

# Two-sided Moment Matching-Based Reduction for MIMO Quadratic-Bilinear Systems

**Maria Cruz Varona**

joint work with Elcio Fiordeliso Junior

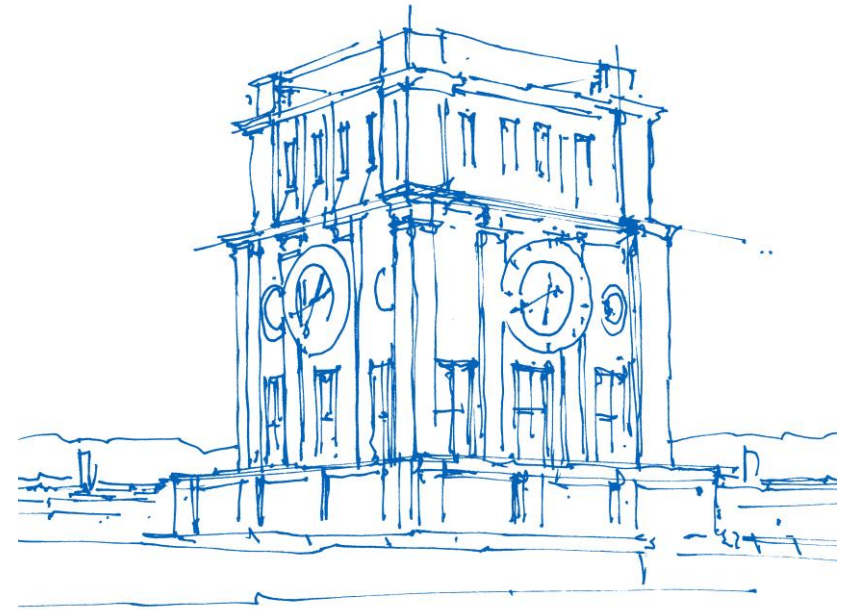
Technical University Munich

Department of Mechanical Engineering

Chair of Automatic Control

11th Elgersburg Workshop

Elgersburg, 20th February 2017



*Uhrenturm der TUM*

# Motivation

Given a large-scale nonlinear control system of the form

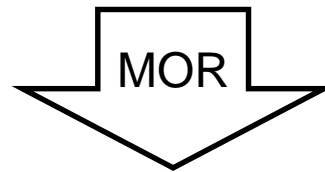
$$\det(\mathbf{E}) \neq 0$$

$$\Sigma : \begin{cases} \mathbf{E}\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t)) + \mathbf{B}\mathbf{u}(t), \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t), \quad \mathbf{x}(0) = \mathbf{x}_0 \end{cases}$$

$$\mathbf{x}(t) \in \mathbb{R}^n$$

with  $\mathbf{E} \in \mathbb{R}^{n \times n}$ ,  $\mathbf{f}(\mathbf{x}(t)) : \mathbb{R}^n \rightarrow \mathbb{R}^n$  and  $\mathbf{B} \in \mathbb{R}^{n \times m}$ ,  $\mathbf{C} \in \mathbb{R}^{q \times n}$

Simulation, design, control and optimization cannot be done efficiently!



Reduced order model (ROM)

$$\Sigma_r : \begin{cases} \mathbf{E}_r \dot{\mathbf{x}}_r(t) = \mathbf{f}_r(\mathbf{x}_r(t)) + \mathbf{B}_r \mathbf{u}(t), \\ \mathbf{y}_r(t) = \mathbf{C}_r \mathbf{x}_r(t), \quad \mathbf{x}_r(0) = \mathbf{x}_{r,0} \end{cases}$$

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

with  $\mathbf{E}_r \in \mathbb{R}^{r \times r}$ ,  $\mathbf{f}_r(\mathbf{x}_r(t)) : \mathbb{R}^r \rightarrow \mathbb{R}^r$  and  $\mathbf{B}_r \in \mathbb{R}^{r \times m}$ ,  $\mathbf{C}_r \in \mathbb{R}^{q \times r}$

$$\text{Goal: } \mathbf{y}_r(t) \approx \mathbf{y}(t)$$

# State-of-the-Art: Overview

## Reduction of nonlinear (parametric) systems

$$\mathbf{E}\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{b}u$$
$$y = \mathbf{c}^T \mathbf{x}$$

- ✓ Simulation-based:
  - POD, TPWL
  - Reduced Basis, Empirical Gramians

## Reduction of bilinear systems

$$\mathbf{E}\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{N}\mathbf{x}u + \mathbf{b}u$$
$$y = \mathbf{c}^T \mathbf{x}$$

- ✓ Carleman bilinearization (approx.)
- ⚠ Large increase of dimension:  $n + n^2$
- ✓ Generalization of well-known methods:
  - Balanced truncation
  - **Krylov subspace methods**
  - **$\mathcal{H}_2$  (pseudo)-optimal approaches**

## Reduction of quadratic-bilinear systems

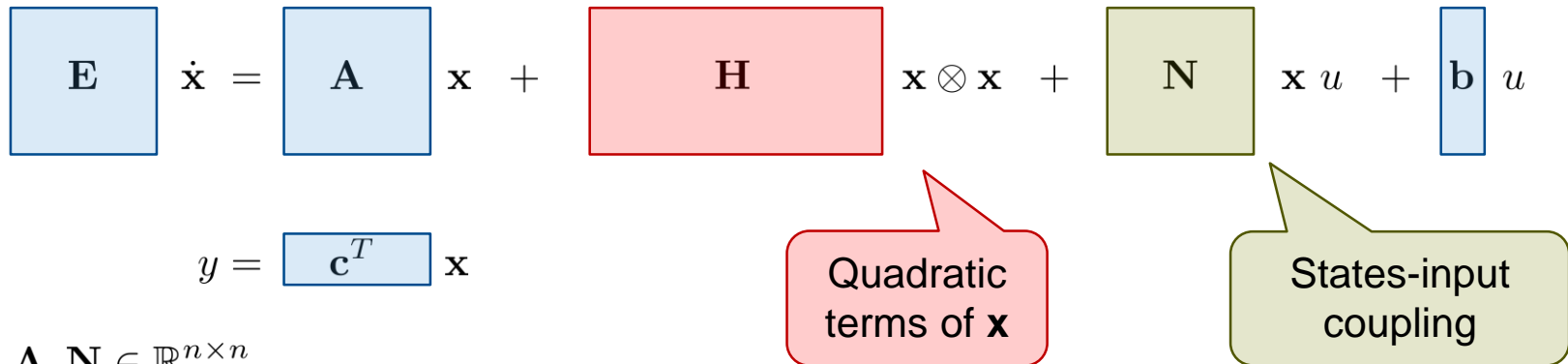
$$\mathbf{E}\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{H}(\mathbf{x} \otimes \mathbf{x}) + \mathbf{N}\mathbf{x}u + \mathbf{b}u$$
$$y = \mathbf{c}^T \mathbf{x}$$

- ✓ **Quadratic-bilinearization** (no approx.!)
- ✓ Minor increase of dimension:  $2n, 3n$
- ✓ Generalization of well-known methods:
  - **Krylov subspace methods**
  - **$\mathcal{H}_2$ -optimal approaches**
- Reduction methods for **MIMO** models

# Quadratic-Bilinearization Process

SISO **Quadratic-bilinear** system:

$$\mathbf{E} \dot{\mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{H} \mathbf{x} \otimes \mathbf{x} + \mathbf{N} \mathbf{x} u + \mathbf{b} u$$

$$y = \mathbf{c}^T \mathbf{x}$$


$$\mathbf{E}, \mathbf{A}, \mathbf{N} \in \mathbb{R}^{n \times n}$$

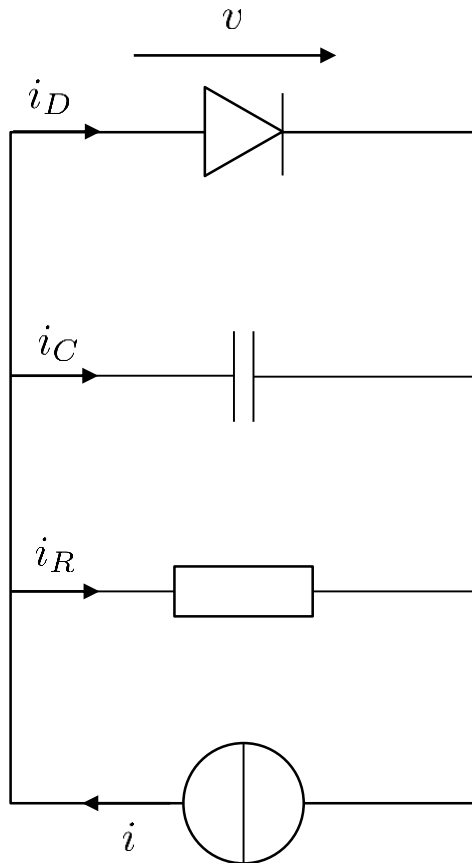
$$\mathbf{H} \in \mathbb{R}^{n \times n^2}: \text{Hessian tensor}$$

$$\mathbf{b}, \mathbf{c} \in \mathbb{R}^n$$

**Objective:** Bring general nonlinear systems to the quadratic-bilinear (QB) form

- 1 **Polynomialization:** Convert nonlinear system into an equivalent **polynomial system**
- 2 **Quadratic-bilinearization:** Convert the polynomial system into a **QBDAE**

# Quadratic-Bilinearization Process – Example



$$i_C + i_R + i_D = i \quad \text{with} \quad \begin{cases} i_C = C\dot{v} \\ i_R = \frac{v}{R} \\ i_D = e^{\alpha v} - 1 \end{cases}$$

**Nonlinear ODE:**  $\dot{v} = \frac{1}{C} \left( -\frac{v}{R} - e^{\alpha v} + 1 + i \right)$

- Polynomialization step:** Introduce new variable and its Lie derivative

$$w = e^{\alpha v} - 1$$

$$\dot{v} = \frac{1}{C} \left( -\frac{v}{R} - w + i \right)$$

$$\dot{w} = (\alpha e^{\alpha v})\dot{v}$$

$$= \frac{\alpha}{C} \left( -\frac{vw}{R} - w^2 + wi - \frac{v}{R} - w + i \right)$$

# Quadratic-Bilinearization Process – Example

**2 Quadratic-bilinearization step:** Convert polynomial system into a QBDAE

$$\dot{v} = \frac{1}{C} \left( -\frac{v}{R} - w + i \right)$$

$$\dot{w} = \frac{\alpha}{C} \left( -\frac{vw}{R} - w^2 + wi - \frac{v}{R} - w + i \right)$$

$$\underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}}_{\mathbf{E}} \underbrace{\begin{bmatrix} \dot{v} \\ \dot{w} \end{bmatrix}}_{\dot{\mathbf{x}}} = \underbrace{\begin{bmatrix} -\frac{1}{RC} & -\frac{1}{C} \\ -\frac{\alpha}{RC} & -\frac{\alpha}{C} \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} v \\ w \end{bmatrix}}_{\mathbf{x}} + \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & -\frac{\alpha}{RC} & 0 & -\frac{\alpha}{C} \end{bmatrix}}_{\mathbf{H}} \underbrace{\begin{bmatrix} v^2 \\ vw \\ vw \\ w^2 \end{bmatrix}}_{\mathbf{x} \otimes \mathbf{x}} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & \frac{\alpha}{C} \end{bmatrix}}_{\mathbf{N}} \underbrace{\begin{bmatrix} v \\ w \end{bmatrix}}_{\mathbf{x}} \underbrace{i}_u + \underbrace{\begin{bmatrix} \frac{1}{C} \\ \frac{\alpha}{C} \end{bmatrix}}_{\mathbf{b}} \underbrace{i}_u$$

Equivalent **representation**

Dimension slightly  
**increased**

Transformation **not unique**

The matrix **H** can be seen as a **tensor**

# Variational Analysis of Nonlinear Systems

[Rugh '81]

**Assumption:** Nonlinear system can be broken down into a series of **homogeneous subsystems** that depend nonlinearly from each other (**Volterra theory**)

For an input of the form  $\alpha u(t)$ , we assume that the response should be of the form

$$\mathbf{x}(t) = \alpha \mathbf{x}_1(t) + \alpha^2 \mathbf{x}_2(t) + \alpha^3 \mathbf{x}_3(t) + \dots$$

Inserting the assumed input and response in the QB system and comparing coefficients of  $\alpha^k$ , we obtain the **variational equations**:

$$\begin{aligned} \mathbf{E}\dot{\mathbf{x}}_1 &= \mathbf{A}\mathbf{x}_1 + \mathbf{b}u \\ \mathbf{E}\dot{\mathbf{x}}_2 &= \mathbf{A}\mathbf{x}_2 + \mathbf{H}\mathbf{x}_1 \otimes \mathbf{x}_1 + \mathbf{N}\mathbf{x}_1 u \\ \mathbf{E}\dot{\mathbf{x}}_3 &= \mathbf{A}\mathbf{x}_3 + \mathbf{H}(\mathbf{x}_1 \otimes \mathbf{x}_2 + \mathbf{x}_2 \otimes \mathbf{x}_1) + \mathbf{N}\mathbf{x}_2 u \\ &\vdots \\ \mathbf{E}\dot{\mathbf{x}}_k &= \mathbf{A}\mathbf{x}_k + \sum_{i=1}^{k-1} \mathbf{H}(\mathbf{x}_i \otimes \mathbf{x}_{k-i}) + \mathbf{N}\mathbf{x}_{k-1} u, \quad k = 4, 5, 6, \dots \end{aligned}$$

# Generalized Transfer Functions (SISO)

[Rugh '81]

Series of generalized transfer functions can be obtained via the [growing exponential approach](#):

## 1<sup>st</sup> subsystem:

$$\mathbf{A}_{s_0} = \mathbf{A} - s_0 \mathbf{E}$$

$$G_1(s_1) = -\mathbf{c}^T (\mathbf{A} - s_1 \mathbf{E})^{-1} \mathbf{b} = -\mathbf{c}^T \mathbf{A}_{s_1}^{-1} \mathbf{b}$$

## 2<sup>nd</sup> subsystem:

$$G_2(s_1, s_2) = -\frac{1}{2} \mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} [\mathbf{H}(\mathbf{A}_{s_1}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_2}^{-1} \mathbf{b} + \mathbf{A}_{s_2}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_1}^{-1} \mathbf{b}) - \mathbf{N}(\mathbf{A}_{s_1}^{-1} \mathbf{b} + \mathbf{A}_{s_2}^{-1} \mathbf{b})]$$

**H is symmetric**

$$\mathbf{H}(\mathbf{u} \otimes \mathbf{v}) = \mathbf{H}(\mathbf{v} \otimes \mathbf{u})$$

$$G_2(s_1, s_2) = -\mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} \left[ \mathbf{H}(\mathbf{A}_{s_1}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_2}^{-1} \mathbf{b}) - \frac{1}{2} \mathbf{N}(\mathbf{A}_{s_1}^{-1} \mathbf{b} + \mathbf{A}_{s_2}^{-1} \mathbf{b}) \right]$$

$$s_1 = s_2 = \sigma$$

$$G_2(\sigma, \sigma) = -\mathbf{c}^T \mathbf{A}_{2\sigma}^{-1} [\mathbf{H}(\mathbf{A}_{\sigma}^{-1} \mathbf{b} \otimes \mathbf{A}_{\sigma}^{-1} \mathbf{b}) - \mathbf{N} \mathbf{A}_{\sigma}^{-1} \mathbf{b}]$$



# Moments of QB-Transfer Functions

**Taylor coefficients** of the transfer function:  $G(s) = \underbrace{G(s_0)}_{m_0} + \underbrace{\frac{dG(s_0)}{ds}}_{m_1} (s - s_0) + \underbrace{\frac{1}{2!} \frac{d^2G(s_0)}{ds^2}}_{m_2} (s - s_0)^2 + \dots$

**1<sup>st</sup> subsystem:**  $G_1(s_1) = -\mathbf{c}^T (\mathbf{A} - s_1 \mathbf{E})^{-1} \mathbf{b} = -\mathbf{c}^T \mathbf{A}_{s_1}^{-1} \mathbf{b}$

$$\mathbf{A}_s = \mathbf{A} - s\mathbf{E}$$

$$\frac{\partial}{\partial s} \mathbf{A}_s^{-1}(s) = -\mathbf{A}_s^{-1} \frac{\partial \mathbf{A}_s}{\partial s} \mathbf{A}_s^{-1} = \mathbf{A}_s^{-1} \mathbf{E} \mathbf{A}_s^{-1}$$

$$\frac{\partial G_1}{\partial s_1} = -\mathbf{c}^T \mathbf{A}_{s_1}^{-1} \mathbf{E} \mathbf{A}_{s_1}^{-1} \mathbf{b}$$

**2<sup>nd</sup> subsystem:**  $G_2(s_1, s_2) = -\frac{1}{2} \mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} [\mathbf{H}(\mathbf{A}_{s_1}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_2}^{-1} \mathbf{b} + \mathbf{A}_{s_2}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_1}^{-1} \mathbf{b}) - \mathbf{N}(\mathbf{A}_{s_1}^{-1} \mathbf{b} + \mathbf{A}_{s_2}^{-1} \mathbf{b})]$

$$\begin{aligned} \frac{\partial G_2}{\partial s_1} = & -\mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} \mathbf{E} \mathbf{A}_{s_1+s_2}^{-1} \mathbf{H}[\mathbf{A}_{s_1}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_2}^{-1} \mathbf{b}] \\ & -\mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} \mathbf{H}[\mathbf{A}_{s_1}^{-1} \mathbf{E} \mathbf{A}_{s_1}^{-1} \mathbf{b} \otimes \mathbf{A}_{s_2}^{-1} \mathbf{b}] \\ & + \frac{1}{2} \mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} \mathbf{E} \mathbf{A}_{s_1+s_2}^{-1} \mathbf{N}[\mathbf{A}_{s_1}^{-1} \mathbf{b} + \mathbf{A}_{s_2}^{-1} \mathbf{b}] \\ & + \frac{1}{2} \mathbf{c}^T \mathbf{A}_{s_1+s_2}^{-1} \mathbf{N}[\mathbf{A}_{s_1}^{-1} \mathbf{E} \mathbf{A}_{s_1}^{-1} \mathbf{b}] \end{aligned}$$

# Multimoments approach (SISO)

---

**Algorithm 1** QB Multimoment Matching (SISO)

---

[Breiten '12]

**Input:**  $\mathbf{E}$ ,  $\mathbf{A}$ ,  $\mathbf{H}$ ,  $\mathbf{N}$ ,  $\mathbf{b}$ ,  $\mathbf{c}$ , shift  $\sigma$ , reduced order of first transfer function  $q_1$   
 and of the second transfer function  $q_2$

**Output:** Projection matrices  $\mathbf{V}$ ,  $\mathbf{W}$

- 1:  $\mathbf{V}_1 = \mathcal{K}_{q_1}(\mathbf{A}_\sigma^{-1}\mathbf{E}, \mathbf{A}_\sigma^{-1}\mathbf{b})$
- 2:  $\mathbf{W}_1 = \mathcal{K}_{q_1}(\mathbf{A}_{2\sigma}^{-T}\mathbf{E}^T, \mathbf{A}_{2\sigma}^{-T}\mathbf{c})$
- 3: **for**  $i = 1 : q_2$  **do**
- 4:      $\mathbf{V}_2^i = \mathcal{K}_{q_2-i+1}(\mathbf{A}_{2\sigma}^{-1}\mathbf{E}, \mathbf{A}_{2\sigma}^{-1}\mathbf{N}\mathbf{V}_1(:, i))$
- 5:      $\mathbf{W}_2^i = \mathcal{K}_{q_2-i+1}(\mathbf{A}_\sigma^{-T}\mathbf{E}^T, \mathbf{A}_\sigma^{-T}\mathbf{N}^T\mathbf{W}_1(:, i))$
- 6:     **for**  $j = 1 : \min(q_2 - i + 1, i)$  **do**
- 7:          $\mathbf{V}_3^{i,j} = \mathcal{K}_{q_2-i+1}(\mathbf{A}_{2\sigma}^{-1}\mathbf{E}, \mathbf{A}_{2\sigma}^{-1}\mathbf{H}(\mathbf{V}_1(:, i) \otimes \mathbf{V}_1(:, j)))$
- 8:          $\mathbf{W}_3^{i,j} = \mathcal{K}_{q_2-i+1}(\mathbf{A}_\sigma^{-T}\mathbf{E}^T, \mathbf{A}_\sigma^{-T}\mathbf{H}^{(2)}(\mathbf{V}_1(:, i) \otimes \mathbf{W}_1(:, j)))$
- 9:     **end for**
- 10: **end for**
- 11:  $\text{span}(\mathbf{V}) = \text{span}(\mathbf{V}_1) \cup \bigcup_i \text{span}(\mathbf{V}_2^i) \cup \bigcup_{i,j} \text{span}(\mathbf{V}_3^{i,j})$
- 12:  $\text{span}(\mathbf{W}) = \text{span}(\mathbf{W}_1) \cup \bigcup_i \text{span}(\mathbf{W}_2^i) \cup \bigcup_{i,j} \text{span}(\mathbf{W}_3^{i,j})$

**linear**

**bilinear**

**quadratic**

$q_1 + q_2^2 + q_2^2$   
 columns per shift

$$\begin{aligned} \frac{\partial^i G_1}{\partial s_1^i}(\sigma) &= \frac{\partial^i G_{1,r}}{\partial s_1^i}(\sigma), & i = 0, \dots, q_1 - 1 \\ \frac{\partial^i G_1}{\partial s_1^i}(2\sigma) &= \frac{\partial^i G_{1,r}}{\partial s_1^i}(2\sigma), & i = 0, \dots, q_1 - 1 \\ \frac{\partial^{i+j}}{\partial s_1^i \partial s_2^j} G_2(\sigma, \sigma) &= \frac{\partial^{i+j}}{\partial s_1^i \partial s_2^j} G_{2,r}(\sigma, \sigma), & i + j \leq 2q_2 - 1 \end{aligned}$$

$$\text{span}(\mathbf{V}) = \text{span}(\mathbf{V}_{\text{lin}}) \cup \text{span}(\mathbf{V}_{\text{b}}) \cup \text{span}(\mathbf{V}_{\text{q}})$$

# Hermite approach (SISO)

Theorem: Two-sided rational interpolation

[Breiten '15]

Let  $\mathbf{E}_r = \mathbf{W}^T \mathbf{E} \mathbf{V}$  be nonsingular,  $\mathbf{A}_r = \mathbf{W}^T \mathbf{A} \mathbf{V}$ ,  $\mathbf{H}_r = \mathbf{W}^T \mathbf{H} (\mathbf{V} \otimes \mathbf{V})$ ,  $\mathbf{N}_r = \mathbf{W}^T \mathbf{N} \mathbf{V}$ ,  $\mathbf{b}_r = \mathbf{W}^T \mathbf{b}$ ,  $\mathbf{c}_r^T = \mathbf{c}^T \mathbf{V}$  with  $\mathbf{V}$ ,  $\mathbf{W} \in \mathbb{R}^{n \times r}$  having full rank such that

$$\text{span}(\mathbf{V}) \supset \text{span}_{i=1, \dots, k} \{ \mathbf{A}_{\sigma_i}^{-1} \mathbf{b}, \mathbf{A}_{2\sigma_i}^{-1} [\mathbf{H}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{b} \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{b}) - \mathbf{N} \mathbf{A}_{\sigma_i}^{-1} \mathbf{b}] \}$$

$$\text{span}(\mathbf{W}) \supset \text{span}_{i=1, \dots, k} \{ \mathbf{A}_{2\sigma_i}^{-T} \mathbf{c}, \mathbf{A}_{\sigma_i}^{-T} [\mathbf{H}^{(2)}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{b} \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{c}) - \frac{1}{2} \mathbf{N}^T \mathbf{A}_{2\sigma_i}^{-T} \mathbf{c}] \}$$

with  $\sigma_i \notin \{ \Lambda(\mathbf{A}, \mathbf{E}), \Lambda(\mathbf{A}_r, \mathbf{E}_r) \}$ .

2 columns  
per shift

Then:

$$G_1(\sigma_i) = G_{1,r}(\sigma_i) \quad \checkmark$$

$$G_1(2\sigma_i) = G_{1,r}(2\sigma_i) \quad \checkmark$$

$$G_2(\sigma_i, \sigma_i) = G_{2,r}(\sigma_i, \sigma_i) \quad \checkmark$$

$$\frac{\partial G_2}{\partial s_j}(\sigma_i, \sigma_i) = \frac{\partial G_{2,r}}{\partial s_j}(\sigma_i, \sigma_i) \quad \checkmark$$

# Krylov subspaces for SISO systems

$$\mathbf{A}_{s_0} = \mathbf{A} - s_0 \mathbf{E}$$

**Multimoments approach** [Gu '11, Breiten '12]:

$$\text{span}(\mathbf{V}) = \text{span}(\mathbf{V}_{\text{lin}}) \cup \text{span}(\mathbf{V}_{\text{b}}) \cup \text{span}(\mathbf{V}_{\text{q}})$$

$$\text{span}(\mathbf{V}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{\sigma}^{-1} \mathbf{b}, \mathbf{A}_{2\sigma}^{-1} \mathbf{N} \mathbf{A}_{\sigma}^{-1} \mathbf{b}, \mathbf{A}_{2\sigma}^{-1} \mathbf{H} (\mathbf{A}_{\sigma}^{-1} \mathbf{b} \otimes \mathbf{A}_{\sigma}^{-1} \mathbf{b}) \right\}$$

$$\text{span}(\mathbf{W}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{2\sigma}^{-T} \mathbf{c}, \mathbf{A}_{2\sigma}^{-T} \mathbf{N}^T \mathbf{A}_{2\sigma}^{-T} \mathbf{c}, \mathbf{A}_{2\sigma}^{-T} \mathbf{H}^{(2)} (\mathbf{A}_{\sigma}^{-1} \mathbf{b} \otimes \mathbf{A}_{2\sigma}^{-T} \mathbf{c}) \right\}$$

$$G_1(\sigma_i) = G_{1,r}(\sigma_i)$$

$$G_1(2\sigma_i) = G_{1,r}(2\sigma_i)$$

$$G_2(\sigma_i, \sigma_i) = G_{2,r}(\sigma_i, \sigma_i)$$

$$\frac{\partial}{\partial s_j} G_2(\sigma_i, \sigma_i) = \frac{\partial}{\partial s_j} G_{2,r}(\sigma_i, \sigma_i)$$

- **Quadratic** and **bilinear** dynamics are treated **separately**
- **Higher-order moments** can be matched
- **3** Krylov directions per shift

**Hermite approach** [Breiten '15]:

$$\text{span}(\mathbf{V}) = \text{span}(\mathbf{V}_{\text{lin}}) \cup \text{span}(\mathbf{V}_{\text{qb}})$$

$$\text{span}(\mathbf{V}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{\sigma}^{-1} \mathbf{b}, \mathbf{A}_{2\sigma}^{-1} [\mathbf{H} (\mathbf{A}_{\sigma}^{-1} \mathbf{b} \otimes \mathbf{A}_{\sigma}^{-1} \mathbf{b}) - \mathbf{N} \mathbf{A}_{\sigma}^{-1} \mathbf{b}] \right\}$$

$$\text{span}(\mathbf{W}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{2\sigma}^{-T} \mathbf{c}, \mathbf{A}_{\sigma}^{-T} \left[ \mathbf{H}^{(2)} (\mathbf{A}_{\sigma}^{-1} \mathbf{b} \otimes \mathbf{A}_{2\sigma}^{-T} \mathbf{c}) - \frac{1}{2} \mathbf{N}^T \mathbf{A}_{2\sigma}^{-T} \mathbf{c} \right] \right\}$$

$$G_1(\sigma_i) = G_{1,r}(\sigma_i)$$

$$G_1(2\sigma_i) = G_{1,r}(2\sigma_i)$$

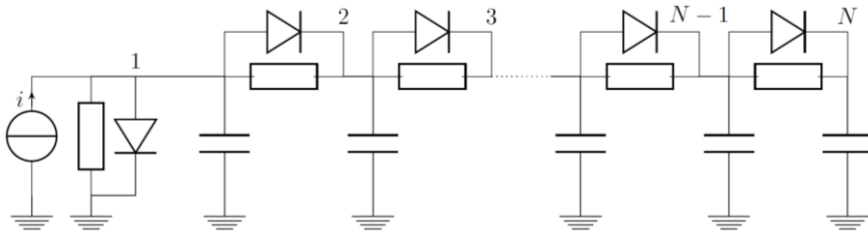
$$G_2(\sigma_i, \sigma_i) = G_{2,r}(\sigma_i, \sigma_i)$$

$$\frac{\partial}{\partial s_j} G_2(\sigma_i, \sigma_i) = \frac{\partial}{\partial s_j} G_{2,r}(\sigma_i, \sigma_i)$$

- **Quadratic and bilinear** dynamics are treated **together (as one)**
- **Only 0th and 1st moments** can be matched
- **2** Krylov directions per shift

# Numerical Examples: SISO RC-Ladder

SISO RC-Ladder model:



**Nonlinearity:**  $g(x) = e^{40x} + x - 1$

**Input/Output:**  $u(t) = e^{-t}$ ;  $y(t) = v_1(t)$

**Reduction information:**

$n = 1000$ ; Shifts  $s_0$  gotten from IRKA

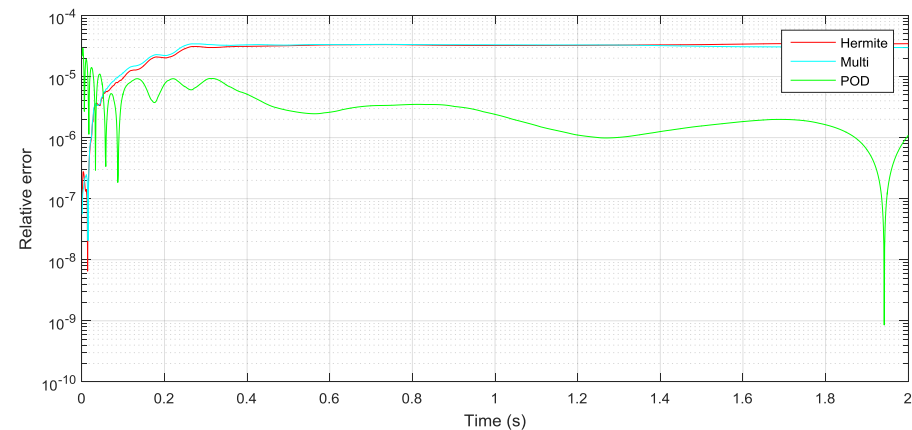
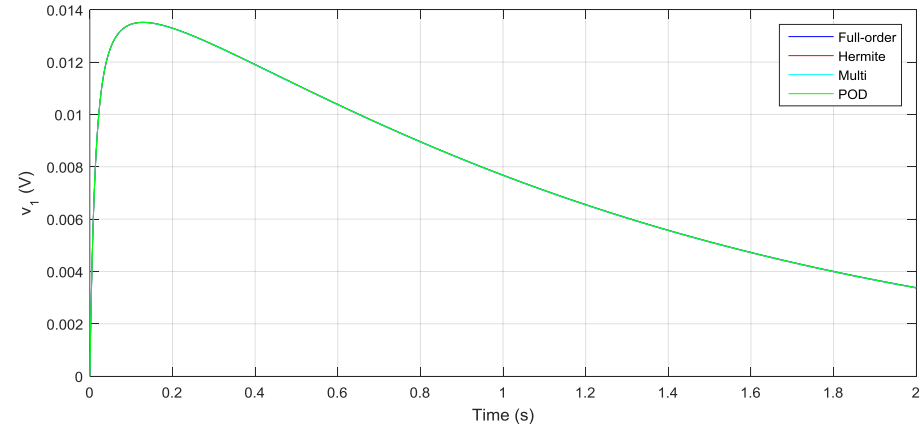
$t_{\text{sim,orig}} = 17.6 \text{ s}$

$r_{\text{her}} = 12$

$r_{\text{multi}} = 18$

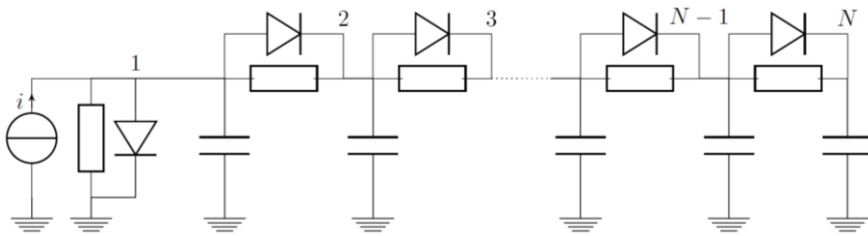
$t_{\text{sim,her}} = 0.116 \text{ s}$

$t_{\text{sim,multi}} = 0.122 \text{ s}$



# Numerical Examples: SISO RC-Ladder

SISO RC-Ladder model:



**Nonlinearity:**  $g(x) = e^{40x} + x - 1$

**Input/Output:**  $u(t) = 1/2 [\cos(2\pi t/10) + 1]$   
 $y(t) = v_1(t)$

**Reduction information:**

$n = 1000$ ; Shifts  $s_0$  gotten from IRKA

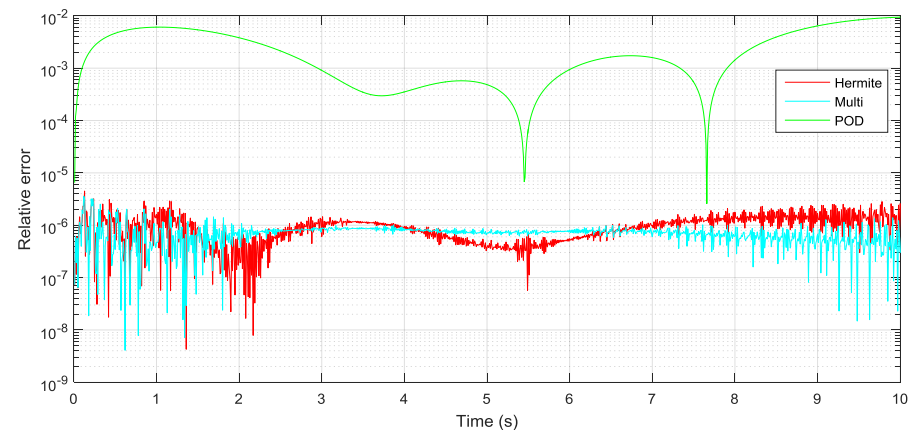
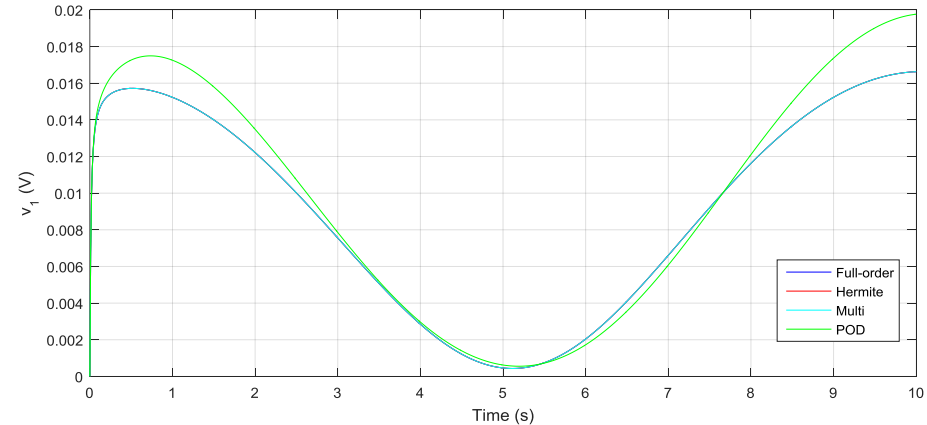
$t_{\text{sim,orig}} = 25.5 \text{ s}$

$r_{\text{her}} = 12$

$r_{\text{multi}} = 18$

$t_{\text{sim,her}} = 0.468 \text{ s}$

$t_{\text{sim,multi}} = 0.788 \text{ s}$



# MIMO quadratic-bilinear systems

MIMO Quadratic-bilinear system:

$$\mathbf{E} \dot{\mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{H} \mathbf{x} \otimes \mathbf{x} + \sum_{j=1}^m \mathbf{N}_j \mathbf{x} u_j + \mathbf{B} \mathbf{u}$$

$$\mathbf{y} = \mathbf{C} \mathbf{x}$$

One bilinear matrix for each input

$$\mathbf{E}, \mathbf{A}, \mathbf{N}_j \in \mathbb{R}^{n \times n}$$

$$\mathbf{H} \in \mathbb{R}^{n \times n^2}: \text{Hessian tensor}$$

$$\mathbf{B} \in \mathbb{R}^{n \times m}, \mathbf{C} \in \mathbb{R}^{p \times n}$$



$$\bar{\mathbf{N}} = [\mathbf{N}_1 \ \mathbf{N}_2 \ \dots \ \mathbf{N}_m] \in \mathbb{R}^{n \times n \cdot m}$$

$$\mathbf{E} \dot{\mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{H} (\mathbf{x} \otimes \mathbf{x}) + \bar{\mathbf{N}} (\mathbf{u} \otimes \mathbf{x}) + \mathbf{B} \mathbf{u}$$

$$\mathbf{y} = \mathbf{C} \mathbf{x}$$

# Transfer matrices of a MIMO QB system

Generalized transfer matrices can be obtained similarly via the [growing exponential approach](#):

**1<sup>st</sup> subsystem:**

$$\mathbf{A}_{s_0} = \mathbf{A} - s_0 \mathbf{E}$$

$$\mathbf{G}_1(s_1) = -\mathbf{C}(\mathbf{A} - s_1 \mathbf{E})^{-1} \mathbf{B} = -\mathbf{C} \mathbf{A}_{s_1}^{-1} \mathbf{B}$$

**2<sup>nd</sup> subsystem:**

$$\mathbf{G}_2(s_1, s_2) = -\frac{1}{2} \mathbf{C} \mathbf{A}_{s_1+s_2}^{-1} \left[ \mathbf{H}(\mathbf{A}_{s_1}^{-1} \mathbf{B} \otimes \mathbf{A}_{s_2}^{-1} \mathbf{B} + \mathbf{A}_{s_2}^{-1} \mathbf{B} \otimes \mathbf{A}_{s_1}^{-1} \mathbf{B}) - \bar{\mathbf{N}}(\mathbf{I}_m \otimes (\mathbf{A}_{s_1}^{-1} \mathbf{B} + \mathbf{A}_{s_2}^{-1} \mathbf{B})) \right]$$



$$s_1 = s_2 = \sigma$$

$$\mathbf{G}_2(\sigma, \sigma) = -\mathbf{C} \mathbf{A}_{2\sigma}^{-1} \left[ \mathbf{H}(\mathbf{A}_{\sigma}^{-1} \mathbf{B} \otimes \mathbf{A}_{\sigma}^{-1} \mathbf{B}) - \bar{\mathbf{N}}(\mathbf{I}_m \otimes \mathbf{A}_{\sigma}^{-1} \mathbf{B}) \right]$$

**Transfer matrices with**

$$\dim(\mathbf{G}_1(s)) = (p, m)$$

$$\dim(\mathbf{G}_2(s_1, s_2)) = (p, m^2)$$

The **quadratic term cannot be simplified**

$$\mathbf{H}(\mathbf{U} \otimes \mathbf{V}) \neq \mathbf{H}(\mathbf{V} \otimes \mathbf{U})$$



# Moments of QB-Transfer Matrices

**1<sup>st</sup> subsystem:**  $G_1(s_1) = -C(A - s_1E)^{-1}B = -CA_{s_1}^{-1}B$

$$A_s = A - sE$$

$$\frac{\partial}{\partial s} A_s^{-1}(s) = -A_s^{-1} \frac{\partial A_s}{\partial s} A_s^{-1} = A_s^{-1} E A_s^{-1}$$

$$\frac{\partial G_1}{\partial s_1} = -CA_{s_1}^{-1}EA_{s_1}^{-1}B$$

**2<sup>nd</sup> subsystem:**  $G_2(s_1, s_2) = -\frac{1}{2}CA_{s_1+s_2}^{-1} [H(A_{s_1}^{-1}B \otimes A_{s_2}^{-1}B + A_{s_2}^{-1}B \otimes A_{s_1}^{-1}B) - \bar{N}(I_m \otimes (A_{s_1}^{-1}B + A_{s_2}^{-1}B))]$

$$\begin{aligned} \frac{\partial G_2}{\partial s_1}(\sigma, \sigma) &= -CA_{2\sigma}^{-1}EA_{2\sigma}^{-1}H(A_{\sigma}^{-1}B \otimes A_{\sigma}^{-1}B) \\ &\quad -\frac{1}{2}CA_{2\sigma}^{-1}H(A_{\sigma}^{-1}EA_{\sigma}^{-1}B \otimes A_{\sigma}^{-1}B + A_{\sigma}^{-1}B \otimes A_{\sigma}^{-1}EA_{\sigma}^{-1}B) \\ &\quad + CA_{2\sigma}^{-1}EA_{2\sigma}^{-1}\bar{N}(I_m \otimes A_{\sigma}^{-1}B) \\ &\quad + \frac{1}{2}CA_{2\sigma}^{-1}\bar{N}(I_m \otimes A_{\sigma}^{-1}EA_{\sigma}^{-1}B) \end{aligned}$$

This term cannot be simplified

$$H(U \otimes V) \neq H(V \otimes U)$$

➔ Matching of 1st moment of 2nd transfer function much more involved!

# Block-Multimoments approach (MIMO)

Idea: Straightforward extension of the **multimoments** approach to the MIMO case

---

## Algorithm 1 QB Multimoment Matching (MIMO)

---

**Input:**  $\mathbf{E}$ ,  $\mathbf{A}$ ,  $\mathbf{H}$ ,  $\bar{\mathbf{N}}$ ,  $\mathbf{B}$ ,  $\mathbf{C}$ , shift  $\sigma$ , reduced order of first transfer function  $q_1$   
and of the second transfer function  $q_2$

**Output:** Projection matrices  $\mathbf{V}$ ,  $\mathbf{W}$

- 1:  $\mathbf{V}_1 = \mathcal{K}_{q_1}(\mathbf{A}_\sigma^{-1}\mathbf{E}, \mathbf{A}_\sigma^{-1}\mathbf{B})$
- 2:  $\mathbf{W}_1 = \mathcal{K}_{q_1}(\mathbf{A}_{2\sigma}^{-T}\mathbf{E}^T, \mathbf{A}_{2\sigma}^{-T}\mathbf{C}^T)$
- 3: **for**  $i = 1 : q_2$  **do**
- 4:      $\mathbf{V}_2^i = \mathcal{K}_{q_2-i+1}(\mathbf{A}_{2\sigma}^{-1}\mathbf{E}, \mathbf{A}_{2\sigma}^{-1}\bar{\mathbf{N}}(\mathbf{I}_m \otimes (\mathbf{A}_\sigma^{-1}\mathbf{E})^{i-1}\mathbf{A}_\sigma^{-1}\mathbf{B}))$
- 5:      $\mathbf{W}_2^i = \mathcal{K}_{q_2-i+1}(\mathbf{A}_\sigma^{-T}\mathbf{E}^T, \mathbf{A}_\sigma^{-T}\bar{\mathbf{N}}^{(2)}(\mathbf{I}_m \otimes (\mathbf{A}_{2\sigma}^{-1}\mathbf{E})^{i-1}\mathbf{A}_{2\sigma}^{-1}\mathbf{B}))$
- 6:     **for**  $j = 1 : \min(q_2 - i + 1, i)$  **do**
- 7:          $\mathbf{V}_3^{i,j} = \mathcal{K}_{q_2-i+1}(\mathbf{A}_{2\sigma}^{-1}\mathbf{E}, \mathbf{A}_{2\sigma}^{-1}\mathbf{H}((\mathbf{A}_\sigma^{-1}\mathbf{E})^{i-1}\mathbf{A}_\sigma^{-1}\mathbf{B} \otimes (\mathbf{A}_\sigma^{-1}\mathbf{E})^{j-1}\mathbf{A}_\sigma^{-1}\mathbf{B}))$
- 8:          $\mathbf{W}_3^{i,j} = \mathcal{K}_{q_2-i+1}(\mathbf{A}_\sigma^{-T}\mathbf{E}^T, \mathbf{A}_\sigma^{-T}\mathbf{H}^{(2)}((\mathbf{A}_\sigma^{-1}\mathbf{E})^{i-1}\mathbf{A}_\sigma^{-1}\mathbf{B} \otimes (\mathbf{A}_{2\sigma}^{-1}\mathbf{E})^{i-1}\mathbf{A}_{2\sigma}^{-1}\mathbf{B}))$
- 9:     **end for**
- 10: **end for**
- 11:  $\text{span}(\mathbf{V}) = \text{span}(\mathbf{V}_1) \cup \bigcup_i \text{span}(\mathbf{V}_2^i) \cup \bigcup_{i,j} \text{span}(\mathbf{V}_3^{i,j})$
- 12:  $\text{span}(\mathbf{W}) = \text{span}(\mathbf{W}_1) \cup \bigcup_i \text{span}(\mathbf{W}_2^i) \cup \bigcup_{i,j} \text{span}(\mathbf{W}_3^{i,j})$

**linear**

**bilinear**

**quadratic**

$m \cdot (q_1 + q_2^2 + q_2^2)$   
columns per shift

$$\begin{aligned} \frac{\partial^i \mathbf{G}_1}{\partial s_1^i}(\sigma) &= \frac{\partial^i \mathbf{G}_{1,r}}{\partial s_1^i}(\sigma), & i = 0, \dots, q_1 - 1 \\ \frac{\partial^i \mathbf{G}_1}{\partial s_1^i}(2\sigma) &= \frac{\partial^i \mathbf{G}_{1,r}}{\partial s_1^i}(2\sigma), & i = 0, \dots, q_1 - 1 \\ \frac{\partial^{i+j}}{\partial s_1^i \partial s_2^j} \mathbf{G}_2(\sigma, \sigma) &= \frac{\partial^{i+j}}{\partial s_1^i \partial s_2^j} \mathbf{G}_{2,r}(\sigma, \sigma), & i + j \leq 2q_2 - 1 \end{aligned}$$

$$\text{span}(\mathbf{V}) = \text{span}(\mathbf{V}_{\text{lin}}) \cup \text{span}(\mathbf{V}_{\text{b}}) \cup \text{span}(\mathbf{V}_{\text{q}})$$

# Block-Hermite approach (MIMO)

Aim: Extension of the **hermite** approach to the MIMO case. **Is that possible??**

**Propositions for Block-Hermite approach:**

1

$$\begin{aligned} \text{span}(\mathbf{V}) &\supset \text{span}_{i=1,\dots,k} \left\{ \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}, \right. \\ &\quad \left. \mathbf{A}_{2\sigma_i}^{-1} \left[ \mathbf{H}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}) - \bar{\mathbf{N}}(\mathbf{I}_m \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}) \right] \right\} \\ \text{span}(\mathbf{W}) &\supset \text{span}_{i=1,\dots,k} \left\{ \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T, \right. \\ &\quad \left. \mathbf{A}_{\sigma_i}^{-T} \left[ \mathbf{H}^{(2)}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T) - \bar{\mathbf{N}}^{(2)}(\mathbf{I}_m \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T) \right] \right\} \end{aligned}$$



**W must be adapted!**

2

$$\begin{aligned} \text{span}(\mathbf{V}) &\supset \text{span}_{i=1,\dots,k} \left\{ \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}, \right. \\ &\quad \left. \mathbf{A}_{2\sigma_i}^{-1} \left[ \mathbf{H}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}) - \bar{\mathbf{N}}(\mathbf{I}_m \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}) \right] \right\} \\ \text{span}(\mathbf{W}) &\supset \text{span}_{i=1,\dots,k} \left\{ \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T, \right. \\ &\quad \left. \mathbf{A}_{\sigma_i}^{-T} \left[ (\mathbf{H} + \mathbf{J})^{(2)}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T) - \bar{\mathbf{N}}^{(2)}(\mathbf{I}_m \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T) \right] \right\} \end{aligned}$$

$$\mathbf{H}(\mathbf{U} \otimes \mathbf{V}) \neq \mathbf{H}(\mathbf{V} \otimes \mathbf{U})$$

$$\mathbf{G}_1(\sigma_i) = \mathbf{G}_{1,r}(\sigma_i) \quad \checkmark$$

$$\mathbf{G}_1(2\sigma_i) = \mathbf{G}_{1,r}(2\sigma_i) \quad \checkmark$$

$$\mathbf{G}_2(\sigma_i, \sigma_i) = \mathbf{G}_{2,r}(\sigma_i, \sigma_i) \quad \checkmark$$

$$\frac{\partial \mathbf{G}_2}{\partial s_j}(\sigma_i, \sigma_i) = \frac{\partial \mathbf{G}_{2,r}}{\partial s_j}(\sigma_i, \sigma_i) \quad \times$$

$$\mathbf{J} = \mathbf{H}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{E} \otimes \mathbf{E}^{-1} \mathbf{A}_{\sigma_i})$$

**m + m<sup>2</sup> columns  
per shift**

# Krylov subspaces for MIMO systems

Idea: Combine **multimoments** and **hermite** approaches!

$$\mathbf{A}_{s_0} = \mathbf{A} - s_0 \mathbf{E}$$

**Block** tensor-based approach:

$$\text{span}(\mathbf{V}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}, \mathbf{A}_{\sigma_i}^{-1} \mathbf{E} \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}, \dots, (\mathbf{A}_{\sigma_i}^{-1} \mathbf{E})^m \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}, \right. \\ \left. \mathbf{A}_{2\sigma_i}^{-1} \left[ \mathbf{H}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}) - \bar{\mathbf{N}}(\mathbf{I}_m \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B}) \right] \right\}$$

quadratic-bilinear

$$\text{span}(\mathbf{W}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T, \mathbf{A}_{\sigma_i}^{-T} \mathbf{H}^{(2)}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T), \right. \\ \left. \mathbf{A}_{\sigma_i}^{-T} \bar{\mathbf{N}}^{(2)}(\mathbf{I}_m \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T) \right\}$$

quadratic

bilinear

$$\frac{\partial^l \mathbf{G}_1}{\partial s^l}(\sigma_i) = \frac{\partial^l \mathbf{G}_{1,r}}{\partial s^l}(\sigma_i) \quad \checkmark \quad l = 0, \dots, m$$

$$\mathbf{G}_1(2\sigma_i) = \mathbf{G}_{1,r}(2\sigma_i) \quad \checkmark$$

$$\mathbf{G}_2(\sigma_i, \sigma_i) = \mathbf{G}_{2,r}(\sigma_i, \sigma_i) \quad \checkmark$$

$$\frac{\partial \mathbf{G}_2}{\partial s_j}(\sigma_i, \sigma_i) = \frac{\partial \mathbf{G}_{2,r}}{\partial s_j}(\sigma_i, \sigma_i) \quad \checkmark \quad j = 1, 2$$

- **Subsystem interpolation**
- **(m+1) + 4** moments matched
- **(m+1)·m + m<sup>2</sup> = m + 2m<sup>2</sup>** columns per shift

# Krylov subspaces for MIMO systems

Idea: Add **tangential directions!**

$$\mathbf{A}_{s_0} = \mathbf{A} - s_0 \mathbf{E}$$

**Tangential** tensor-based approach:

$$\text{span}(\mathbf{V}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i, \mathbf{A}_{\sigma_i}^{-1} \mathbf{E} \mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i, \dots, (\mathbf{A}_{\sigma_i}^{-1} \mathbf{E})^m \mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i, \right. \\ \left. \mathbf{A}_{2\sigma_i}^{-1} \left[ \mathbf{H}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i) - \bar{\mathbf{N}}(\mathbf{r}_i \otimes \mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i) \right] \right\}$$

$$\text{span}(\mathbf{W}) \supset \text{span}_{i=1, \dots, k} \left\{ \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T \mathbf{l}_i, \mathbf{A}_{\sigma_i}^{-T} \mathbf{H}^{(2)}(\mathbf{A}_{\sigma_i}^{-1} \mathbf{B} \mathbf{r}_i \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T \mathbf{l}_i), \right. \\ \left. \mathbf{A}_{\sigma_i}^{-T} \bar{\mathbf{N}}^{(2)}(\mathbf{r}_i \otimes \mathbf{A}_{2\sigma_i}^{-T} \mathbf{C}^T \mathbf{l}_i) \right\}$$

$$\left[ \frac{\partial^l \mathbf{G}_1}{\partial s^l}(\sigma_i) \right] \mathbf{r}_i = \left[ \frac{\partial^l \mathbf{G}_{1,r}}{\partial s^l}(\sigma_i) \right] \mathbf{r}_i \quad l = 0, \dots, m$$

$$\mathbf{l}_i^T [\mathbf{G}_1(2\sigma_i)] = \mathbf{l}_i^T [\mathbf{G}_{1,r}(2\sigma_i)]$$

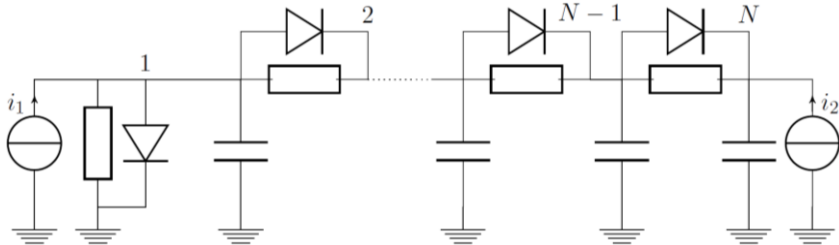
$$[\mathbf{G}_2(\sigma_i, \sigma_i)] (\mathbf{r}_i \otimes \mathbf{r}_i) = [\mathbf{G}_{2,r}(\sigma_i, \sigma_i)] (\mathbf{r}_i \otimes \mathbf{r}_i)$$

$$\mathbf{l}_i^T \left[ \frac{\partial \mathbf{G}_2}{\partial s_j}(\sigma_i, \sigma_i) \right] (\mathbf{r}_i \otimes \mathbf{r}_i) = \mathbf{l}_i^T \left[ \frac{\partial \mathbf{G}_{2,r}}{\partial s_j}(\sigma_i, \sigma_i) \right] (\mathbf{r}_i \otimes \mathbf{r}_i) \quad j = 1, 2$$

- **Tangential sub-system interpolation**
- **(m+1) + 4** moments matched
- **3** columns per shift

# Numerical Examples: MIMO RC-Ladder

MIMO RC-Ladder model:



**Nonlinearity:**  $g(x) = e^{40x} + x - 1$

**Inputs/Outputs:**  $\mathbf{u}(t) = \sin(2t) \cdot [1 \ 1]^T$   
 $\mathbf{y}(t) = [v_1(t) \ v_{N-1,N}]^T$

**Reduction information:**

$n = 800$ ; Shifts  $s_0$  gotten from IRKA

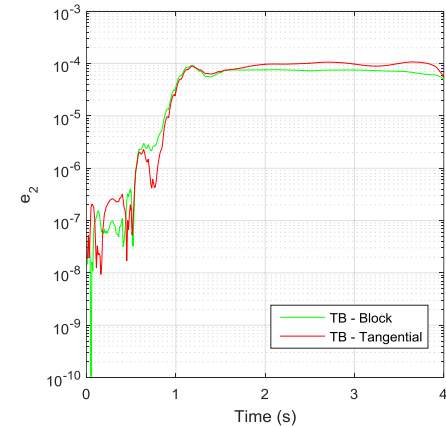
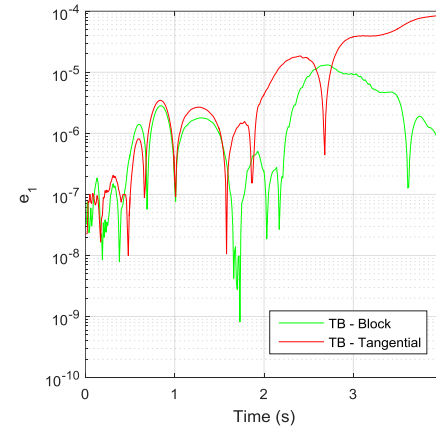
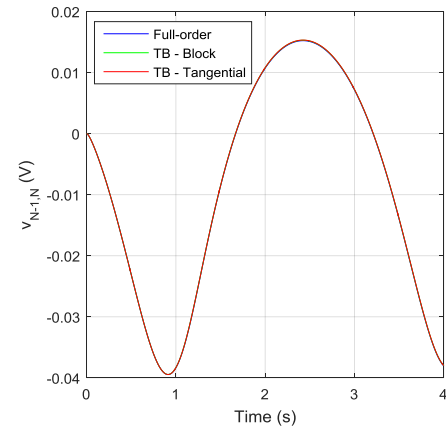
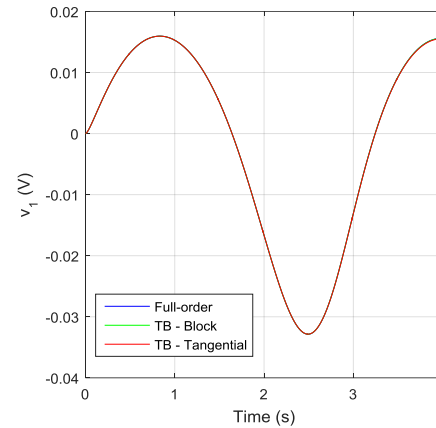
$t_{\text{sim,orig}} = 17.4 \text{ s}$

$r_{\text{block}} = 30$

$r_{\text{tang}} = 21$

$t_{\text{sim,block}} = 0.232 \text{ s}$

$t_{\text{sim,tang}} = 0.109 \text{ s}$



# Numerical Examples: FitzHugh-Nagumo

$$\epsilon \frac{\partial v}{\partial t}(x, t) = \epsilon^2 \frac{\partial^2 v}{\partial x^2}(x, t) + f(v(x, t)) - w(x, t) + g$$

$$\frac{\partial w}{\partial t}(x, t) = hv(x, t) - \gamma w(x, t) + g$$

**Nonlinearity:**  $f(v) = v(v - 0.1)(1 - v)$

**Inputs:**  $\mathbf{u}(t) = \begin{bmatrix} 5 \cdot 10^4 t^3 e^{-15t} \\ 1 \end{bmatrix}$

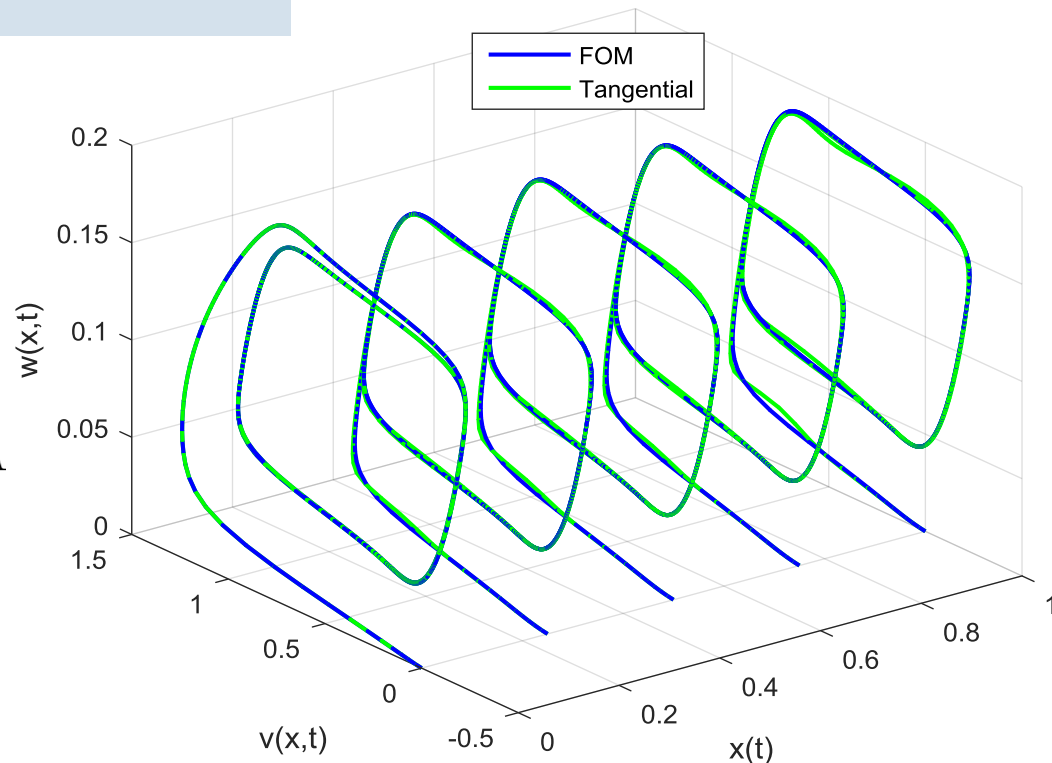
**Reduction information:**

$n = 1500$ ; Shifts  $s_0$  gotten from IRKA

$t_{sim,orig} = 518$  s

$r_{tang} = 15$

$t_{sim,tang} = 0.631$  s



# Conclusions & Outlook

## Summary:

- Many **smooth nonlinear systems** can be equivalently transformed into QB systems
- Systems theory and Krylov subspaces for SISO QB systems
- Extension of systems theory and Krylov subspaces to **MIMO case**

## Conclusions:

- Transfer matrices make Krylov subspace methods more complicated in MIMO case
- **Tangential directions**: good option
- **Choice of shifts and tangential directions** plays an important role

## Outlook:

- **Optimal** choice of **shifts** (comparison with T-QB-IRKA)
- **Stability preserving** methods
- Other **benchmark** models

Thank you for your attention!