

# Linear-Quadratic Control of DAEs with an Application to Flow Control Problems

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# Differential-Algebraic Systems/Descriptor Systems

Linear time-invariant differential-algebraic systems/descriptor systems

$$\frac{d}{dt}Ex(t) = Ax(t) + Bu(t)$$

where

- $E, A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}$ ,
- $E$  is typically **singular**, but assume that  $sE - A$  is regular, i. e.,  $\det(sE - A) \neq 0$ ,
- state  $x \in \mathcal{L}_{loc}^2(\mathbb{R}, \mathbb{R}^n)$ , input  $u \in \mathcal{L}_{loc}^2(\mathbb{R}, \mathbb{R}^m)$ .

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## Typical applications

- network models: electrical circuits, gas networks, constrained multi-body systems, ...
- **semi-discretization of PDEs (e. g., Navier-Stokes)**,
- linearization of non-linear DAEs,
- ....

# The Linear-Quadratic Optimal Control Problem

Linear-quadratic optimal control problem: Minimize

$$\mathcal{J}(x, u) := \int_0^{\infty} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau$$

with  $Q = Q^T \in \mathbb{R}^{n \times n}$ ,  $S \in \mathbb{R}^{n \times m}$ , and  $R = R^T \in \mathbb{R}^{m \times m}$  subject to

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## Problems:

- feasibility, i. e., is

$$V^+(Ex_0) := \inf \left\{ \mathcal{J}(x, u) : \frac{d}{dt} Ex = Ax + Bu, \quad Ex(0) = Ex_0, \quad \lim_{t \rightarrow \infty} Ex(t) = 0 \right\}$$

finite for all consistent  $x_0$ ?

- optimal value  $V^+(Ex_0)$ ?
- existence and uniqueness of optimal controls ( $\rightsquigarrow$  regularity)?

# Geometric Concepts

a) behavior:

$$\mathfrak{B}_{[E,A,B]} := \{(x, u) \in \mathcal{L}_{\text{loc}}^2(\mathbb{R}, \mathbb{R}^n) \times \mathcal{L}_{\text{loc}}^2(\mathbb{R}, \mathbb{R}^m) : \frac{d}{dt}Ex = Ax + Bu\}.$$

b) system space: smallest subspace in  $\mathbb{R}^{n+m}$  such that

$$\begin{pmatrix} x(t) \\ u(t) \end{pmatrix} \in \mathcal{V}_{\text{sys}} \quad \forall (x, u) \in \mathfrak{B}_{[E,A,B]} \text{ and almost all } t \in \mathbb{R}.$$

c) space of consistent initial differential variables:

$$\mathcal{V}_{\text{diff}} := \{x_0 \in \mathbb{R}^n : \exists (x, u) \in \mathfrak{B}_{[E,A,B]} \text{ with } Ex(0) = Ex_0\}.$$

A system is called **impulse controllable**, if  $\mathcal{V}_{\text{diff}} = \mathbb{R}^n$ .

# Examples

## Example 1

Minimize 
$$\mathcal{J}(x, u) = \int_0^{\infty} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau$$

subject to 
$$\frac{d}{dt}x(t) = -x(t), \quad x(0) = x_0, \quad \lim_{t \rightarrow \infty} x(t) = 0.$$

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$$\begin{aligned} &\text{Minimize} && \mathcal{J}(x, u) = \int_0^\infty \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^\top \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau \\ &\text{subject to} && \frac{d}{dt}x(t) = -x(t), \quad x(0) = x_0, \quad \lim_{t \rightarrow \infty} x(t) = 0. \end{aligned}$$

### Observation:

$$\mathcal{J}(x, u) = \int_0^\infty 2x(\tau)u(\tau)d\tau$$

can be made arbitrarily large and negative, since  $u(\cdot)$  has no influence on the dynamics.



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$\implies V(Ex_0) = -\infty$  for all  $x_0 \in \mathbb{R} \implies$  infeasible problem.

# Examples

## Example 2

Minimize

$$\mathcal{J}(x, u) = \int_0^{\infty} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau$$

subject to

$$\frac{d}{dt}x(t) = -u(t), \quad x(0) = x_0, \quad \lim_{t \rightarrow \infty} x(t) = 0.$$

# Examples

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### Observation:

- For  $x_0 \neq 0$  we have  $\mathcal{J}(x, u) > 0$  for all solutions  $(x, u)$  with  $x(0) = x_0$ .
- For  $u_k = k \cdot \chi_{[0, k-1]} \cdot x_0$  we have

$$\mathcal{J}(x_k, u_k) = \frac{1}{3k} x_0^2 \xrightarrow{k \rightarrow \infty} 0.$$

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$$\mathcal{J}(x_k, u_k) = \frac{1}{3k} x_0^2 \xrightarrow{k \rightarrow \infty} 0.$$

$\implies V(E x_0) = 0$  for all  $x_0 \in \mathbb{R}$ , but for  $x_0 \neq 0$  there exists no solution attaining this value  $\implies$  singular problem.

- 1 Introduction
- 2 Conditions for Feasibility
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# Conditions for Feasibility

## Reminder: Optimal value

$$V^+(E_{x_0}) := \inf \left\{ \mathcal{J}(x, u) : \frac{d}{dt} Ex = Ax + Bu, Ex(0) = E_{x_0}, \lim_{t \rightarrow \infty} Ex(t) = 0 \right\}$$

## Necessary condition for feasibility

$$V^+(E_{x_0}) < \infty \quad \forall x_0 \in \mathcal{V}_{\text{diff}}$$

holds if and only if the system is **behaviorally stabilizable**, i. e., for all  $x_0 \in \mathcal{V}_{\text{diff}}$  there exists a solution  $(x, u)$  with  $Ex(0) = E_{x_0}$  and  $\lim_{t \rightarrow \infty} Ex(t) = 0$ .

Algebraically:

$$\text{rank} \begin{bmatrix} -\lambda E + A & B \end{bmatrix} = n \quad \forall \lambda \in \overline{\mathbb{C}}^+.$$

# Conditions for Feasibility

## (Virtual) storage functions

A function  $V : E\mathcal{V}_{\text{diff}} \rightarrow \mathbb{R}$  is called (virtual) storage function for the optimal control problem if  $V$  is continuous,  $V(0) = 0$  and for all solutions  $(x, u)$  we have

$$V(Ex(t_1)) - V(Ex(t_2)) \leq \int_{t_1}^{t_2} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau.$$

For  $t_1 = 0$ ,  $t_2 \rightarrow \infty$ , and  $Ex(0) = Ex_0$ ,  $\lim_{t \rightarrow \infty} Ex(t) = 0$  we obtain

$$V(Ex_0) \leq \mathcal{J}(x, u).$$



# Conditions for Feasibility

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For  $t_1 = 0$ ,  $t_2 \rightarrow \infty$ , and  $Ex(0) = Ex_0$ ,  $\lim_{t \rightarrow \infty} Ex(t) = 0$  we obtain

$$V(Ex_0) \leq \mathcal{J}(x, u).$$

## Sufficient condition for feasibility

If the system is behaviorally stabilizable and there exists a storage function, then

$$-\infty < V(Ex_0) \leq V^+(Ex_0) < \infty \quad \forall x_0 \in \mathcal{V}_{\text{diff}}.$$

# Quadratic Storage Functions

## Notation

For symmetric  $M, N \in \mathbb{R}^{n \times n}$  and a subspace  $\mathcal{V} \subseteq \mathbb{R}^n$  we write

- $M \geq_{\mathcal{V}} N \quad :\iff \quad v^T M v \geq v^T N v \quad \forall v \in \mathcal{V},$
- $M =_{\mathcal{V}} N \quad :\iff \quad v^T M v = v^T N v \quad \forall v \in \mathcal{V}.$

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## Quadratic storage functions and KYP inequality

[REIS, RENDEL, V. '15]

The function  $V : E\mathcal{V}_{\text{diff}} \rightarrow \mathbb{R}$  is a quadratic storage function, i. e.,

$$V(Ex_0) = x_0^T E^T P E x_0 \quad \text{for} \quad P = P^T \in \mathbb{R}^{n \times n}.$$

if and only if the **KYP inequality**

$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} \succeq_{\mathcal{V}_{\text{sys}}} 0, \quad P = P^T$$

is fulfilled.

# Quadratic Storage Functions

## Quadratic storage functions and KYP inequality

If  $V(Ex_0) = x_0^T E^T P E x_0$  is a quadratic storage function, then there exist  $K \in \mathbb{R}^{q \times n}$  and  $L \in \mathbb{R}^{q \times m}$  such that

$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} =_{\mathcal{V}_{\text{sys}}} \begin{bmatrix} K^T \\ L^T \end{bmatrix} \begin{bmatrix} K & L \end{bmatrix}, \quad P = P^T$$

# Quadratic Storage Functions

For  $(x, u)$  with  $Ex(0) = Ex_0$  and  $\lim_{t \rightarrow \infty} Ex(t) = 0$  it holds

$$x_0^T E^T P E x_0 = - \int_0^{\infty} \frac{d}{d\tau} (x(\tau)^T E^T P E x(\tau)) d\tau$$

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 &= - \int_0^\infty (Ax(\tau) + Bu(\tau))^T P E x(\tau) + x(\tau)^T E^T P (Ax(\tau) + Bu(\tau)) d\tau
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 &= - \int_0^\infty (A x(\tau) + B u(\tau))^T P E x(\tau) + x(\tau)^T E^T P (A x(\tau) + B u(\tau)) d\tau \\
 &= \int_0^\infty \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \begin{bmatrix} -E^T P A - A^T P E & -E^T P B \\ -B^T P E & 0 \end{bmatrix} \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau
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 &= \int_0^\infty \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \left( \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} - \begin{bmatrix} K^T K & K^T L \\ L^T K & L^T L \end{bmatrix} \right) \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau
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 &= \int_0^\infty \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix}^T \left( \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} - \begin{bmatrix} K^T K & K^T L \\ L^T K & L^T L \end{bmatrix} \right) \begin{pmatrix} x(\tau) \\ u(\tau) \end{pmatrix} d\tau \\
 &= \mathcal{J}(x, u) - \|Kx + Lu\|_{\mathcal{L}^2([0, \infty), \mathbb{R}^q)}^2.
 \end{aligned}$$

- 1 Introduction
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- 3 Existence, Uniqueness, and Construction of Optimal Controls**
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# Relation to the Optimal Control Problem

If the optimal control problem is feasible then the optimal value function  $V^+$  is quadratic, i. e.,

$$V^+(Ex_0) = x_0^T E^T P E x_0,$$

where

$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} = v_{\text{sys}} \begin{bmatrix} K^T \\ L^T \end{bmatrix} \begin{bmatrix} K & L \end{bmatrix}, \quad P = P^T$$

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## Implications:

- There exists a sequence  $((x_k, u_k))_{k \in \mathbb{N}}$  of  $\mathcal{L}_2$ -solutions with  $Ex_k(0) = Ex_0$  and  $\lim_{t \rightarrow \infty} Ex_k(t) = 0$  with

$$\lim_{k \rightarrow \infty} \|Kx_k + Lu_k\|_{\mathcal{L}^2([0, \infty), \mathbb{R}^q)}^2 = 0.$$

- An optimal control fulfills the **optimality DAE**

$$\frac{d}{dt} \begin{bmatrix} E & 0 \\ 0 & 0 \end{bmatrix} \begin{pmatrix} x(t) \\ u(t) \end{pmatrix} = \begin{bmatrix} A & B \\ K & L \end{bmatrix} \begin{pmatrix} x(t) \\ u(t) \end{pmatrix}, \quad Ex(0) = Ex_0, \quad \lim_{t \rightarrow \infty} Ex(t) = 0.$$

# Lur'e Equations

We have

$$V^+(Ex_0) = x_0^T E^T P E x_0,$$

where

$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} =_{\mathcal{V}_{\text{sys}}} \begin{bmatrix} K^T \\ L^T \end{bmatrix} [K \quad L], \quad P = P^T. \quad (\text{LE})$$

We can choose  $q$  such that  $K \in \mathbb{R}^{q \times n}$  and  $L \in \mathbb{R}^{q \times m}$  fulfill the extra condition

$$\text{rank}_{\mathbb{R}(s)} \begin{bmatrix} -sE + A & B \\ K & L \end{bmatrix} = n + q. \quad (\text{rk})$$

## Definition

We call a triple  $(P, K, L) \in \mathbb{R}^{n \times n} \times \mathbb{R}^{q \times n} \times \mathbb{R}^{q \times m}$  solution of the **Lur'e equation (LE)**, if (LE) and (rk) are satisfied.

# Stabilizing Solutions

Solutions of the Lur'e equation corresponding to  $V^+$  have further structure: A solution  $(P, K, L)$  of the Lur'e equation is called **stabilizing**, if

$$\text{rank} \begin{bmatrix} -\lambda E + A & B \\ K & L \end{bmatrix} = n + q \quad \forall \lambda \in \mathbb{C}^+.$$

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## Existence and uniqueness

[REIS, RENDEL, V. '15]

Assume that the KYP inequality is solvable. Then we have:

- **Existence:** system is behaviorally stabilizable  $\Rightarrow \exists$  stabilizing solution.
- **Uniqueness:**  $(P_1, K_1, L_1), (P_2, K_2, L_2)$  stabilizing solutions  $\Rightarrow E^T P_1 E =_{\mathcal{V}_{\text{diff}}} E^T P_2 E$ .
- **Extremality:**  $(P, K, L)$  is stabilizing solution of the Lur'e equation  $\Rightarrow E^T P E \geq_{\mathcal{V}_{\text{diff}}} E^T \tilde{P} E$  for all solutions  $\tilde{P}$  of the KYP inequality.



# Existence and Uniqueness of Optimal Controls

Reminder: optimality DAE

$$\frac{d}{dt} \begin{bmatrix} E & 0 \\ 0 & 0 \end{bmatrix} \begin{pmatrix} x(t) \\ u(t) \end{pmatrix} = \begin{bmatrix} A & B \\ K & L \end{bmatrix} \begin{pmatrix} x(t) \\ u(t) \end{pmatrix}, \quad Ex(0) = Ex_0, \quad \lim_{t \rightarrow \infty} Ex(t) = 0.$$

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## Corollary

- If for all  $x_0 \in \mathcal{V}_{\text{diff}}$  there exists an optimal control, then

$$\text{rank} \begin{bmatrix} -\lambda E + A & B \\ K & L \end{bmatrix} = n + q \quad \forall \lambda \in \overline{\mathbb{C}^+}.$$

- If for all  $x_0 \in \mathcal{V}_{\text{diff}}$  there exists a **unique** optimal control, then

$$\text{rank} \begin{bmatrix} -\lambda E + A & B \\ K & L \end{bmatrix} = n + m \quad \forall \lambda \in \overline{\mathbb{C}^+}.$$

**Remark:** An equivalence of such statements can be proven for **impulse controllable** systems.

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# Approaches Based on Matrix Inequalities

## Our KYP Inequality

$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} \succeq_{\mathcal{V}_{\text{sys}}} 0, \quad P = P^T$$

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### ■ Geerts '89–'94:

$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} \succeq 0, \quad P = P^T$$

Remarks:

- assumptions:  $\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} = \begin{bmatrix} C^T \\ D^T \end{bmatrix} [C \quad D] \succeq 0$ , however  $sE - A \in \mathbb{R}[s]^{k \times n}$  may be singular,
- $(E, A, B)$  is impulse controllable  $\Rightarrow \exists$  maximal solution of the LMI solving the optimal control problem,
- no theory for non-impulse controllable systems!

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$$\begin{bmatrix} E^T P A + A^T P E + Q & E^T P B + S \\ B^T P E + S^T & R \end{bmatrix} \geq_{\mathcal{V}_{\text{sys}}} 0, \quad P = P^T$$

### ■ Brüll '11:

$$\begin{bmatrix} A^T P_1 + P_1^T A + Q & A^T P_2 + P_1^T B + S \\ B^T P_1 + P_2^T A + S^T & B^T P_2 + P_2^T B + R \end{bmatrix} \geq 0,$$

$$E^T P_1 = P_1^T E, \quad E^T P_2 = 0$$

Remarks:

- assumptions:  $(E, A, B)$  is completely controllable,
- also generalization of the KYP inequality to higher-order and behavioral systems.

# Approaches Based on Matrix Equations

## Our Lur'e Equation

$$\begin{bmatrix} E^T X A + A^T X E + Q & E^T X B + S \\ B^T X E + S^T & R \end{bmatrix} = v_{\text{sys}} \begin{bmatrix} K^T \\ L^T \end{bmatrix} [K \quad L], \quad X = X^T$$

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- If  $E = I_n$ , then our Lur'e equation reduces to the [standard Lur'e equation](#) [REIS '11]

$$\begin{bmatrix} A^T X + X A + Q & X B + S \\ B^T X + S^T & R \end{bmatrix} = \begin{bmatrix} K^T \\ L^T \end{bmatrix} \begin{bmatrix} K & L \end{bmatrix}, \quad X = X^T.$$



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$$\begin{bmatrix} A^T X + X A + Q & X B + S \\ B^T X + S^T & R \end{bmatrix} = \begin{bmatrix} K^T \\ L^T \end{bmatrix} \begin{bmatrix} K & L \end{bmatrix}, \quad X = X^T.$$

- If further  $R$  is invertible, then  $\text{rank} \begin{bmatrix} K & L \end{bmatrix} = m$  and  $K$  and  $L$  can be eliminated to obtain an [algebraic Riccati equation](#)

$$A^T X + X A + Q - (X B + S) R^{-1} (B^T X + S^T) = 0, \quad X = X^T.$$

# Approaches Based on Matrix Equations

## Our Lur'e Equation

$$\begin{bmatrix} E^T X A + A^T X E + Q & E^T X B + S \\ B^T X E + S^T & R \end{bmatrix} = v_{\text{sys}} \begin{bmatrix} K^T \\ L^T \end{bmatrix} \begin{bmatrix} K & L \end{bmatrix}, \quad X = X^T$$

- **Kurina '93:** generalized algebraic Riccati equation:

$$A^T X + X A + Q - (X B + S) R^{-1} (B^T X + S^T) = 0, \quad E^T X = X^T E$$

Remarks:

- assumptions:  $\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \geq 0$ ,  $R > 0$ ,  $(E, A, B)$  impulse controllable,
- solution analysis: Katayama/Minamino '92 and Katayama/Kawamoto/Takaba '99, in particular solvability of an “algebraic quadratic matrix equation” necessary for existence of stabilizing solutions.

# Approaches Based on Matrix Equations

## Our Lur'e Equation

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- **Mehrmann '91:** generalized algebraic Riccati equation:

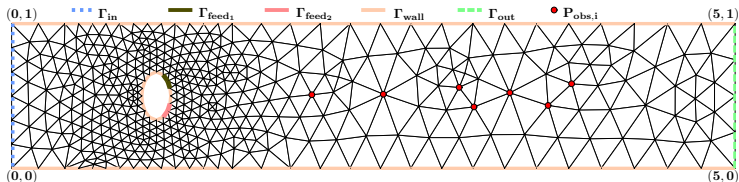
$$A^T X E + E^T X A + Q - (E^T X B + S) R^{-1} (B^T X E + S^T) = 0, \quad X = X^T$$

Remarks:

- assumptions:  $\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \geq 0$ ,  $R > 0$ ,  $(E, A, B)$  impulse controllable,
- solution of optimal control problems using even boundary value problems.

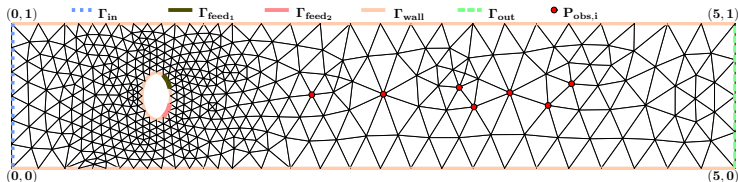
- 1 Introduction
- 2 Conditions for Feasibility
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# Example: von Kármán vortex street



**Goal:** stabilization of the fields towards a desired stationary solution  $(\mathbf{w}(x), \chi_s(x))$ .

# Example: von Kármán vortex street



**Goal:** stabilization of the fields towards a desired stationary solution  $(\mathbf{w}(x), \chi_s(x))$ .

**Model:** linearized Navier-Stokes equation [BÄNSCH, BENNER, SAAK, WEICHELDT '15]

$$\begin{aligned} \frac{\partial}{\partial t} \mathbf{z}(t, x) - \frac{1}{\text{Re}} \Delta \mathbf{z}(t, x) + (\mathbf{w}(x) \cdot \nabla) \mathbf{z}(t, x) + (\mathbf{z}(t, x) \cdot \nabla) \mathbf{w}(x) + \nabla \mathbf{p}(t, x) &= 0, \\ \text{div } \mathbf{z}(t, x) &= 0, \\ &+ \text{initial conditions} / + \text{boundary conditions}, \end{aligned}$$

**Here:**

- $\mathbf{z}(t, x)$  - difference between actual and desired velocities,
- $\mathbf{p}(t, x)$  - difference between actual and desired pressure.

# Discretization and Optimal Control Problem

## Spatial discretization

$$\frac{d}{dt} \begin{bmatrix} M & 0 \\ 0 & 0 \end{bmatrix} \begin{pmatrix} z(t) \\ p(t) \end{pmatrix} = \begin{bmatrix} A & G^T \\ G & 0 \end{bmatrix} \begin{pmatrix} z(t) \\ p(t) \end{pmatrix} + \begin{bmatrix} B_1 \\ 0 \end{bmatrix} u(t), \quad (\text{DAE})$$

where  $M > 0$  and  $G$  has full row rank.

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where  $M > 0$  and  $G$  has full row rank.

## Optimal control problem

Minimize

$$\mathcal{J}(z, p, u) := \int_0^\infty \begin{pmatrix} z(\tau) \\ p(\tau) \\ u(\tau) \end{pmatrix}^T \begin{bmatrix} Q & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & R \end{bmatrix} \begin{pmatrix} z(\tau) \\ p(\tau) \\ u(\tau) \end{pmatrix} d\tau$$

with  $Q \geq 0$  and  $R > 0$  subject to (DAE) and

$$z(0) = z_0, \quad \lim_{t \rightarrow \infty} z(t) = 0.$$



## Lur'e Equation and System Space

## Lur'e equation

$$\begin{bmatrix} MX_{11}A + A^T X_{11}M + MX_{12}G + G^T X_{12}^T M + Q & MX_{11}G^T & MX_{11}B_1 \\ & GX_{11}M & 0 \\ & B_1^T X_{11}M & 0 \\ & & R \end{bmatrix}$$

$$= \nu_{\text{sys}} \begin{bmatrix} K_1^T \\ K_2^T \\ L^T \end{bmatrix} [K_1 \quad K_2 \quad L], \quad X = X^T = \begin{bmatrix} X_{11} & X_{12} \\ X_{12}^T & X_{22} \end{bmatrix}$$

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## System space

Define projector  $\Pi = I_{n_z} - G^T(GM^{-1}G^T)^{-1}GM^{-1}$ . We have

- $\frac{d}{dt} Mz(t) = \Pi Az(t) + \Pi B_1 u(t),$
- $p(t) = -(GM^{-1}G^T)^{-1}GM^{-1}Az(t) - (GM^{-1}G^T)^{-1}GM^{-1}B_1 u(t),$

# Lur'e Equation and System Space

## Lur'e equation

$$\begin{bmatrix} MX_{11}A + A^T X_{11}M + MX_{12}G + G^T X_{12}^T M + Q & MX_{11}G^T & MX_{11}B_1 \\ & GX_{11}M & 0 \\ & B_1^T X_{11}M & 0 \\ & & R \end{bmatrix} = \mathcal{V}_{\text{sys}} \begin{bmatrix} K_1^T \\ K_2^T \\ L^T \end{bmatrix} [K_1 \quad K_2 \quad L], \quad X = X^T = \begin{bmatrix} X_{11} & X_{12} \\ X_{12}^T & X_{22} \end{bmatrix}$$

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Define projector  $\Pi = I_{n_z} - G^T(GM^{-1}G^T)^{-1}GM^{-1}$ . We have

- $\frac{d}{dt} Mz(t) = \Pi A z(t) + \Pi B_1 u(t)$ ,
- $p(t) = -(GM^{-1}G^T)^{-1}GM^{-1}A z(t) - (GM^{-1}G^T)^{-1}GM^{-1}B_1 u(t)$ ,

$$\implies \mathcal{V}_{\text{sys}} = \text{im} \begin{bmatrix} -(GM^{-1}G^T)^{-1}GM^{-1}A & -(GM^{-1}G^T)^{-1}GM^{-1}B_1 \\ 0 & I_m \end{bmatrix}$$

# Reduced Lur'e Equation

## Reduced Lur'e Equation

Projection on  $\mathcal{V}_{\text{sys}}$  leads to

$$\begin{bmatrix} MX_{11}\Pi A + A^T\Pi^T X_{11}M + MX_{12}G + G^T X_{12}^T M + Q & MX_{11}\Pi B_1 \\ B_1^T\Pi^T X_{11}M & R \end{bmatrix} = \begin{bmatrix} K^T \\ L^T \end{bmatrix} \begin{bmatrix} K & L \end{bmatrix}, \quad GX_{11}M = 0.$$

# Projected Riccati Equation

Use Schur complement:

$$\begin{aligned} MX_{11}\Pi A + A^T\Pi^T X_{11}M + MX_{12}G + G^T X_{12}^T M + Q \\ - MX_{11}\Pi B_1 R^{-1} B_1^T \Pi^T X_{11}M = 0, \quad X_{11} = X_{11}^T. \end{aligned}$$

# Projected Riccati Equation

Use Schur complement:

$$\begin{aligned}
 & MX_{11}\Pi A + A^T\Pi^T X_{11}M + MX_{12}G + G^T X_{12}^T M + Q \\
 & \quad - MX_{11}\Pi B_1 R^{-1} B_1^T \Pi^T X_{11}M = 0, \quad X_{11} = X_{11}^T.
 \end{aligned}$$

Left-multiply by  $\Pi$  and right-multiply by  $\Pi^T$  and use  $\Pi M = M\Pi^T$  and  $G\Pi^T = 0$ :

$$\begin{aligned}
 & M\Pi^T X_{11}\Pi A\Pi^T + \Pi A^T \Pi^T X_{11}\Pi M + \Pi Q\Pi^T \\
 & \quad - M\Pi^T X_{11}\Pi B_1 R^{-1} B_1^T \Pi^T X_{11}\Pi^T M = 0, \quad X_{11} = X_{11}^T.
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 - M\Pi^T X_{11}\Pi B_1 R^{-1} B_1^T \Pi^T X_{11}\Pi^T M = 0, \quad X_{11} = X_{11}^T.
 \end{aligned}$$

Then  $\tilde{X} = \Pi^T X_{11} \Pi$  is a solution of the **projected algebraic Riccati equation**

[BENNER, STYKEL '14], [HEILAND '15]

$$\begin{aligned}
 M\tilde{X}\Pi A \Pi^T + \Pi A^T \Pi^T \tilde{X}M + \Pi Q \Pi^T \\
 - M\tilde{X}\Pi B_1 R^{-1} B_1^T \Pi^T \tilde{X}M = 0, \quad \tilde{X} = \tilde{X}^T = \Pi^T \tilde{X} \Pi.
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[BENNER, STYKEL '14], [HEILAND '15]

$$\begin{aligned}
 M\tilde{X}\Pi A \Pi^T + \Pi A^T \Pi^T \tilde{X}M + \Pi Q \Pi^T \\
 - M\tilde{X}\Pi B_1 R^{-1} B_1^T \Pi^T \tilde{X}M = 0, \quad \tilde{X} = \tilde{X}^T = \Pi^T \tilde{X} \Pi.
 \end{aligned}$$

Also related to the **constrained algebraic Riccati equation**

[HEILAND '14]

$$\begin{aligned}
 A^T X_{11}M + M^T X_{11}A - M^T X_{11}B_1 R^{-1} B_1^T X_{11}M \\
 + MX_{12}G + G^T X_{12}^T M + Q = 0, \quad X_{11} = X_{11}^T, \quad GX_{11}M = 0.
 \end{aligned}$$



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# Conclusions and Further Results

## Conclusion

- feasibility conditions in terms of existence of storage functions,
- Lur'e equations and their solution properties,
- existence and uniqueness conditions for optimal controls,
- application to flow control problems.

# Conclusions and Further Results

## Conclusion

- feasibility conditions in terms of existence of storage functions,
- Lur'e equations and their solution properties,
- existence and uniqueness conditions for optimal controls,
- application to flow control problems.

## Further results

- relation to **even boundary value problems** of the form

$$\frac{d}{dt} \begin{bmatrix} 0 & E & 0 \\ -E^T & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} \mu(t) \\ x(t) \\ u(t) \end{pmatrix} = \begin{bmatrix} 0 & A & B \\ A^T & Q & S \\ B^T & S^T & R \end{bmatrix} \begin{pmatrix} \mu(t) \\ x(t) \\ u(t) \end{pmatrix},$$

$$Ex(0) = Ex_0, \quad \lim_{t \rightarrow \infty} E^T \mu(t) = 0,$$

- analysis of the associated **even matrix pencil**.

Thank you for your Attention!

# References

- T. Reis. Lur'e Equations and Even Matrix Pencils, *Linear Algebra Appl.*, 434:152–173, 2011.
- P. Benner and T. Stykel. Numerical Solution of Projected Algebraic Riccati Equations, *SIAM J. Matrix Anal. Appl.*, 52(2):581–600, 2014.
- J. Heiland. *Decoupling and Optimization of Differential-Algebraic Equations with Application in Flow Control*, Dissertation, Technische Universität Berlin, 2014.
- M. Voigt. *On Linear-Quadratic Optimal Control and Robustness of Differential-Algebraic Systems*, Dissertation, Otto-von-Guericke-Universität Magdeburg, 2015.
- E. Bänsch, P. Benner, J. Saak, and H. Weichelt. Riccati-Based Boundary Feedback Stabilization of Incompressible Navier-Stokes Flow, *SIAM J. Sci. Comput.*, 37(2):A832–A858, 2015.
- T. Reis, O. Rendel, and M. Voigt. The Kalman-Yakubovich-Popov inequality for differential-algebraic systems, *Linear Algebra Appl.*, 485:153–193, 2015.