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Model reduction of singular switched systems in discrete time

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System class and motivation

$$E_{\sigma(k)}x(k+1) = A_{\sigma(k)}x(k) + B_{\sigma(k)}u(k)$$

$$y(k) = C_{\sigma(k)}x(k) + D_{\sigma(k)}u(k)$$

- › $x : \mathbb{N} \rightarrow \mathbb{R}^n$ state, $u : \mathbb{N} \rightarrow \mathbb{R}^m$ input, $y : \mathbb{N} \rightarrow \mathbb{R}^p$ output
- › $\sigma : \mathbb{N} \rightarrow \{1, 2, \dots, n\}$ **switching signal**
- › $E_1, E_2, \dots, E_n, A_1, A_2, \dots, A_n \in \mathbb{R}^{n \times n}$ with **E -matrices possibly singular**
- › $B_1, B_2, \dots, B_n \in \mathbb{R}^{n \times m}$, $C_1, C_2, \dots, C_n \in \mathbb{R}^{p \times n}$

Motivation

- › Leontief economic model (LUENBERGER 1977)
- › discretization of continuous-time switched DAEs (e.g. switched electrical circuits)

Goal

Find **reduced model** with approximately the same input-output behavior

Key challenges

Challenge 1

Surprisingly complex solution theory

Challenge 2

How to incorporate the switching signal in model reduction method?

Solution theory

Simple homogeneous example

$$E_{\sigma(k)}x(k+1) = A_{\sigma(k)}x(k) \quad (\text{hSSS})$$

Example

Consider (hSSS) with

$$E_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \quad A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad E_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Nonswitched solution behavior

$$\begin{aligned} \sigma \equiv 1 : \quad & \left. \begin{aligned} x_1(k+1) &= x_1(k) \\ 0 &= x_2(k) \end{aligned} \right\} \rightsquigarrow x(k) = \begin{pmatrix} c_1 \\ 0 \end{pmatrix} \quad \forall k \in \mathbb{N} \\ \sigma \equiv 2 : \quad & \left. \begin{aligned} 0 &= x_1(k) \\ x_2(k+1) &= x_2(k) \end{aligned} \right\} \rightsquigarrow x(k) = \begin{pmatrix} 0 \\ c_2 \end{pmatrix} \quad \forall k \in \mathbb{N} \end{aligned}$$

Simple homogeneous example

$$E_{\sigma(k)}x(k+1) = A_{\sigma(k)}x(k) \quad (\text{hSSS})$$

Example

Consider (hSSS) with

$$E_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \quad A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad E_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Switched solution behavior $\sigma(k) = \begin{cases} 1, & k < k_s \\ 2, & k \geq k_s \end{cases}$

For $k < k_s$ we have $x(k) = \begin{pmatrix} c_1 \\ 0 \end{pmatrix}$ and for $k = k_s - 1$ also $x_1(k_s) = x_1(k_s - 1) = c_1$

BUT: For $k = k_s$ also $0 = x_1(k_s)$, hence $c_1 = 0$ necessary!

Furthermore $x_2(k_s)$ not constraint by mode 1 $\rightsquigarrow x_2(k) = c_2$ for all $k \geq k_s$

$\rightsquigarrow x(k) = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$ for $k < k_s$ and $x(k) = \begin{pmatrix} 0 \\ c_2 \end{pmatrix}$ for $k \geq k_s$

Simple homogeneous example

$$E_{\sigma(k)}x(k+1) = A_{\sigma(k)}x(k) \quad (\text{hSSS})$$

Example

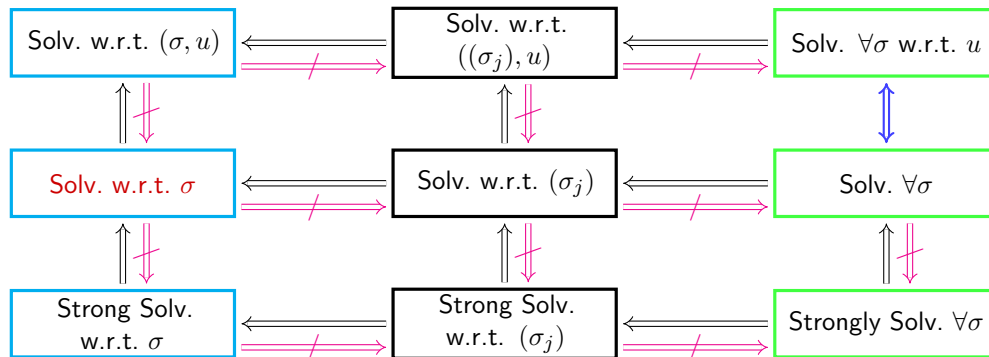
Consider (hSSS) with

$$E_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \quad A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad E_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

No existence and uniqueness of solutions!

- › **Non-existence**: Not all solutions from the past can be extended to a global solution
- › **Non-uniqueness**: Single initial value leads to multiple solutions in the future
- › **Non-causality**: Loss of causality w.r.t. to switching signal
- › Above problems occur despite the **individual modes being regular and index-1**
- › Considering **input** complicates situation further

Solvability concepts: overview



Sutrisno et al.: “Discrete-time switched descriptor systems: How to solve them?”, Math. Control Signals Syst. (2025). <https://doi.org/10.1007/s00498-025-00419-7> (open access)

Solvability characterization

Notation for (E_i, A_i, B_i) :

$$\mathcal{S}_i := A_i^{-1}(\text{im } E_i), \quad \widehat{\mathcal{S}}_i := A_i^{-1}(\text{im}[E_i, B_i]), \quad \widehat{\mathcal{R}}_i := E_i^{-1}(\text{im}[A_i, B_i])$$

Definition

The family $\{(E_i, A_i, B_i)\}_{i \in \{1, \dots, n\}}$ is called **switched index-1** w.r.t. $\sigma : \Longleftrightarrow$

- › $\text{im } B_i \subseteq \text{im}[E_i, A_i] \quad \forall i \quad \text{and}$
- › $\widehat{\mathcal{R}}_{\sigma(k)} + \widehat{\mathcal{S}}_{\sigma(k+1)} \subseteq \ker E_{\sigma(k)} \oplus \mathcal{S}_{\sigma(k+1)} \quad \forall k$

Theorem (Solvability characterization)

(SSS) with given σ is solvable $\Longleftrightarrow \{(E_i, A_i, B_i)\}_i$ is switched index-1 w.r.t. σ

Relationship to index 1

Fact: (E, A) is regular and index 1 $\Longleftrightarrow \ker E \oplus \mathcal{S} = \mathbb{R}^n$

BUT: regularity and index-1 is **neither necessary nor sufficient** for switched index-1!

Explicite solution formula

Notation:

› $\Pi_{\mathcal{V}}^{\mathcal{W}} : \mathcal{V} + \mathcal{W} \rightarrow \mathcal{V}$ denotes any (not necessarily unique) projector such that

$$\Pi_{\mathcal{V}}^{\mathcal{W}} \mathcal{V} = \mathcal{V} \quad \text{and} \quad \Pi_{\mathcal{V}}^{\mathcal{W}} \mathcal{W} = \mathcal{V} \cap \mathcal{W}$$

› M^+ denotes any (not necessarily unique) generalized inverse of M , i.e. $MM^+M = M$

Theorem

(SSS) is solvable w.r.t. σ , then x is a solution on $[k_0, k_1]$ if $x(k_0) \in \mathcal{S}_{\sigma(k_0)} - \{B_{\sigma(k_0)}^a u(k_0)\}$ and

$$x(k+1) = \Phi_{\sigma(k+1), \sigma(k)} x(k) + \Psi_{\sigma(k+1), \sigma(k)}^c u(k) + \Psi_{\sigma(k+1), \sigma(k)}^a u(k+1)$$

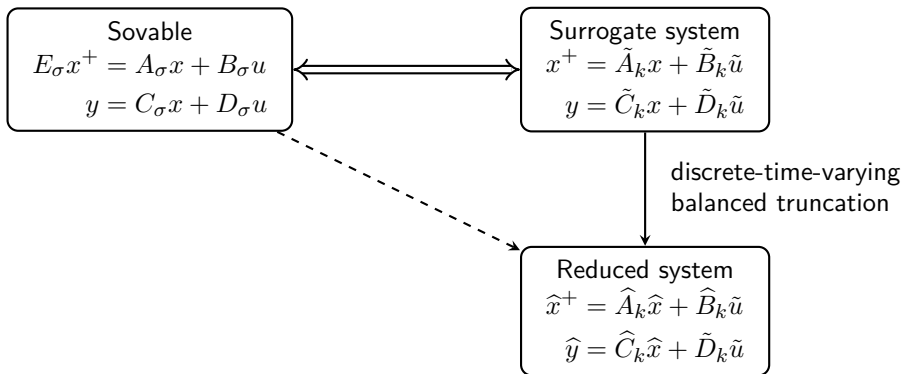
where

$$\Phi_{i,j} := \Pi_{\mathcal{S}_i}^{\ker E_j} E_j^+ \Pi_{\text{im } E_j}^{\text{im } A_j} A_j, \quad \Psi_{i,j}^c := \Pi_{\mathcal{S}_i}^{\ker E_j} B_j^c, \quad \Psi_{i,j}^a := (\Pi_{\mathcal{S}_i}^{\ker E_j} - I) B_i^a,$$

$$B_j^c := E_j^+ \Pi_{\text{im } E_j}^{\text{im } A_j} B_j, \quad B_i^a := -A_i^+ \Pi_{\text{im } A_i}^{\text{im } E_i} B_i$$

Surrogate system and reduced model

With $\tilde{u}(k) := \begin{pmatrix} u(k) \\ u(k+1) \end{pmatrix}$ and $\tilde{A}_k := \Phi_{\sigma(k+1), \sigma(k)}$, $\tilde{B}_k := [\Psi_{\sigma(k+1), \sigma(k)}^c, \Psi_{\sigma(k+1), \sigma(k)}^a]$,
 $\tilde{C}_k := C_{\sigma(k)}$, $\tilde{D}_k := [D_\sigma, 0]$ we then have:



Discrete-time-varying balanced truncation

Time-varying Gramians

$$\begin{aligned}x(k+1) &= \tilde{A}_k x(k) + \tilde{B}_k \tilde{u}(k) \\ y(k) &= \tilde{C}_k x(k) + \tilde{D}_k \tilde{u}(k)\end{aligned}\tag{Surr}$$

Definition (Controllability and observability Gramians)

$$\begin{aligned}P_{k_0} &:= 0, & P_{k+1} &:= \tilde{A}_k P_k \tilde{A}_k^\top + \tilde{B}_k \tilde{B}_k^\top, & k &= k_0, k_0 + 1, \dots, k_f - 1 \\ Q_{k_f} &:= \tilde{C}_{k_f}^\top \tilde{C}_{k_f}, & Q_{k-1} &:= \tilde{A}_{k-1}^\top Q_k \tilde{A}_{k-1} + \tilde{C}_{k-1}^\top \tilde{C}_{k-1}, & k &= k_f, k_f - 1, \dots, k_0 + 1\end{aligned}$$

Theorem (Input and output energy)

$$\begin{aligned}\forall x_k \in \text{im } P_k: \quad & x_k^\top P_k^+ x_k = \min \left\{ \sum_{\ell=k_0}^{k-1} u(\ell)^\top u(\ell) \mid \begin{array}{l} u \text{ is s.t. solution } x \text{ of (Surr)} \\ \text{satisfies } x(k_0) = 0 \text{ and } x(k) = x_k \end{array} \right\} \\ \forall \text{ solutions } x \text{ of (Surr) on } [k, k_f]: \quad & x(k)^\top Q_k x(k) = \sum_{\ell=k}^{k_f} y(\ell)^\top y(\ell)\end{aligned}$$

Time-varying balancing

$$\begin{aligned}x(k+1) &= \tilde{A}_k x(k) + \tilde{B}_k \tilde{u}(k) \\ y(k) &= \tilde{C}_k x(k) + \tilde{D}_k \tilde{u}(k)\end{aligned}\tag{Surr}$$

Definition (Balanced system)

(Surr) is called **balanced** $:\Longleftrightarrow \exists$ positive definite diagonal matrix $\Sigma_k, \Sigma_k^r, \Sigma_k^o$:

$$P_k = \text{diag}(\Sigma_k, \Sigma_k^r, 0, 0) \quad \text{and} \quad Q_k = \text{diag}(\Sigma_k, 0, \Sigma_k^o, 0)$$

Theorem (cf. Thm. 7.5 in ZHOU & DOYLE 1999)

There **always exists** a (time-varying) coordinate transformation resulting in a **balanced system**.

Note: For $x(k) = T_k z(k)$ the transformed system is

$$\begin{aligned}z(k+1) &= \bar{A}_k z(k) + \bar{B}_k \tilde{u}(k) \\ y(k) &= \bar{C}_k z(k) + \bar{D}_k \tilde{u}(k)\end{aligned}\quad \text{with}$$

$$\bar{A}_k := T_{k+1}^{-1} \tilde{A}_k T_k, \quad \bar{B}_k := T_{k+1}^{-1} \tilde{B}_k, \quad \bar{C}_k := \tilde{C}_k T_k, \quad \text{and} \quad \bar{P}_k = T_k^{-1} P_k T_k^{-\top}, \quad \bar{Q}_k = T_k^{\top} Q_k T_k$$

Time-varying balanced truncation

For each k choose reduction size r_k (e.g. by defining threshold for diagonal entries in Σ_k) and let

$$\Pi_k^l := [I_{r_k} \ 0]T_k^{-1} \quad \text{and} \quad \Pi_k^r := T_k \begin{bmatrix} I_{r_k} \\ 0 \end{bmatrix}$$

The reduced model is then

$$\begin{aligned} \hat{x}(k+1) &= \hat{A}_k \hat{x}(k) + \hat{B}_k \begin{bmatrix} u(k) \\ u(k+1) \end{bmatrix} \\ y(k) &= \hat{C}_k \hat{x}(k) + D_k u(k) \end{aligned}$$

with

$$\hat{A}_k := \Pi_{k+1}^l \tilde{A}_k \Pi_k^r, \quad \hat{B}_k := \Pi_{k+1}^l \tilde{B}_k, \quad \hat{C}_k := \tilde{C}_k \Pi_k^r$$

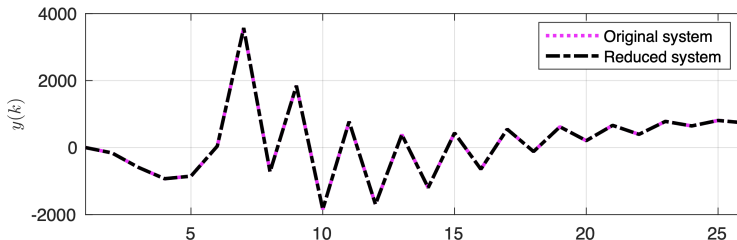
Example

$$E_{\sigma(k)}x(k+1) = A_{\sigma(k)}x(k) + B_{\sigma(k)}u(k)$$

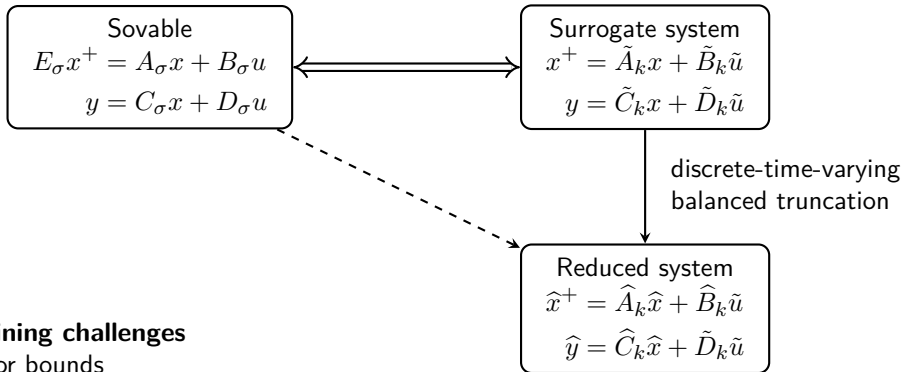
$$y(k) = C_{\sigma(k)}x(k) + D_{\sigma(k)}u(k)$$

- › $n = 100$, $m = p = 1$, $\text{rank } E_i = 50$, otherwise **random matrices**
- › $[k_0, k_f] = [1, 2, \dots, 26]$, switching sequence $(1, 2, 1, 2, 1)$ with switching times $(6, 11, 16, 21)$
- › With reduction threshold 0.1 the reduced model sizes are

k	1	2	3	4	5	6	7	...	19	20	21	22	23	24	25	26
r_k	0	2	4	6	6	6	7	...	7	6	6	5	4	3	2	1



Summary



Remaining challenges

- › Error bounds
- › Robust and efficient numerical implementations
- › Uncertain switching signal