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Model reduction of switched systems via midpoint Gramians

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Problem formulation

Switched linear ODEs with state jumps

$$\begin{aligned}\dot{x} &= A_{\sigma}x + B_{\sigma}u \\ x(t_k^+) &= J_k^x x(t_k^-) + J_k^v v_k \\ y &= C_{\sigma}x\end{aligned}$$

$$\sigma : [t_0, t_f) \rightarrow \{0, 1, 2, \dots, m\}$$

$$A_0, A_1, \dots, A_m, J_0^x, J_1^x, \dots, J_m^x \in \mathbb{R}^{n \times n}$$

$$B_0, \dots, B_m \in \mathbb{R}^{n \times m_u}, J_0^v, \dots, J_m^v \in \mathbb{R}^{n \times m_v}$$

$$C_0, C_1, \dots, C_m \in \mathbb{R}^{p \times n}$$

Reduced model

$$\begin{aligned}\dot{\hat{x}} &= \hat{A}_{\sigma} \hat{x} + \hat{B}_{\sigma} u \\ \hat{x}(t_k^+) &= \hat{J}_k^x \hat{x}(t_k^-) + \hat{J}_k^v v_k \\ \hat{y} &= \hat{C}_{\sigma} z\end{aligned}$$

$$\hat{A}_k \in \mathbb{R}^{r_k \times r_k}, \hat{J}_k^x \in \mathbb{R}^{r_k \times r_{k-1}}$$

$$\hat{B}_k \in \mathbb{R}^{r_k \times m_u}, \hat{J}_k^v \in \mathbb{R}^{r_k \times m_v}$$

$$\hat{C}_k \in \mathbb{R}^{p \times r_k}$$

Motivation

- › Switched differential-algebraic equations
- › Most general linear system class (covers switched and impulsive systems)

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Reduced model

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$$\hat{C}_k \in \mathbb{R}^{p \times r_k}$$

Related research

- › Simultaneous balancing (MONSHIZADEH et al. 2012)
- › Output-depending switching (PAPADOPOULUS & PRANDINI 2016)
- › Enveloping (non-switched) system (SCHULZE & UNGER 2018)
- › Gramian-based approaches (PETREZCKY, GOSEA, ...)

Novel viewpoint

Consider switched linear ODE (without jumps) as special case of **time-varying linear system**

$$\dot{x} = A(t)x + B(t)u$$

$$y = C(t)x$$

In particular, consider switching signal as **given** time-varying system parameter

Existing approaches unsuitable

Existing approaches (IMAE, SHOKOOHI, SILVERMAN, VERRIEST):

- › Smoothness of coefficients assumed
- › Reduced model is fully time-varying (not piecewise-constant)
- › State jumps not considered

Challenge 1: Naive mode-wise reduction unsuitable

Example: Naive mode-wise reduction is not working

on $[t_0, t_1)$:

$$\dot{x} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} x + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u$$

$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} x$$

on $[t_1, t_f)$:

$$\dot{x} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u$$

$$y = \begin{bmatrix} 0 & 1 \end{bmatrix} x$$

Each mode is input-output equivalent to same scalar system

$$\dot{z} = u, \quad y = z$$

But **outputs do not match** anymore after switch!

Reducability of modes is effected by other modes

In example:

Second state is **unobservable** in first mode, but becomes **observable** in second mode

Challenge 2: Different reduced state-dimensions

Example: Reduced switched system with non-equal state-dimensions

on $[t_0, t_1)$:

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} u$$

$$y = [0 \ 1 \ 0] x$$

on $[t_1, t_f)$:

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} u$$

$$y = [1 \ 0 \ 0] x$$

Reduced system (with identical input-output behavior):

on $[t_0, t_1)$:

$$\dot{z}^0 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} z^0 + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u$$

$$y = [0 \ 1] z^0$$

on $[t_1, t_f)$:

$$\dot{z}^1 = 0 \cdot z^1 + u$$

$$y = z^1$$

with concatenation condition: $z^1(t_1) = [1 \ 0] z^0(t_1)$

Reduced system necessarily contains jumps

Jumps occur in reduced model even if original system does not contain jumps

Challenge 3: Duration depend reduction

Reducability may depend on mode durations

Example:

on $[t_0, t_1)$:

$$\dot{x} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} x + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u$$

$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} x$$

on $[t_1, t_2)$:

$$\dot{x} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} x$$

$$y = 0$$

on $[t_2, t_f)$

$$\dot{x} = 0$$

$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} x$$

For $t_2 - t_1 = 2k\pi$ reduction possible to

on $[t_0, t_1)$:

$$\dot{z}^0 = 0 \cdot z^0 + u$$

$$y = z^0$$

on $[t_1, t_2)$:

no state

$$y = 0$$

on $[t_2, t_f)$

$$\dot{z}^2 = 0$$

$$y = z^2$$

But for almost all other switching durations: First two modes **not reducible!**

Duration-dependent reduction methods?

Effective reduction method necessarily duration dependent, but poses numerical challenges.

Challenge 4: Two types of input

$$\begin{aligned}\dot{x} &= A_{\sigma}x + B_{\sigma}u \\ x(t_k^+) &= J_k^x x(t_k^-) + J_k^v v_k \\ y &= C_{\sigma}x\end{aligned}$$

Decoupling of inputs possible?

What does “difficult to control” mean for this system class?

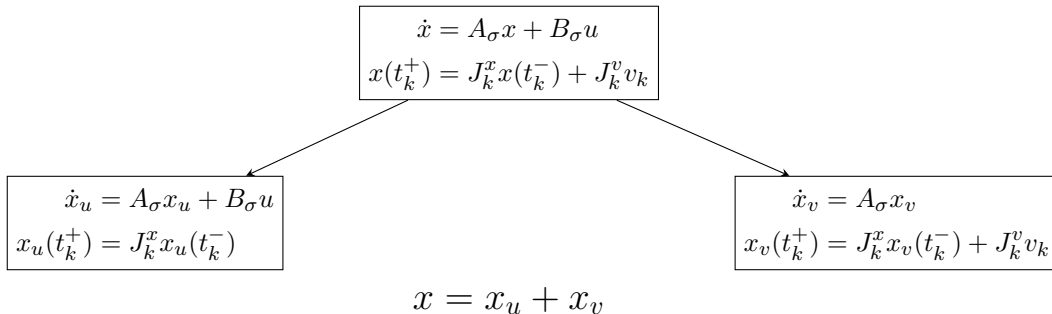
Content

System models and challenges

Reduction procedure

Academic example and summary

Decoupling of inputs and overall reduction method



Key idea for model reduction

Identify **difficult to reach** and **difficult to observe** states via suitable **Gramians**:

- › Calculated two types of reachability Gramians (one for u and one for v_k)
- › Calculate observability Gramian
- › Apply balanced truncation via **midpoint Gramians**

Time-varying reachability Gramian

Consider system with input u only (i.e. $v_k = 0$)

Definition (Time-varying reachability Gramian)

$$t \in (t_0, t_1] : \mathcal{P}^\sigma(t) := \int_{t_0}^t e^{A_0(\tau-t_0)} B_0 B_0^\top e^{A_0^\top(\tau-t_0)} d\tau$$

$$t \in (t_k, t_{k+1}] : \mathcal{P}^\sigma(t) := e^{A_k(t-t_k)} J_k^x \mathcal{P}^\sigma(t_k) J_k^{x\top} e^{A_k^\top(t-t_k)} + \int_{t_k}^t e^{A_k(\tau-t_k)} B_k B_k^\top e^{A_k^\top(\tau-t_k)} d\tau$$

Theorem (Required input energy to reach x_t on $[t_0, t]$)

$\text{im } P^\sigma(t^-)$ is the *reachability space* of the switched system with jumps and for all $x_t \in \text{im } P_k(t^-)$:

$$\min_{\substack{u \\ 0 \rightarrow x_t}} \int_{t_0}^t u(t)^\top u(t) dt = x_t^\top P^\sigma(t^-)^\dagger x_t.$$

Time-varying observability Gramian

Consider homogeneous switched system (i.e. $u = 0$ and $v_k = 0$).

Definition (Time-varying observability Gramian)

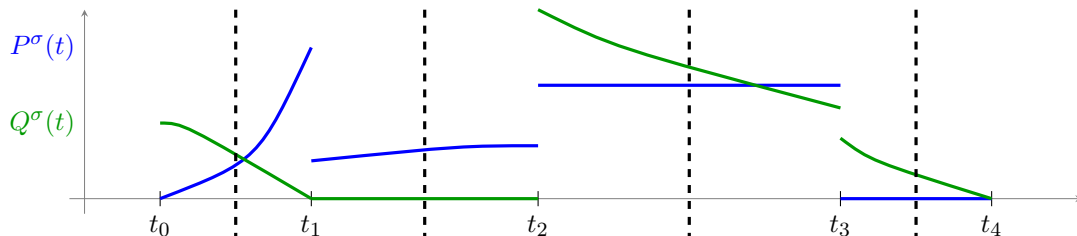
$$\begin{aligned} t \in [t_m, t_f) : \quad \mathcal{Q}^\sigma(t) &:= \int_t^{t_f} e^{A_m^\top(t_f-\tau)} C_m^\top C_m e^{A_m(t_f-\tau)} d\tau \\ t \in [t_k, t_{k+1}) : \quad \mathcal{Q}^\sigma(t) &:= e^{A_k^\top(t_{k+1}-t)} J_{k+1}^{x^\top} \mathcal{Q}^\sigma(t_{k+1}) J_{k+1}^x e^{A_k(t_{k+1}-t)} \\ &\quad + \int_t^{t_{k+1}} e^{A_k^\top(t_{k+1}-\tau)} C_k^\top C_k e^{A_k(t_{k+1}-\tau)} d\tau \end{aligned}$$

Theorem (Observable output energy from x_t on $[t, t_f]$)

$\ker \mathcal{Q}^\sigma(t^+)$ is the *unobservable space* of the switched system with jumps and for all $x_t \in \mathbb{R}^n$:

$$\int_t^{t_f} y(t)^\top y(t) dt = x_t^\top \mathcal{Q}^\sigma(t^+) x_t.$$

Midpoint Gramians



Fully time-varying Gramians

› need **one** reachability and **one** observability Gramian per mode

› $\rightsquigarrow$ consider midpoint Gramians: $P^\sigma(\frac{t_k+t_{k+1}}{2})$ and $Q^\sigma(\frac{t_k+t_{k+1}}{2})$

Effect of discrete input v_k on reachability Gramian?

$P^\sigma(t)$ only considers reachability w.r.t. continuous input u , effect of v_k **not yet considered**

$\rightsquigarrow$ utilize decoupling $x = x_u + x_v$

Discrete reachability Gramian

Consider switched system with $u = 0$:

$$\dot{x} = A_{\sigma} x$$

$$x(t_k^+) = J_k^x x(t_k^-) + J_k^v v_k$$

Solution $x(\frac{t_k+t_{k+1}}{2})$ at midpoints is given by solution of **discrete time** system

$$x_{k+1}^m = A_k^m x_k^m + B_k^m v_k$$

with

$$A_k^m := e^{A_k \frac{t_{k+1}-t_k}{2}} J_k^x e^{A_{k-1} \frac{t_k-t_{k-1}}{2}} \quad \text{and} \quad B_k^m := e^{A_k \frac{t_{k+1}-t_k}{2}} J_k^v$$

Definition (Discrete reachability Gramian)

$$P_k^v := A_k^m P_{k-1}^v A_k^{m\top} + B_k^v B_k^{v\top}$$

with either $P_{-1}^v := 0$ for $x^m(0) = 0$ or $P_{-1}^v := \gamma X_0 X_0^\top$ for $x(0) \in \text{im } X_0$

Midpoint based balanced truncation

Proposed reduction method

Mode-wise balanced truncation with w.r.t. combined midpoint reachability Gramian

$P_k^m := P^\sigma\left(\frac{t_k+t_{k+1}}{2}\right) + \lambda P_k^v$ and midpoint observability Gramian $Q_k^m := P^\sigma\left(\frac{t_k+t_{k+1}}{2}\right)$

Reminder: Balanced Truncation

Given: Midpoint Gramians (P_k^m, Q_k^m)

Method:

1. Find **balancing** transformation T_k , such that Gramians P_k^m, Q_k^m are **equal and diagonal**
2. Balanced Gramians $\rightsquigarrow$ how **difficult to reach and observe** are state directions
3. Remove simultaneously difficult to reach and observe state directions
 $\rightsquigarrow$ **left- and right-projection** matrices W_k, V_k as corresponding rows/columns of T_k^{-1}/T_k

Overall reduction algorithm for switched impulsive systems

$$\begin{aligned} \dot{x} &= A_k x + B_k u, & \text{on } (t_k, t_{k+1}) \\ \Sigma_\sigma : \quad x(t_k^+) &= J_k x(t_k^-) + J_k^v v_k, & k = 0, 1, 2, \dots, \quad x(t_0^-) \in \text{im } X_0 \\ y &= C_k x \end{aligned}$$

Algorithm

Step 1a: Calculate midpoint reachability Gramians P_k^m forward in time w.r.t. u and v_k

Step 1b: Calculate midpoint observability Gramians Q_k^m backward in time

Step 2a: Based on singular values of $P_k^m Q_k^m$ decide on reduction order r_k

Step 2b: Calculate left/right projectors W_k, V_k via **standard balanced truncation**

Step 3: Calculate reduced modes $(\hat{A}_k, \hat{B}_k, \hat{C}_k) := (W_k A_k V_k, \quad W_k B_k, \quad C_k V_k)$

Step 4: Calculate reduced jump maps $\hat{J}_k^x := W_k J_k^x V_{k-1}$ and $\hat{J}_k^v := W_k J_k^v$

Step 5: Calculate $\hat{X}_0 = I_{r_{-1}}$ with $r_{-1} := \dim \text{im } X_0 - \dim(\text{im } X_0 \cap \ker W_0 J_0^x)$

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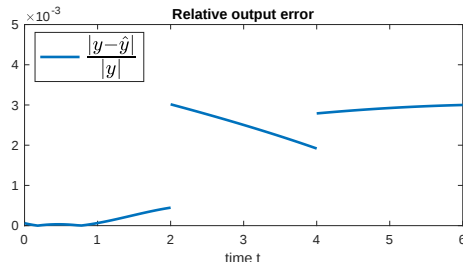
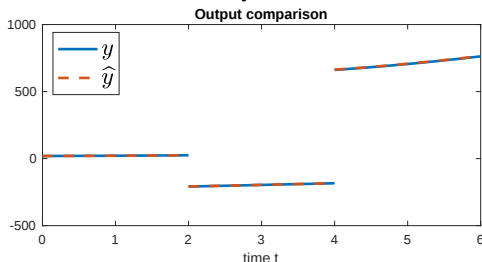
Random medium size example

Consider a switched system with 3 random modes of sizes $n_1 = 50$, $n_2 = 60$, $n_3 = 40$ and with non-zero initial conditions in $\text{im } X_0$ with dimension 5

Reduction parameters:

- › $\lambda = 1$ (weight of discrete reachability Gramian)
- › $\gamma = 0.1$ (weight of initial conditions)
- › $\varepsilon_k = 10^{-3}$ (Hankel singular values threshold)

↪ reduced switched system with reduced sizes $r_0 = 8$, $r_1 = 10$, $r_2 = 6$



Summary

- › Midpoint-based balanced truncation method, suitable for switched linear systems with
 - known switching signal
 - mode-dependent state dimension
 - state-jumps
 - arbitrary non-zero initial values
- › Remaining challenges
 - resolve numerical challenges with (almost) singular Gramians
 - relax dependence on exact knowledge of switching signal
 - error bounds
 - extension to nonlinear case



Hossain & T.: Midpoint based balanced truncation for switched linear systems with known switching signal. IEEE TAC 2024.



Hossain & T.: Model reduction for switched differential-algebraic equations with known switching signal. DAE Panel 2025 (Matlab implementation available on Zenodo).



T., Sutrisno, Thuan & Ha: Model reduction of singular switched systems in discrete time. ECC 2025.