

# Towards Output Krylov Subspace-Based Nonlinear Moment Matching

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## 1. INTRODUCTION

The transfer of the moment matching reduction concept from linear to nonlinear systems has been pioneered over the last years by Astolfi [2010a]. In this and further publications, the focus lies on the extension of *input Krylov subspace*-based moment matching to the nonlinear case. The generalization is based on the steady-state interpretation of moment matching and involves the difficult solution of a nonlinear partial differential equation (PDE).

Moreover, the time-domain interpretation of *output Krylov subspace*-based moment matching has been also investigated for linear systems (Astolfi [2010b], Ionescu [2016]) using the dual Sylvester equation, and transferred to the nonlinear case in Ionescu and Astolfi [2013, 2016].

The aim of this short contribution is (i) to comprehensively explain the steady-state perception of *output Krylov moment matching* given by Ionescu [2016]. Another goal is (ii) to state our progress concerning a practicable, *projective* output Krylov subspace-based nonlinear moment matching method, so that this and further topics can be discussed at the conference.

## 2. LINEAR MOMENT MATCHING

Consider a large-scale, linear time-invariant (LTI), asymptotically stable, state-space model of the form

$$\mathbf{E} \dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t), \quad \mathbf{y}(t) = \mathbf{C} \mathbf{x}(t), \quad (1)$$

where  $\det(\mathbf{E}) \neq 0$  and  $\mathbf{x}(t) \in \mathbb{R}^n$ ,  $\mathbf{u}(t) \in \mathbb{R}^m$ ,  $\mathbf{y}(t) \in \mathbb{R}^p$  denote the state, inputs and outputs of the system. The goal of model order reduction is to approximate the full order model (FOM) (1) by a reduced order model (ROM)

$$\mathbf{E}_r \dot{\mathbf{x}}_r(t) = \mathbf{A}_r \mathbf{x}_r(t) + \mathbf{B}_r \mathbf{u}(t), \quad \mathbf{y}_r(t) = \mathbf{C}_r \mathbf{x}_r(t), \quad (2)$$

of much lower dimension  $r \ll n$  with  $\mathbf{E}_r = \mathbf{W}^\top \mathbf{E} \mathbf{V}$ ,  $\mathbf{A}_r = \mathbf{W}^\top \mathbf{A} \mathbf{V}$ ,  $\mathbf{B}_r = \mathbf{W}^\top \mathbf{B}$  and  $\mathbf{C}_r = \mathbf{C} \mathbf{V}$ , such that  $\mathbf{y}(t) \approx \mathbf{y}_r(t)$ . The main task in this *projection-based* setting consists in finding suitable (orthogonal) reduction matrices  $\mathbf{V}, \mathbf{W} \in \mathbb{R}^{n \times r}$  that span appropriate subspaces.

### 2.1 Frequency-domain perception of moment matching

The transfer function of (1) is  $\mathbf{G}(s) = \mathbf{C}(s\mathbf{E} - \mathbf{A})^{-1}\mathbf{B}$ .

*Definition 1.* The moments  $\mathbf{m}_i(\sigma)$  of  $\mathbf{G}(s)$  at a complex expansion point  $\sigma \in \mathbb{C}$  are given by

$$\mathbf{m}_i(\sigma) = (-1)^i \mathbf{C}((\sigma\mathbf{E} - \mathbf{A})^{-1}\mathbf{E})^i (\sigma\mathbf{E} - \mathbf{A})^{-1}\mathbf{B} \in \mathbb{R}^{p \times m}.$$

If  $\mathbf{W}$  is chosen as basis of an *output* Krylov subspace

$$\text{span} \left\{ (\mu_1\mathbf{E} - \mathbf{A})^{-1}\mathbf{C}^\top \mathbf{l}_1, \dots, (\mu_r\mathbf{E} - \mathbf{A})^{-1}\mathbf{C}^\top \mathbf{l}_r \right\} \subseteq \text{ran}(\mathbf{W}), \quad (3)$$

then *left* tangential multipoint interpolation is achieved:

$$\mathbf{l}_i^\top \mathbf{G}(\mu_i) = \mathbf{l}_i^\top \mathbf{G}_r(\mu_i) \Leftrightarrow \mathbf{l}_i^\top \mathbf{m}_0(\mu_i) = \mathbf{l}_i^\top \mathbf{m}_{r,0}(\mu_i). \quad (4)$$

Hereby, the 0-th tangential output moments are defined as  $\mathbf{m}_0^\top(\mu_i, \mathbf{l}_i) := \mathbf{l}_i^\top \mathbf{m}_0(\mu_i) = \mathbf{w}_i^\top \mathbf{B}$  with  $\mathbf{w}_i^\top = \mathbf{l}_i^\top \mathbf{C}(\mu_i\mathbf{E} - \mathbf{A})^{-1}$ . Suitable shifts  $\mu_i \in \mathbb{C} \setminus \lambda(\mathbf{E}^{-1}\mathbf{A})$  and left tangential directions  $\mathbf{l}_i \in \mathbb{C}^p$  should be chosen for a good approximation.

Any basis of an output Krylov subspace can be interpreted as the solution  $\mathbf{W}$  of the following Sylvester equation:

$$\mathbf{E}^\top \mathbf{W} \mathbf{S}_w^\top - \mathbf{A}^\top \mathbf{W} = \mathbf{C}^\top \mathbf{L}, \quad (5)$$

where  $\mathbf{S}_w = \text{diag}(\mu_1, \dots, \mu_r) \in \mathbb{C}^{r \times r}$  and  $\mathbf{L} = [\mathbf{l}_1, \dots, \mathbf{l}_r] \in \mathbb{C}^{p \times r}$ , such that the pair  $(\mathbf{S}_w, \mathbf{L}^\top)$  is controllable.

### 2.2 Time-domain perception of moment matching

*Theorem 1.* Consider the signal generator

$$\dot{\mathbf{x}}_r^w(t) = \mathbf{S}_w \mathbf{x}_r^w(t) - \mathbf{L}^\top \mathbf{y}(t), \quad \mathbf{x}_r^w(0) = \mathbf{x}_{r,0}^w, \quad (6a)$$

$$\mathbf{d}(t) = \mathbf{x}_r^w(t) - \mathbf{W}^\top \mathbf{E} \mathbf{x}(t). \quad (6b)$$

Consider the interconnection between (1) and (6) as in Fig. 1. Let  $\mathbf{W}$  be the unique solution of (5) and  $\mathbf{V}$  such that  $\det(\mathbf{W}^\top \mathbf{E} \mathbf{V}) \neq 0$ . Furthermore, let  $\mathbf{x}_{r,0}^w = \mathbf{0}$ . Then, the steady-state response of  $\mathbf{d}(t)$  and  $\boldsymbol{\varepsilon}(t)$  match, i.e.  $\mathbf{d}_{\text{ss}}(t) = \boldsymbol{\varepsilon}_{\text{ss}}(t)$  (see Fig. 1).

*Lemma 1.* For an asymptotically stable FOM,  $\mathbf{u}(t) = \mathbf{0}$ ,  $\mathbf{x}_0 \neq \mathbf{0}$  arbitrary and  $\mathbf{x}_{r,0}^w = \mathbf{0}$ , the steady-state response ( $t \rightarrow \infty$ ) of  $\mathbf{x}_r^w(t)$  is given by  $\mathbf{x}_{r,ss}^w(t) = -e^{\mathbf{S}_w t} \mathbf{W}^\top \mathbf{E} \mathbf{x}_0$ , where  $\mathbf{w}_i^\top = \mathbf{l}_i^\top \mathbf{C}(\mu_i\mathbf{E} - \mathbf{A})^{-1}$ . Due to (6b) and  $\mathbf{x}(t) = e^{\mathbf{E}^{-1}\mathbf{A}t} \mathbf{x}_0 \xrightarrow{t \rightarrow \infty} \mathbf{0}$ , the steady-state of  $\mathbf{d}(t)$  is  $\mathbf{d}_{\text{ss}}(t) = \mathbf{x}_{r,ss}^w(t)$ .

Further note that the interconnected system ((1) and (6)) is equivalent to the system (cf. Fig. 1)

$$\dot{\mathbf{d}}(t) = \mathbf{S}_w (\mathbf{x}_r^w(t) - \mathbf{W}^\top \mathbf{E} \mathbf{x}(t)) - \mathbf{W}^\top \mathbf{B} \mathbf{u}(t), \quad \mathbf{d}(0) = -\mathbf{W}^\top \mathbf{E} \mathbf{x}_0.$$

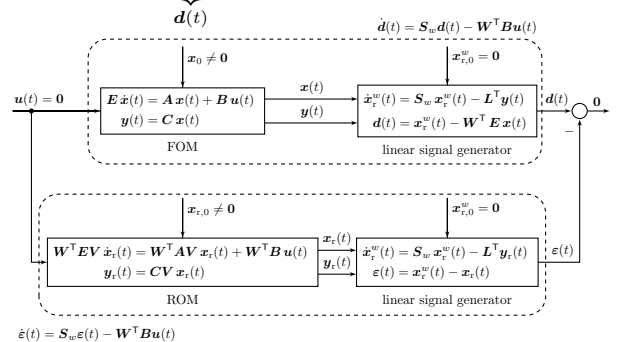


Fig. 1. Time-domain interpretation of  $\mathbf{W}$ -sided moment matching for linear systems (“FOM/ROM drives the signal generator”).

Thus, the solution for  $\mathbf{u}(t) = \mathbf{0}$  is given by  $\mathbf{d}(t) = e^{\mathbf{S}_w t} \mathbf{d}(0) = -e^{\mathbf{S}_w t} \mathbf{W}^\top \mathbf{E} \mathbf{x}_0$ , which corresponds to the solution before. Moreover, for  $\mathbf{u}(t) = \mathbf{0}$  and  $\mathbf{x}_r^w(t) = \mathbf{W}^\top \mathbf{E} \mathbf{x}(t)$  it follows

$$\dot{\mathbf{d}}(t) \Big|_{\mathbf{x}_r^w = \mathbf{W}^\top \mathbf{E} \mathbf{x}, \mathbf{u} = \mathbf{0}} = \mathbf{0}. \quad (7)$$

The  $r \times n$  Sylvester equation can be derived as follows. First insert the linear approximation ansatz  $\mathbf{x}_r(t) = \mathbf{W}^\top \mathbf{E} \mathbf{x}(t)$  with  $\mathbf{x}_r(t) \stackrel{!}{=} \mathbf{x}_r^w(t)$  in (6a). Then, the linear system (1) for  $\mathbf{u}(t) = \mathbf{0}$  and arbitrary  $\mathbf{x}_0 \neq \mathbf{0}$  is plugged in, yielding

$$\mathbf{0} = \left( \mathbf{S}_w \mathbf{W}^\top \mathbf{E} - \mathbf{W}^\top \mathbf{A} - \mathbf{L}^\top \mathbf{C} \right) \cdot \mathbf{x}(t). \quad (8)$$

### 3. NONLINEAR MOMENT MATCHING

Consider now a large-scale, nonlinear time-invariant, in  $\mathbf{x}_{\text{eq}} = \mathbf{0}$  exponentially stable, state-space model of the form

$$\begin{aligned} \mathbf{E} \dot{\mathbf{x}}(t) &= \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)), & \mathbf{x}(0) &= \mathbf{x}_0, \\ \mathbf{y}(t) &= \mathbf{h}(\mathbf{x}(t)), \end{aligned} \quad (9)$$

with smooth mappings  $\mathbf{f}(\mathbf{x}, \mathbf{u}) : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$  and  $\mathbf{h}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^p$ . The reduction is performed by a nonlinear Petrov-Galerkin projection using the mappings  $\mathbf{x}(t) \approx \boldsymbol{\nu}(\mathbf{x}_r(t))$  and  $\boldsymbol{\omega}(\mathbf{x}(t))$ , together with their corresponding Jacobians  $\tilde{\mathbf{V}}(\mathbf{x}_r) = \partial \boldsymbol{\nu}(\mathbf{x}_r) / \partial \mathbf{x}_r$ ,  $\tilde{\mathbf{W}}(\mathbf{x})^\top = (\partial \boldsymbol{\omega}(\mathbf{x}) / \partial \mathbf{x})|_{\mathbf{x} = \boldsymbol{\nu}(\mathbf{x}_r)}$ . This yields the nonlinear ROM

$$\begin{aligned} \tilde{\mathbf{E}}_r \dot{\mathbf{x}}_r(t) &= \frac{\partial \boldsymbol{\omega}(\mathbf{x}(t))}{\partial \mathbf{x}(t)} \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) \Big|_{\mathbf{x}(t) = \boldsymbol{\nu}(\mathbf{x}_r(t))}, & (10) \\ \mathbf{y}_r(t) &= \mathbf{h}(\boldsymbol{\nu}(\mathbf{x}_r(t))), \end{aligned}$$

with  $\tilde{\mathbf{E}}_r = \tilde{\mathbf{W}}(\mathbf{x})^\top \mathbf{E} \tilde{\mathbf{V}}(\mathbf{x}_r)$  and the initial condition  $\mathbf{x}_r(0) = \arg \min \|\boldsymbol{\nu}(\mathbf{x}_{r,0}) - \mathbf{x}_0\|_2^2$  (cf. `lsqnonlin` in `MATLAB`).

#### 3.1 Time-domain perception of $\mathbf{W}$ -sided moment matching

*Theorem 2.* Consider the interconnection of the nonlinear system (9) with the nonlinear signal generator

$$\dot{\mathbf{x}}_r^w(t) = \mathbf{s}_w(\mathbf{x}_r^w(t), \mathbf{y}(t)), \quad \mathbf{x}_r^w(0) = \mathbf{x}_{r,0}^w, \quad (11a)$$

$$\mathbf{d}(t) = \boldsymbol{\Omega}(\mathbf{x}_r^w(t), \mathbf{x}(t)), \quad (11b)$$

where  $\mathbf{s}_w(\mathbf{x}_r^w, \mathbf{y}) : \mathbb{R}^r \times \mathbb{R}^p \rightarrow \mathbb{R}^r$  and  $\boldsymbol{\Omega}(\mathbf{x}_r^w, \mathbf{x}) : \mathbb{R}^r \times \mathbb{R}^n \rightarrow \mathbb{R}^r$  are smooth mappings such that  $\mathbf{s}_w(\mathbf{0}, \mathbf{0}) = \mathbf{0}$ ,  $\boldsymbol{\Omega}(\mathbf{0}, \mathbf{0}) = \mathbf{0}$  and  $(\partial \boldsymbol{\Omega}(\mathbf{x}_r^w, \mathbf{x}) / \partial \mathbf{x}_r^w)|_{(\mathbf{0}, \mathbf{0})}$  is full rank. Further assume that there exists a smooth mapping  $\boldsymbol{\omega}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^r$  such that  $\boldsymbol{\Omega}(\boldsymbol{\omega}(\mathbf{x}), \mathbf{x}) = \mathbf{0}$ , i.e.  $\mathbf{d}$  restricted to the manifold  $\mathbf{x}_r^w = \boldsymbol{\omega}(\mathbf{x})$  is zero. Then, the steady-state response of  $\mathbf{d}(t)$  and  $\boldsymbol{\varepsilon}(t)$  match (see Fig. 2), where the mapping  $\boldsymbol{\Omega}(\mathbf{x}_r^w, \mathbf{x})$  is the unique solution of the following PDE

$$\frac{\partial \boldsymbol{\Omega}(\mathbf{x}_r^w, \mathbf{x})}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}, \mathbf{0}) = - \frac{\partial \boldsymbol{\Omega}(\mathbf{x}_r^w, \mathbf{x})}{\partial \mathbf{x}_r^w} \mathbf{s}_w(\mathbf{x}_r^w, \mathbf{h}(\mathbf{x})) \Big|_{\mathbf{x}_r^w = \boldsymbol{\omega}(\mathbf{x})}.$$

#### 3.2 Nonlinear input-affine case

Consider now a large-scale, nonlinear time-invariant system (9) with  $\mathbf{f}(\mathbf{x}, \mathbf{u}) = \tilde{\mathbf{f}}(\mathbf{x}) + \mathbf{G}(\mathbf{x})\mathbf{u}$ , where  $\tilde{\mathbf{f}}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^n$  and  $\mathbf{G}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$  are smooth mappings.

*Theorem 3.* Consider the interconnection of a nonlinear (input-affine) system with the input-affine generator

$$\mathbf{s}_w(\mathbf{x}_r^w(t), \mathbf{y}(t))$$

$$\dot{\mathbf{x}}_r^w(t) = \tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) - \mathbf{L}(\mathbf{x}_r^w(t)) \mathbf{y}(t), \quad \mathbf{x}_r^w(0) = \mathbf{x}_{r,0}^w, \quad (12a)$$

$$\mathbf{d}(t) = \underbrace{\mathbf{x}_r^w(t) - \boldsymbol{\omega}(\mathbf{x}(t))}_{\boldsymbol{\Omega}(\mathbf{x}_r^w(t), \mathbf{x}(t))}, \quad (12b)$$

$$\boldsymbol{\Omega}(\mathbf{x}_r^w(t), \mathbf{x}(t))$$

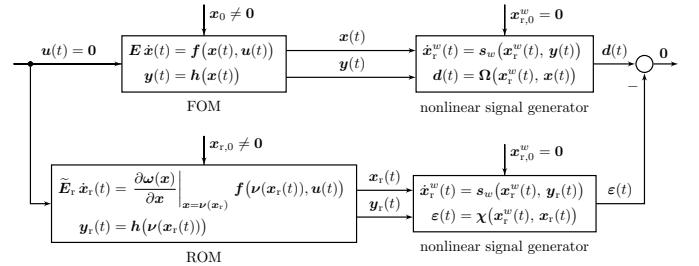


Fig. 2. Time-domain interpretation of  $\mathbf{W}$ -sided moment matching for nonlinear systems (adapted from Ionescu [2016]).

where  $\tilde{\mathbf{s}}_w(\mathbf{x}_r^w) : \mathbb{R}^r \rightarrow \mathbb{R}^r$ ,  $\mathbf{L}(\mathbf{x}_r^w) : \mathbb{R}^r \rightarrow \mathbb{R}^{r \times p}$  and  $\boldsymbol{\omega}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^r$ . Then, the steady-state of  $\mathbf{d}(t)$  and  $\boldsymbol{\varepsilon}(t)$  match, where  $\boldsymbol{\omega}(\mathbf{x})$  is the unique solution of the PDE

$$\frac{\partial \boldsymbol{\omega}(\mathbf{x})}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}, \mathbf{0}) = \tilde{\mathbf{s}}_w(\mathbf{x}_r^w) - \mathbf{L}(\mathbf{x}_r^w) \mathbf{h}(\mathbf{x}) \Big|_{\mathbf{x}_r^w = \boldsymbol{\omega}(\mathbf{x})}. \quad (13)$$

The Sylvester-like PDE (13) can be derived as follows. First, the nonlinear approximation ansatz  $\mathbf{x}_r(t) = \boldsymbol{\omega}(\mathbf{x}(t))$  with  $\mathbf{x}_r(t) \stackrel{!}{=} \mathbf{x}_r^w(t)$  is substituted in (12a). Afterwards, the nonlinear system  $\mathbf{E} \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t))$ ,  $\mathbf{y}(t) = \mathbf{h}(\mathbf{x}(t))$  for  $\mathbf{u}(t) = \mathbf{0}$  is plugged in, yielding the  $r \times 1$  equation (13).

### 4. PRACTICABLE $\mathbf{W}$ -SIDED MODEL REDUCTION BY NONLINEAR MOMENT MATCHING

The first step towards a practical method consists in applying a linear projection  $\mathbf{x}_r^w(t) = \boldsymbol{\omega}(\mathbf{x}(t)) = \mathbf{W}^\top \mathbf{E} \mathbf{x}(t)$ . (cf. Cruz Varona et al. [2019]).

*Nonlinear signal generator* In this case, the PDE (13) becomes the following nonlinear system of equations

$$\mathbf{W}^\top \mathbf{f}(\mathbf{x}(t), \mathbf{0}) = \tilde{\mathbf{s}}_w(\mathbf{W}^\top \mathbf{E} \mathbf{x}(t)) - \mathbf{L}(\mathbf{W}^\top \mathbf{E} \mathbf{x}(t)) \mathbf{h}(\mathbf{x}(t)), \quad (14)$$

where the triple  $(\tilde{\mathbf{s}}_w, \mathbf{L}, \mathbf{x}_0)$  is user-defined. Note that the underdetermined system consists of  $r$  equations for  $r \cdot n$  unknowns in  $\mathbf{W}^\top \in \mathbb{R}^{r \times n}$ , and a row-wise consideration for each  $\mathbf{w}_i^\top \in \mathbb{R}^{1 \times n}$ ,  $i = 1, \dots, r$  does not help any further.

*Linear signal generator* Interconnecting the nonlinear system (9) with the linear signal generator (6), where  $\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) = \mathbf{S}_w \mathbf{x}_r^w(t)$  and  $\mathbf{L}(\mathbf{x}_r^w(t)) = \mathbf{L}^\top$ , yields

$$\mathbf{W}^\top \mathbf{f}(\mathbf{x}(t), \mathbf{0}) = \mathbf{S}_w \mathbf{W}^\top \mathbf{E} \mathbf{x}(t) - \mathbf{L}^\top \mathbf{h}(\mathbf{x}(t)), \quad (15)$$

which is a *linear* system of equations.

*Zero signal generator* This special (linear) signal generator, where  $\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) = \mathbf{0}$  and  $\mathbf{L}(\mathbf{x}_r^w(t)) = \mathbf{L}^\top$ , yields

$$\mathbf{W}^\top \mathbf{f}(\mathbf{x}(t), \mathbf{0}) = -\mathbf{L}^\top \mathbf{h}(\mathbf{x}(t)), \quad (16)$$

which is again a *linear* system of equations.

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# Towards Output Krylov Subspace-Based Nonlinear Moment Matching

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## Abstract

In this contribution, we report our progress concerning a practicable, projective method for output nonlinear moment matching. First, we explain the time-domain interpretation of output Krylov subspace-based moment matching for linear systems. Then, based on [Ionescu and Astolfi 2016], the steady-state perception of output moments and moment matching for nonlinear systems is given. Finally, some simplifications to approximate the solution of the arising partial differential equation (PDE) are proposed towards a practical, numerical algorithm for nonlinear model order reduction.

## Linear systems

### Linear time-invariant systems

Consider a large-scale ( $n \gg 10^3$ ), linear time-invariant (LTI), asymptotically stable, MIMO state-space model of the form:

$$\begin{aligned} \mathbf{E} \dot{\mathbf{x}}(t) &= \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t), & \mathbf{x}(0) &= \mathbf{x}_0, \\ \mathbf{y}(t) &= \mathbf{C} \mathbf{x}(t), \end{aligned}$$

with non-singular descriptor matrix, i.e.  $\det(\mathbf{E}) \neq 0$ .

The input-output behavior of LTI systems is characterized in the frequency-domain by the transfer function matrix

$$\mathbf{G}(s) = \mathbf{C}(s\mathbf{E} - \mathbf{A})^{-1} \mathbf{B} \in \mathbb{C}^{p \times m}.$$

### Steady-state of interconnected system

Consider the signal generator

$$\begin{aligned} \dot{\mathbf{x}}_r^w(t) &= \mathbf{S}_w \mathbf{x}_r^w(t) - \mathbf{L}^T \mathbf{y}(t), & \mathbf{x}_r^w(0) &= \mathbf{x}_{r,0}^w, \\ \mathbf{d}(t) &= \mathbf{x}_r^w(t) - \mathbf{W}^T \mathbf{E} \mathbf{x}(t), \end{aligned}$$

with  $\mathbf{S}_w = \text{diag}(\mu_1, \dots, \mu_r) \in \mathbb{C}^{r \times r}$  and  $\mathbf{L} = [\mathbf{l}_1, \dots, \mathbf{l}_r] \in \mathbb{C}^{p \times r}$ .

The steady-state of the interconnected system from Fig. 1 is

$$\begin{aligned} \mathbf{x}_r^w(t) &= \int_0^t -e^{\mathbf{S}_w(t-\tau)} \mathbf{L}^T \mathbf{C} e^{\mathbf{E}^{-1} \mathbf{A} \tau} \mathbf{x}_0 d\tau + e^{\mathbf{S}_w t} \mathbf{x}_{r,0}^w, \\ \mathbf{x}_{r,i}^w(t) &= e^{\mu_i t} \left( \mathbf{x}_{r,0,i}^w - \mathbf{l}_i^T \mathbf{C} (\mu_i \mathbf{E} - \mathbf{A})^{-1} \mathbf{E} \mathbf{x}_0 \right) + \mathbf{l}_i^T \mathbf{C} (\mu_i \mathbf{E} - \mathbf{A})^{-1} e^{\mu_i t} \mathbf{A} \mathbf{x}_0 \\ &\xrightarrow{t \rightarrow \infty} -e^{\mu_i t} \mathbf{w}_i^T \mathbf{E} \mathbf{x}_0 \quad \text{and} \quad \mathbf{d}_{ss}(t) = \mathbf{x}_{r,ss}^w(t) = -e^{\mathbf{S}_w t} \mathbf{W}^T \mathbf{E} \mathbf{x}_0. \end{aligned}$$

### Projective Model Order Reduction

The goal of model order reduction is to find a reduced order model (ROM) of much lower dimension  $r \ll n$ :

$$\begin{aligned} \mathbf{W}^T \mathbf{E} \mathbf{V} \dot{\mathbf{x}}_r(t) &= \mathbf{W}^T \mathbf{A} \mathbf{V} \mathbf{x}_r(t) + \mathbf{W}^T \mathbf{B} \mathbf{u}(t), & \mathbf{x}_r(0) &= \mathbf{x}_{r,0}, \\ \mathbf{y}_r(t) &= \mathbf{C} \mathbf{V} \mathbf{x}_r(t), \end{aligned}$$

with  $\mathbf{x}_r(0) = (\mathbf{W}^T \mathbf{E} \mathbf{V})^{-1} \mathbf{W}^T \mathbf{E} \mathbf{x}(0)$ , such that  $\mathbf{y}(t) \approx \mathbf{y}_r(t)$ .

In this *Petrov-Galerkin projection* setting, the main task is to find suitable reduction matrices  $\mathbf{V}, \mathbf{W}$ . One numerically efficient linear reduction technique relies on the concept of implicit moment matching by *rational Krylov subspaces*.

### Frequency-domain Output Moment Matching

If  $\mathbf{W}$  is chosen as basis of an *output* Krylov subspace  $\text{span} \left\{ (\mu_1 \mathbf{E} - \mathbf{A})^{-T} \mathbf{C}^T \mathbf{l}_1, \dots, (\mu_r \mathbf{E} - \mathbf{A})^{-T} \mathbf{C}^T \mathbf{l}_r \right\} \subseteq \text{ran}(\mathbf{W})$ , then the ROM fulfills the *left* tangential multipoint conditions

$$\mathbf{l}_i^T \mathbf{G}(\mu_i) = \mathbf{l}_i^T \mathbf{G}_r(\mu_i) \Leftrightarrow \mathbf{l}_i^T \mathbf{m}_0(\mu_i) = \mathbf{l}_i^T \mathbf{m}_{r,0}(\mu_i).$$

Hereby, the 0th tangential output moments are defined as

$$\mathbf{m}_0^T(\mu_i, \mathbf{l}_i) := \mathbf{l}_i^T \mathbf{m}_0(\mu_i) = \mathbf{w}_i^T \mathbf{B}, \quad \mathbf{w}_i^T = \mathbf{l}_i^T \mathbf{C} (\mu_i \mathbf{E} - \mathbf{A})^{-1}.$$

$\mathbf{W}$  can be also interpreted as solution of the Sylvester equation  $\mathbf{E}^T \mathbf{W} \mathbf{S}_w^T - \mathbf{A}^T \mathbf{W} = \mathbf{C}^T \mathbf{L}$ .

### Time-domain Output Moment Matching

The 0th tangential output moments at  $\{\mu_i, \mathbf{l}_i\}$  are related to the (well-defined) steady-state of  $\mathbf{d}(t)$  from Fig. 1:

$$\mathbf{m}_0^T(\mu_i, \mathbf{l}_i) = \mathbf{w}_i^T \mathbf{B} \Leftrightarrow \mathbf{d}_{ss}(t) = -e^{\mathbf{S}_w t} \mathbf{W}^T \mathbf{E} \mathbf{x}_0 = - \begin{bmatrix} e^{\mu_1 t} \mathbf{w}_1^T \mathbf{E} \mathbf{x}_0 \\ \vdots \\ e^{\mu_r t} \mathbf{w}_r^T \mathbf{E} \mathbf{x}_0 \end{bmatrix},$$

where  $\mathbf{W}$  is the unique solution of the Sylvester equation.

Thus, output moment matching in time-domain corresponds to the interpolation of the steady-state of  $\mathbf{d}(t)$  and  $\varepsilon(t)$ :

$$\mathbf{d}_{ss,i}(t) = -e^{\mu_i t} \mathbf{w}_i^T \mathbf{E} \mathbf{x}_0 \equiv -e^{\mu_i t} \mathbf{l}_i^T \mathbf{C}_r (\mu_i \mathbf{E}_r - \mathbf{A}_r)^{-1} \mathbf{E}_r \mathbf{x}_{r,0} = \varepsilon_{ss,i}(t),$$

where  $\mathbf{V}$  is arbitrary but such that  $\det(\mathbf{W}^T \mathbf{E} \mathbf{V}) \neq 0$ .

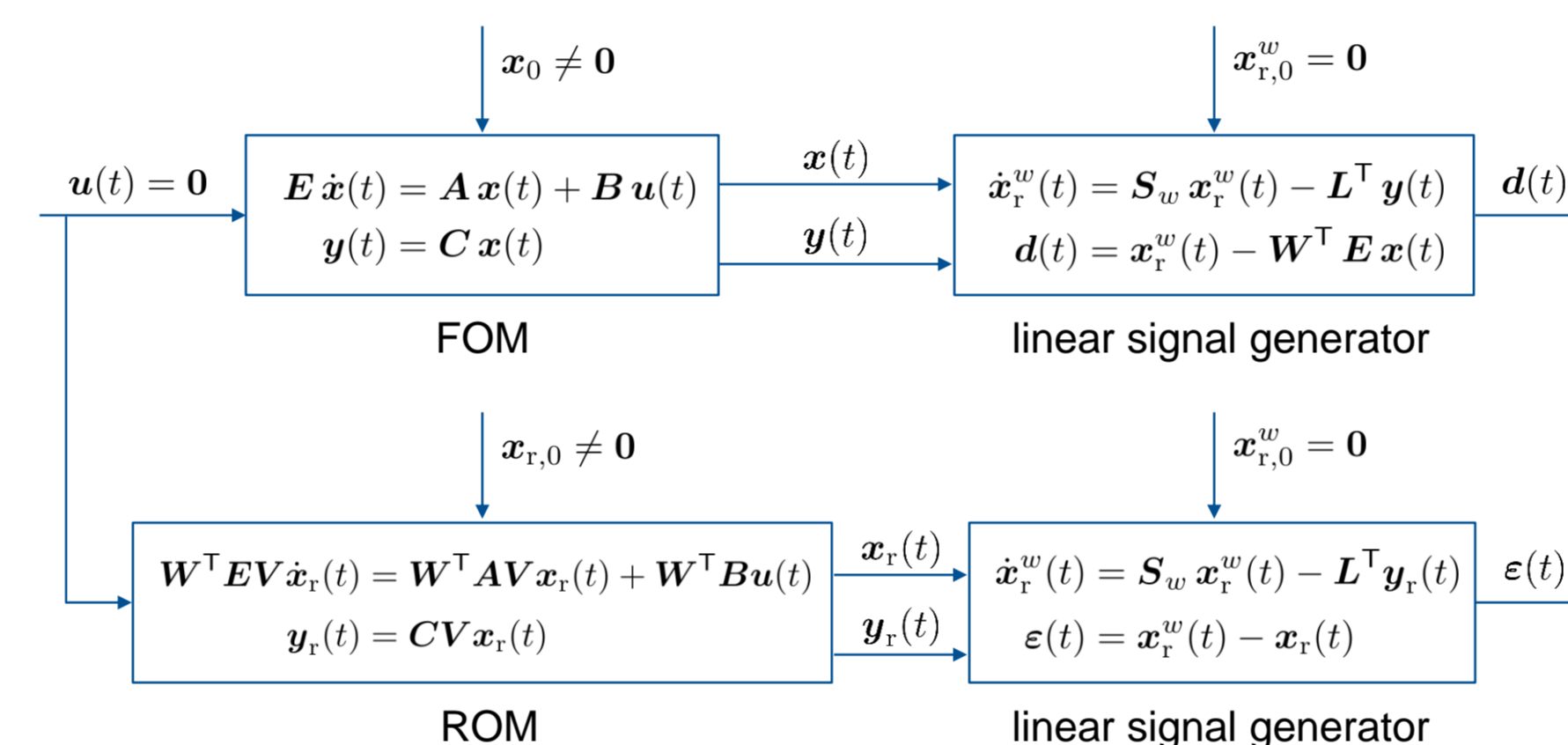


Fig. 1. Time-domain interpretation of output moment matching for linear systems: "System drives the signal generator".

## Nonlinear systems

### Nonlinear time-invariant systems

Consider now a large-scale, nonlinear time-invariant (NLTI), in  $\mathbf{x}_{eq} = \mathbf{0}$  exponentially stable, MIMO state-space model of the form:

$$\begin{aligned} \mathbf{E} \dot{\mathbf{x}}(t) &= \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)), & \mathbf{x}(0) &= \mathbf{x}_0, \\ \mathbf{y}(t) &= \mathbf{h}(\mathbf{x}(t)), \end{aligned}$$

with mappings  $\mathbf{f}(\mathbf{x}, \mathbf{u}) : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$  and  $\mathbf{h}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^p$ . For the sake of simplicity, we consider the input-affine case later on, where

$$\mathbf{f}(\mathbf{x}, \mathbf{u}) = \tilde{\mathbf{f}}(\mathbf{x}) + \mathbf{G}(\mathbf{x}) \mathbf{u} = \tilde{\mathbf{f}}(\mathbf{x}) + \sum_{j=1}^m \mathbf{g}_j(\mathbf{x}) u_j.$$

### Steady-state of interconnected system

Consider the nonlinear, input-affine signal generator

$$\begin{aligned} \dot{\mathbf{x}}_r^w(t) &= \tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) - \mathbf{L}(\mathbf{x}_r^w(t)) \mathbf{y}(t), & \mathbf{x}_r^w(0) &= \mathbf{x}_{r,0}^w, \\ \mathbf{d}(t) &= \mathbf{x}_r^w(t) - \omega(\mathbf{x}(t)), \end{aligned}$$

with user-defined  $\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) : \mathbb{R}^r \rightarrow \mathbb{R}^r$ ,  $\mathbf{L}(\mathbf{x}_r^w(t)) : \mathbb{R}^r \rightarrow \mathbb{R}^{r \times p}$ .

The steady-state of the interconnected system (cf. Fig. 1) is

$$\begin{aligned} \mathbf{x}_r^w(t) &= \mathbf{x}_{r,h}^w(t) + \mathbf{x}_{r,p}^w(t) \\ &= \tilde{\mathbf{s}}_w(\mathbf{x}_{r,0}^w) - \frac{\partial \omega(\mathbf{x})}{\partial \mathbf{x}} \mathbf{E} \mathbf{x}_0 + \frac{\partial \omega(\mathbf{x})}{\partial \mathbf{x}} \tau(\mathbf{x}_0^w) \\ &\xrightarrow{t \rightarrow \infty} \tilde{\mathbf{s}}_w \left( -\frac{\partial \omega(\mathbf{x})}{\partial \mathbf{x}} \mathbf{E} \mathbf{x}_0 \right) \quad \text{and} \quad \mathbf{d}_{ss}(t) = \mathbf{x}_{r,ss}^w(t). \end{aligned}$$

### Output Nonlinear Moments

The 0th output nonlinear moments at  $(\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)), \mathbf{L}(\mathbf{x}_r^w(t)), \mathbf{x}_0)$  are related to the (well-defined) steady-state of  $\mathbf{d}(t)$

$$\mathbf{m}_0^T(\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)), \mathbf{L}(\mathbf{x}_r^w(t)), \mathbf{x}_0) \Leftrightarrow \mathbf{d}_{ss}(t) = \tilde{\mathbf{s}}_w \left( -\frac{\partial \omega(\mathbf{x})}{\partial \mathbf{x}} \mathbf{E} \mathbf{x}_0 \right),$$

where  $\omega(\mathbf{x})$  is the unique solution of the Sylvester-like PDE

$$\frac{\partial \omega(\mathbf{x})}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}, \mathbf{0}) = \tilde{\mathbf{s}}_w(\mathbf{x}_r^w) - \mathbf{L}(\mathbf{x}_r^w) \mathbf{h}(\mathbf{x}) \Big|_{\mathbf{x}_r^w = \omega(\mathbf{x})}.$$

This PDE represents the nonlinear counterpart of

$$\mathbf{W}^T \mathbf{A} \mathbf{x}(t) = \mathbf{S}_w \mathbf{W}^T \mathbf{E} \mathbf{x}(t) - \mathbf{L}^T \mathbf{C} \mathbf{x}(t).$$

Note that the PDE has the dimension  $r \times 1$ , and not  $r \times n$ .

### Nonlinear Petrov-Galerkin projection

One way to reduce NLTI systems is to apply a nonlinear Petrov-Galerkin projection using the mappings  $\mathbf{x} \approx \nu(\mathbf{x}_r)$  and  $\omega(\mathbf{x})$

$$\begin{aligned} \tilde{\mathbf{E}}_r \dot{\mathbf{x}}_r(t) &= \frac{\partial \omega(\mathbf{x}(t))}{\partial \mathbf{x}(t)} \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) \Big|_{\mathbf{x}(t) = \nu(\mathbf{x}_r(t))}, & \mathbf{x}_r(0) &= \mathbf{x}_{r,0}, \\ \mathbf{y}_r(t) &= \mathbf{h}(\nu(\mathbf{x}_r(t))), \end{aligned}$$

with  $\tilde{\mathbf{E}}_r = \tilde{\mathbf{W}}(\mathbf{x})^T \mathbf{E} \tilde{\mathbf{V}}(\mathbf{x}_r)$  and  $\mathbf{x}_r(0) = \arg \min_{\mathbf{x}_{r,0}} \|\nu(\mathbf{x}_{r,0}) - \mathbf{x}_0\|_2^2$ . In this setting, the main task is to find suitable nonlinear reduction mappings  $\nu(\mathbf{x}_r)$ ,  $\omega(\mathbf{x})$  and their Jacobians

$$\tilde{\mathbf{V}}(\mathbf{x}_r) = \partial \nu(\mathbf{x}_r) / \partial \mathbf{x}_r, \quad \tilde{\mathbf{W}}(\mathbf{x})^T = (\partial \omega(\mathbf{x}) / \partial \mathbf{x}) \Big|_{\mathbf{x} = \nu(\mathbf{x}_r)}.$$

### Output Nonlinear Moment Matching

The PDE can be derived as follows:

- 1.) Insert the ansatz  $\mathbf{x}_r^w(t) = \omega(\mathbf{x}(t))$  in the signal generator.
- 2.) Substitute the nonlinear system with  $\mathbf{u}(t) = \mathbf{0}$ .

Output nonlinear moment matching can be interpreted in time-domain as the interpolation of the steady-state of  $\mathbf{d}(t)$  and  $\varepsilon(t)$  (cf. Fig. 1):

$$\mathbf{d}_{ss}(t) = \tilde{\mathbf{s}}_w \left( -\frac{\partial \omega(\mathbf{x})}{\partial \mathbf{x}} \mathbf{E} \mathbf{x}_0 \right) \equiv \varepsilon_{ss}(t),$$

where  $\omega(\mathbf{x})$  is the unique solution of the Sylvester-like PDE and  $\nu(\mathbf{x}_r)$  is arbitrary but such that  $\det(\tilde{\mathbf{W}}^T \mathbf{E} \tilde{\mathbf{V}}) \neq 0$ .

## Practicable W-sided Model Reduction by Approximated Nonlinear Moment Matching

Since the PDE is difficult to solve, we propose here some simplifications to approximate its solution and achieve a practical method for output nonlinear moment matching.

The first simplification step consists in applying a linear projection  $\mathbf{x}_r^w(t) = \omega(\mathbf{x}(t)) = \mathbf{W}^T \mathbf{E} \mathbf{x}(t)$  instead of the nonlinear reduction mapping  $\omega(\mathbf{x}(t))$ . In the following, we distinguish three different signal generator cases.

**Nonlinear signal generator:** In this case, the PDE becomes the following *algebraic* nonlinear system of equations

$$\mathbf{W}^T \mathbf{f}(\mathbf{x}(t), \mathbf{0}) = \tilde{\mathbf{s}}_w(\mathbf{W}^T \mathbf{E} \mathbf{x}(t)) - \mathbf{L}(\mathbf{W}^T \mathbf{E} \mathbf{x}(t)) \mathbf{h}(\mathbf{x}(t)),$$

where the triple  $(\tilde{\mathbf{s}}_w, \mathbf{L}, \mathbf{x}_0)$  is user-defined. Note that the above system is underdetermined,

consisting of  $r$  equations for  $r \cdot n$  unknowns in  $\mathbf{W}^T \in \mathbb{R}^{r \times n}$ . A row-wise consideration for each  $\mathbf{w}_i^T \in \mathbb{R}^{1 \times n}$ ,  $i = 1, \dots, r$  does – at first – not help any further.

**Linear signal generator:** Interconnecting the nonlinear system with a linear signal generator, where  $\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) = \mathbf{S}_w \mathbf{x}_r^w(t)$  and  $\mathbf{L}(\mathbf{x}_r^w(t)) = \mathbf{L}^T$ , yields

$$\mathbf{W}^T \mathbf{f}(\mathbf{x}(t), \mathbf{0}) = \mathbf{S}_w \mathbf{W}^T \mathbf{E} \mathbf{x}(t) - \mathbf{L}^T \mathbf{h}(\mathbf{x}(t)).$$

This is a *linear* system of equations, since the searched solution *does not* depend nonlinearly.

**Zero signal generator:** For this special case, where  $\tilde{\mathbf{s}}_w(\mathbf{x}_r^w(t)) = \mathbf{0}$ ,  $\mathbf{L}(\mathbf{x}_r^w(t)) = \mathbf{L}^T$ , it follows

$$\mathbf{W}^T \mathbf{f}(\mathbf{x}(t), \mathbf{0}) = -\mathbf{L}^T \mathbf{h}(\mathbf{x}(t)),$$

which is again a linear system of equations.

# Towards Output Krylov Subspace-Based Nonlinear Moment Matching

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## Abstract

In this contribution, we report our progress concerning a practicable, projective method for output nonlinear moment matching. First, we explain the time-domain interpretation of output Krylov subspace-based moment matching for linear systems. Then, based on [Ionescu and Astolfi 2016], the steady-state perception of output moments and moment matching for nonlinear systems is given. Finally, some simplifications to approximate the solution of the arising partial differential equation (PDE) are proposed towards a practical, numerical algorithm for nonlinear model order reduction.

## Nonlinear systems (cont.)

### Possible approach to achieve a practical algorithm

**Nonlinear signal generator:** The afore obtained nonlinear system is underdetermined

$$\mathbf{W}^T \mathbf{f}(x(t), \mathbf{0}) = \tilde{s}_w(\mathbf{W}^T \mathbf{E} x(t)) - \mathbf{L}(\mathbf{W}^T \mathbf{E} x(t)) \mathbf{h}(x(t)),$$

consisting of  $r$  equations for  $r \cdot n$  unknowns in  $\mathbf{W}^T \in \mathbb{R}^{r \times n}$ . A row-wise consideration for each  $w_i^T \in \mathbb{R}^{1 \times n}$ ,  $i = 1, \dots, r$  might help, if  $n$  (relevant) initial states  $x_{0,\ell} \in \mathbb{R}^n$ ,  $\ell = 1, \dots, n$  are taken, yielding well-determined systems of equations of the form:

$$w_i^T \{ \mathbf{f}(x_{0,\ell}, \mathbf{0}) \}_{\ell=1}^n = \{ \tilde{s}_{w_i}(w_i^T \mathbf{E} x_{0,\ell}) \}_{\ell=1}^n - \{ l_i^T(w_i^T \mathbf{E} x_{0,\ell}) \mathbf{h}(x_{0,\ell}) \}_{\ell=1}^n, \quad i = 1, \dots, r.$$

Herein,  $x_{r,i}^w(\ell) = w_i^T \mathbf{E} x_{0,\ell} \in \mathbb{R}$ ,  $\tilde{s}_{w_i}(x_{r,i}^w(\ell)) : \mathbb{R} \rightarrow \mathbb{R}$ ,  $l_i^T(x_{r,i}^w(\ell)) : \mathbb{R} \rightarrow \mathbb{R}^{1 \times p}$  is used instead of  $x_r^w(t) = \mathbf{W}^T \mathbf{E} x(t) \in \mathbb{R}^r$ ,  $\tilde{s}_w(x_r^w(t)) : \mathbb{R}^r \rightarrow \mathbb{R}^r$ ,  $\mathbf{L}(x_r^w(t)) : \mathbb{R}^r \rightarrow \mathbb{R}^{r \times p}$ .

### Simulation-free Output Nonlinear Moment Matching Algorithm

Based on the proposed simplifications – i.e. (i) linear projection, (ii) row-wise consideration and (iii)  $n$  initial states  $\{x_{0,\ell}\}_{\ell=1}^n$  – we are now ready to state our practical algorithm for projective, output nonlinear moment matching:

#### Algorithm 1 Output Nonlinear Moment Matching (O-NLMM)

**Input:**  $\mathbf{E}$ ,  $\mathbf{f}(x, \mathbf{u})$ ,  $\tilde{s}_{w_i}(\cdot)$ ,  $l_i^T(\cdot)$ , initial states  $\{x_{0,\ell}\}_{\ell=1}^n$ , initial guesses  $w_{0,i}$

**Output:** orthogonal basis  $\mathbf{W}$

```

1: for i = 1 : r do
2:   for l = 1 : n do
3:     A = [A, f(x_{0,l}, 0)]
4:     xril=@(w) w' * E x_{0,l}
5:     swil=@(w) \tilde{s}_{w_i}(xril), yil=@(w) l_i^T(xril) h(x_{0,l})
6:     \tilde{s}_w^T(w) = [\tilde{s}_w^T(w), swil], y_w^T(w) = [y_w^T(w), yil]
7:   end for
8:   fun=@(w) A^T * w - \tilde{s}_w(w) + y_w(w)
9:   Jfun=@(w) A^T - \partial \tilde{s}_w(w) / \partial w + \partial y_w(w) / \partial w
10:  w_i = Newton(fun, w_{0,i}, Jfun)
11:  W(:, i) ← w_i
12:  W = gramSchmidt(w_i, W) ▷ optional
13: end for

```

The inner for-loop is used to iteratively construct the (sparse) matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$ , as well as the row-vector functions  $\tilde{s}_w^T(w) \in \mathbb{R}^{1 \times n}$  and  $y_w^T(w) \in \mathbb{R}^{1 \times n}$ , which depend on  $w_i \hat{=} w \in \mathbb{R}^{n \times 1}$ .

### Computational Aspects

The above algorithm is given for the most general case of a nonlinear signal generator. In this case, nonlinear systems of equations (NLSEs) of full order dimension  $n$  have to be solved (cf. line 8-10). These NLSEs can be solved using either a self-programmed Newton-Raphson scheme:

#### Algorithm 1 Newton-Raphson

**Input:** fun(x), x0, Jfun, Opts

**Output:** root x

```

1: tol = Opts.AbsTol
2: xcurr = x0, fcurr = fun(xcurr)
3: iter = 0
4: while norm(fcurr) > tol do
5:   iter = iter + 1
6:   if iter > Opts.MaxIter then
7:     break
8:   end if
9:   fcurr = fun(xcurr)
10:  dxcurr = Jfun(xcurr) \ fcurr
11:  xcurr = xcurr - dxcurr
12:  tol = Opts.RelTol * norm(fcurr) + Opts.AbsTol
13: end while
14: x = xcurr

```

or a built-in `fsolve` routine (same holds for our proposed Input NLMM algorithm).

For the Newton-Raphson scheme, it is highly recommended to supply the analytical Jacobian  $Jfun(w)$  of the residual  $fun(w)$ , in order to achieve a faster computation and avoid the approximation via finite differences. Moreover, good initial guesses  $w_{0,i}$  can considerably speed-up the convergence of the Newton method.

In line 10, a *direct* solver (e.g. “\” in MATLAB) or an *iterative* solver (e.g. `pcg`) can be used.

**Linear signal generator:** With the proposed approach, the underdetermined *linear* system

$$\mathbf{W}^T \mathbf{f}(x(t), \mathbf{0}) = \mathbf{S}_w \mathbf{W}^T \mathbf{E} x(t) - \mathbf{L}^T \mathbf{h}(x(t))$$

becomes

$$w_i^T \{ \mu_i \mathbf{E} x_{0,\ell} - \mathbf{f}(x_{0,\ell}, \mathbf{0}) \}_{\ell=1}^n = \{ l_i^T \mathbf{h}(x_{0,\ell}) \}_{\ell=1}^n, \quad i = 1, \dots, r$$

which consists of  $n$  equations for  $n$  unknowns in  $w_i^T$ , for each  $i = 1, \dots, r$ .

**Zero signal generator:** The underdetermined *linear* system from before becomes

$$w_i^T \{ -\mathbf{f}(x_{0,\ell}, \mathbf{0}) \}_{\ell=1}^n = \{ l_i^T \mathbf{h}(x_{0,\ell}) \}_{\ell=1}^n, \quad i = 1, \dots, r$$

which is also well-determined ( $n$  equations for  $n$  unknowns).

### Output Nonlinear Moment Matching for linear/zero signal generator

As seen above, the proposed simplifications yield *linear* systems of equations (LSEs) in case of a linear or zero signal generator. Therefore, the O-NLMM algorithm can be simplified as follows:

#### Algorithm 1 O-NLMM for linear/zero signal generator

**Input:**  $\mathbf{E}$ ,  $\mathbf{f}(x, \mathbf{u})$ , shifts  $\mu_i$ , tangential directions  $l_i^T$ , initial states  $\{x_{0,\ell}\}_{\ell=1}^n$

**Output:** orthogonal basis  $\mathbf{W}$

```

1: for i = 1 : r do
2:   for l = 1 : n do
3:     A_{\mu_i} = [A_{\mu_i}, \mu_i E x_{0,l} - f(x_{0,l}, 0)]
4:     y_l^w(\ell) = l_i^T h(x_{0,l})
5:     y_w^T = [y_w^T, y_l^w(\ell)]
6:   end for
7:   Solve w_i^T A_{\mu_i} = y_w^T or A_{\mu_i}^T w_i = y_w : w_i^T = y_w^T / A_{\mu_i} ⇔ w_i = A_{\mu_i}^T \setminus y_w
8:   W(:, i) ← w_i
9:   W = gramSchmidt(w_i, W) ▷ optional
10: end for

```

Due to the linearity of  $\tilde{s}_{w_i}(w_i) = w_i^T \mu_i \mathbf{E} x_{0,\ell}$  and  $y_{i,\ell}^w(w_i) = l_i^T \mathbf{h}(x_{0,\ell})$  w.r.t. the unknown  $w_i$ , the (sparse, possibly complex) “shifted” matrix  $\mathbf{A}_{\mu_i} \in \mathbb{C}^{n \times n}$  (cf. line 3) as well as the *constant* row-vector  $y_w^T \in \mathbb{C}^{1 \times n}$  (cf. line 5) can be constructed, yielding the well-known LSEs  $\mathbf{A}_{\mu_i}^T w_i = y_w$ . These LSEs can be solved using a *direct* (“\” in MATLAB) or an *iterative* solver (e.g. `pcg`). Remarkably, no Newton-Raphson scheme is required at all in this case.

### Analysis, Discussion and Limitations

At this point, we want to briefly discuss the proposed simplifications, as well as the degrees of freedom and limitations of the presented O-NLMM algorithm.

**Adequate selection of the projection ansatz.** The simple choice of a linear projection  $x_r^w(t) = \omega(x(t)) = \mathbf{W}^T \mathbf{E} x(t)$  is motivated by its easy and frequent use in comparison to nonlinear projections. Nevertheless, a more sophisticated projection, like e.g. a polynomial series expansion ansatz, might be superior and even indispensable in certain cases.

**Appropriate choice of the signal generator.** The signal generator  $(\tilde{s}_w(x_r^w(t)), \mathbf{L}(x_r^w(t)))$  determines (1) the ansatz for the dynamics  $x_r^w(t)$  and (2) the “weighting” of the output. In case of a linear signal generator,  $\tilde{s}_w(x_r^w(t)) = \mathbf{S}_w x_r^w(t)$  and  $\mathbf{L}(x_r^w(t)) = \mathbf{L}^T$  holds, meaning that complex exponentials  $e^{\mu_i t}$  and left tangential directions  $l_i^T$  are being employed. Regardless of their (questionable) suitability, an expansion-based generator ansatz can be also used.

**Obtaining a state-independent matrix equation.** In the Sylvester-like PDE from above, the state vector  $x(t)$  cannot be factored out so easily like in the linear case. In fact, the key to obtain a state-independent matrix equation of dimension  $r \times n$  lies on both the choice of an adequate projection ansatz and signal generator, customized for the nonlinear system.

**Limitations of the row-wise consideration.** If a linear projection is applied and the factorization of  $x(t)$  does not succeed, then the underdetermined system from above is obtained. The proposed row-wise consideration, together with the initial states  $\{x_{0,\ell}\}_{\ell=1}^n$ , has the limitation that the underdetermined equation is generally not fulfilled, since the (nonlinear) couplings in  $\mathbf{W}^T \mathbf{f}(x(t), \mathbf{0})$ ,  $\tilde{s}_w(\mathbf{W}^T \mathbf{E} x(t))$ ,  $\mathbf{L}(\mathbf{W}^T \mathbf{E} x(t))$  are not being considered.

**Approximating output nonlinear moments.** What moments are being matched, when we apply the O-NLMM algorithm? Since the PDE is not being solved, the “true” output nonlinear moments  $m_0^T(\tilde{s}_w(x_r^w(t)), \mathbf{L}(x_r^w(t)), x_0)$  are not exactly matched. Instead, we are *approximately* matching these moments at the chosen data  $(\tilde{s}_{w_i}(x_{r,i}^w(\ell)), l_i^T(x_{r,i}^w(\ell)), x_{0,\ell})$ .