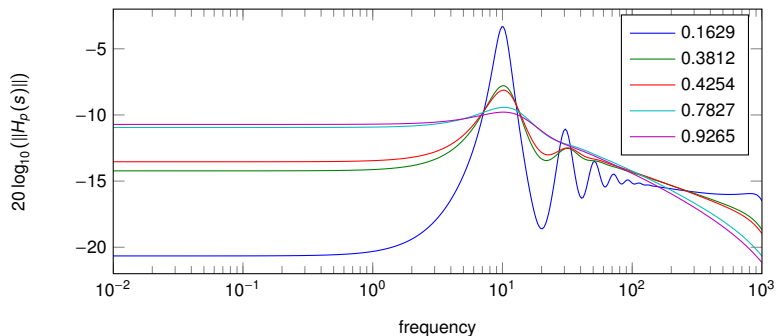
Anemometer (1D)

Transfer function of a parametrized LTI system for different choices of p :



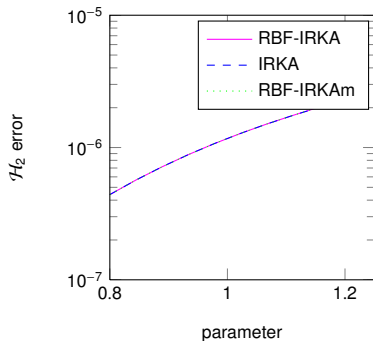
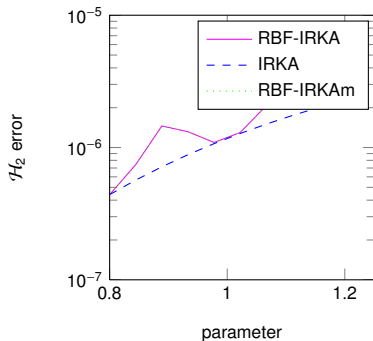
Synthetic example

Transfer function of a parametrized LTI system for different choices of p :



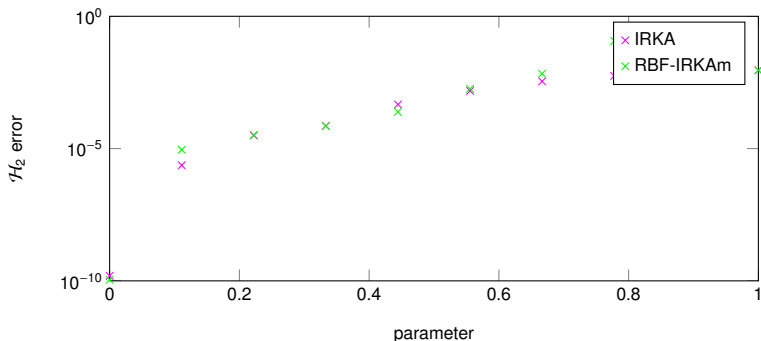
Error evaluation, Timoshenko beam

\mathcal{H}_2 error of the reduced parametrized system using IRKA (no interpolation), IRKA with RBF (interpolation), IRKA and medium-size model with RBF – three vs. five interpolation points:



Error evaluation, Anemometer (1D)

\mathcal{H}_2 error of the reduced parametrized system of size 4 using IRKA (no interpolation), IRKA and medium-size model with RBF – five interpolation points:



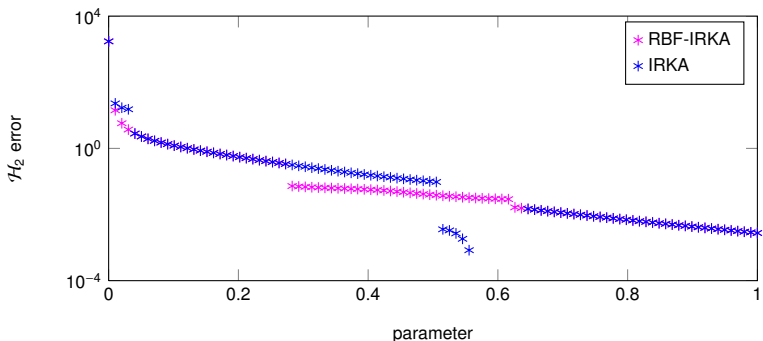
Error evaluation, Anemometer (3D)

\mathcal{H}_2 error of the reduced parametrized system using IRKA (no interpolation), IRKA and medium-size model with RBF – different reduced sized (r) and number of interpolation points (N):

	$r = 4, N = 5$	$r = 8, N = 5$	$r = 8, N = 10$
RBF-IRKAm	3.21×10^{-5}	1×10^{-6}	1×10^{-8}
IRKA	3.19×10^{-5}	3×10^{-8}	2×10^{-8}

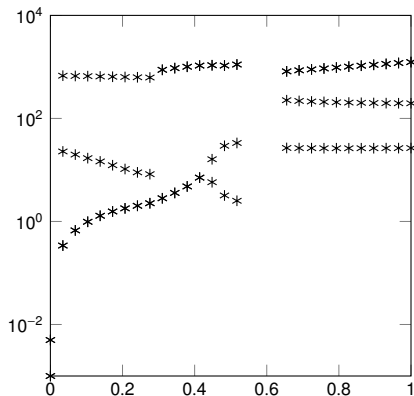
Error evaluation, synthetic example

\mathcal{H}_2 error of the reduced parametrized system using IRKA (no interpolation), IRKA with RBF – several p :



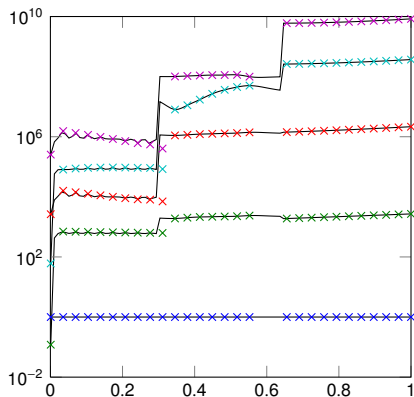
Clustering, synthetic example

Eigenvalues $\Sigma(p)$ of the reduced system matrix, for $r = 4$ and several p (dots):



Clustering, synthetic example

Coefficients $f(p)$ of the corresponding characteristic polynomial, for $r = 4$ and several p (colored dots), and approximation $\tilde{f}(p)$ (black line):



Parametric model order reduction

- ▶ Parametric linear time-invariant systems
- ▶ \mathcal{H}_2 optimal model order reduction (IRKA)
- ▶ *RBF interpolation* of $\Sigma(p)$ using coefficients of the characteristic polynomial
- ▶ *Clustering* guided by the norm of the reproducing kernel Hilbert space innate to a radial basis
- ▶ *Medium-size model* and projection to interpolated $\Sigma(p)$
- ▶ Numerical results (synthetic as well as simple practical test problems)

Open problems

- ▶ Stable *root finding* (minimum polynomial?)
- ▶ Nonlinear systems (*bilinear* systems)
- ▶ Transfer RBF *error bounds* to reduced model

Thank you for your attention!