

# Introduction to PDE-Constrained Optimization

## Part I

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## Our Motivation for the Research

**PDE-constrained optimization:**  $\mathcal{X}_{\text{ad}}$  suitable set of admissible solutions

$$\min J(y, u) \quad \text{subject to (s.t.)} \quad (y, u) \text{ solves a PDE system and } (y, u) \in \mathcal{X}_{\text{ad}} \quad (\mathbf{P})$$

**Optimal Design** (e.g., shape or topology optimization):

- What is an optimal configuration for a given application?

**Optimal Control** (e.g., drug treatment for patients, autonomous driving):

- How should/can we control a time-dependent process with partial/uncertain measurement information in order to guarantee stability of the process?

**Parameter Estimation/Inverse Problems** (e.g., lithium-ion battery models):

- Which unknown (and not measurable) PDE parameters should be chosen so that the PDE model describes the real phenomena sufficiently accurate?

**Optimal Experimental Design:**

- How should we carry out experiments to get measurements so that the unknown PDE parameters can be optimally estimated?

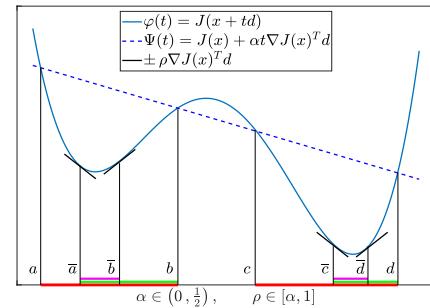
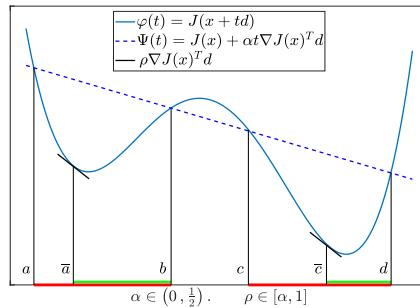
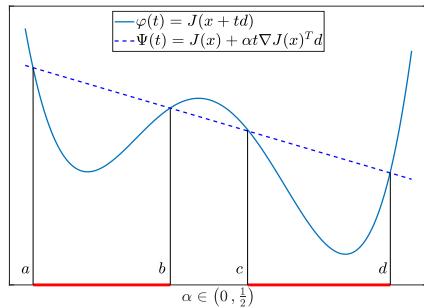
## Outline of the Talk

1 Constrained Nonlinear Optimization

2 Optimization of Linear Dynamical Systems

3 Optimization of Linear Elliptic PDEs

# 1 Constrained Nonlinear Optimization



## References:

- [1] Kelley: *Iterative Methods for Optimization*, SIAM, 1999
- [2] Luenberger/Ye; *Linear and Nonlinear Programming*, Springer, 2016
- [3] Nocedal/Wright: *Numerical Optimization*, Springer, 2006

# Finite-Dimensional Optimization

## Minimization Problem:

$$\min_x J(x) \quad \text{subject to (s.t.)} \quad x \in \mathbb{R}^n \text{ satisfies } e(x) = 0 \text{ in } \mathbb{R}^m \quad (\mathbf{P}_1)$$

with cost functional  $J : \mathbb{R}^n \rightarrow \mathbb{R}$  and equality constraint function  $e : \mathbb{R}^n \rightarrow \mathbb{R}^m$  ( $n \geq m$ )

**Set of feasible points:**  $\mathcal{F}(\mathbf{P}_1) = \{x \in \mathbb{R}^n \mid e(x) = 0\}$

**Existence of solutions:** proof by arguments from analysis

- assumptions on  $J$  and  $e$  (continuity)
- properties of the admissible set  $\mathcal{F}(\mathbf{P}_1)$  (closedness, boundedness, ...)
- boundedness of minimizing sequences
- extraction of convergent subsequence (Bolzano-Weierstraß)

**Bad News:** no constructive procedure available for getting an optimal solution  $\bar{x}$

## First-Order Optimality Conditions – 1

**Minimization Problem:**  $J$  and  $e$  continuously differentiable

$$\min_x J(x) \quad \text{subject to (s.t.)} \quad x \in \mathbb{R}^n \text{ satisfies } e(x) = 0 \text{ in } \mathbb{R}^m \quad (\mathbf{P}_1)$$

**Locally Optimal Solution:**  $\bar{x} \in \mathcal{F}(\mathbf{P}_1) = \{x \in \mathbb{R}^n \mid e(x) = 0\}$

**Lagrange Functional:**  $\mathcal{L}(x, p) = J(x) + \langle e(x), p \rangle_{\mathbb{R}^m} = J(x) + \sum_{i=1}^m e_i(x)p_i$  for  $(x, p) \in \mathbb{R}^n \times \mathbb{R}^m$

**Constrained Qualification Condition:** Jacobian matrix  $e'(\bar{x}) \in \mathbb{R}^{m \times n}$  is surjective  
 $\Rightarrow$  Tangent plane to the closed set  $\mathcal{F}(\mathbf{P}_1)$  at  $\bar{x}$  is characterized by  $\ker e'(\bar{x})$ .

**KKT Conditions:** If  $e'(\bar{x})$  is surjective, there exists a unique  $\bar{p} = (\bar{p}_i) \in \mathbb{R}^m$  such that

$$\nabla_x \mathcal{L}(\bar{x}, \bar{p}) = \nabla J(\bar{x}) + \sum_{i=1}^m \bar{p}_i \nabla e_i(\bar{x}) \stackrel{!}{=} 0 \in \mathbb{R}^n, \quad \nabla_p \mathcal{L}(\bar{x}, \bar{p}) = e(\bar{x}) \stackrel{!}{=} 0 \in \mathbb{R}^m$$

## First-Order Optimality Conditions – 2

**Notations:**  $\nabla J(x) \in \mathbb{R}^{n \times 1}$  (column vector),  $e'(x) = \begin{pmatrix} \nabla e_1(x)^\top \\ \vdots \\ \nabla e_m(x)^\top \end{pmatrix} \in \mathbb{R}^{m \times n}$  with  $\text{rank } e'(x) \leq m \leq n$ .

**KKT Conditions:** If  $e'(\bar{x})$  is surjective, there exists a unique  $\bar{p} \in \mathbb{R}^m$  such that

$$\nabla_x \mathcal{L}(\bar{x}, \bar{p}) = \nabla J(\bar{x}) + \sum_{i=1}^m \bar{p}_i \nabla e_i(\bar{x}) = \nabla J(\bar{x}) + e'(\bar{x})^\top \bar{p} \stackrel{!}{=} 0 \in \mathbb{R}^n, \quad \nabla_p \mathcal{L}(\bar{x}, \bar{p}) = e(\bar{x}) \stackrel{!}{=} 0 \in \mathbb{R}^m$$

### Comments:

- $\nabla J(\bar{x}) \in \text{span} \{ \nabla e_1(\bar{x}), \dots, \nabla e_m(\bar{x}) \} \subset \mathbb{R}^n$
- $e'(\bar{x})^\top \bar{p} = -\nabla J(\bar{x})$  and  $e'(\bar{x})^\top$  is injective  $\Rightarrow$  uniqueness of  $\bar{p}$
- $n+m$  equations  $\nabla_x \mathcal{L}(\bar{x}, \bar{p}) = 0$  and  $\nabla_p \mathcal{L}(\bar{x}, \bar{p}) = 0$  for  $n+m$  unknowns  $(\bar{x}, \bar{p})$
- If  $J$  and  $e$  are twice continuously differentiable, apply Newton's method

$$\begin{pmatrix} \nabla_{xx} \mathcal{L}(x^k, p^k) & e'(x^k)^\top \\ e'(x^k) & 0 \end{pmatrix} \begin{pmatrix} x_\delta \\ p_\delta \end{pmatrix} = - \begin{pmatrix} \nabla_x \mathcal{L}(x^k, p^k) \\ \nabla_p \mathcal{L}(x^k, p^k) \end{pmatrix}, \quad (x^{k+1}, p^{k+1}) = (x^k, p^k) + (x_\delta, p_\delta)$$

## Second-Order Optimality Conditions

**Minimization Problem:**  $J$  and  $e$  twice continuously differentiable

$$\min_x J(x) \quad \text{subject to (s.t.)} \quad x \in \mathbb{R}^n \text{ satisfies } e(x) = 0 \text{ in } \mathbb{R}^m \quad (\mathbf{P}_1)$$

**Necessary KKT Conditions:** If  $e'(\bar{x})$  is surjective, there exists a unique  $\bar{p} \in \mathbb{R}^n$  such that

$$\nabla J(\bar{x}) + e'(\bar{x})^\top \bar{p} \stackrel{!}{=} 0 \in \mathbb{R}^n, \quad e(\bar{x}) \stackrel{!}{=} 0 \in \mathbb{R}^m \quad (1)$$

**Second-Order Sufficient Optimality Conditions:** If  $(\bar{x}, \bar{p})$  satisfy (1) and  $e'(\bar{x})$  is surjective, there exists a unique  $\bar{p} \in \mathbb{R}^n$  such that

$$v^\top \nabla_{xx} \mathcal{L}(\bar{x}, \bar{p}) v > 0 \quad \text{for all } v \in \ker e'(\bar{x}) \setminus \{0\}$$

where  $\nabla_{xx} \mathcal{L}(\bar{x}, \bar{p}) = \nabla^2 J(\bar{x}) + \sum_{i=1}^m p_i \nabla^2 e_i(\bar{x}) \in \mathbb{R}^{n \times n}$  holds.

## Quadratic Programming

**Consider:**  $A \in \mathbb{R}^{m \times n}$  surjective,  $Q \in \mathbb{R}^{n \times n}$  symmetric & positive definite on  $\ker A$ ,  $q \in \mathbb{R}^n$ ,  $b \in \mathbb{R}^m$ ,  $c \in \mathbb{R}$

$$\min_x J(x) = \frac{1}{2} x^\top Q x - q^\top x + c \quad \text{s.t.} \quad x \in \mathcal{F}(\mathbf{P}_1) = \{x \in \mathbb{R}^n \mid e(x) = Ax - b = 0\} \quad (\mathbf{P}_1)$$

**Sufficient KKT Conditions:** Since  $e'(\bar{x}) = A$  is surjective, there is a unique  $\bar{p} \in \mathbb{R}^n$  such that

$$\nabla J(\bar{x}) + e'(\bar{x})^\top \bar{p} = Q\bar{x} - q + A^\top \bar{p} \stackrel{!}{=} 0 \in \mathbb{R}^n, \quad e(\bar{x}) = A\bar{x} - b \stackrel{!}{=} 0 \in \mathbb{R}^m$$

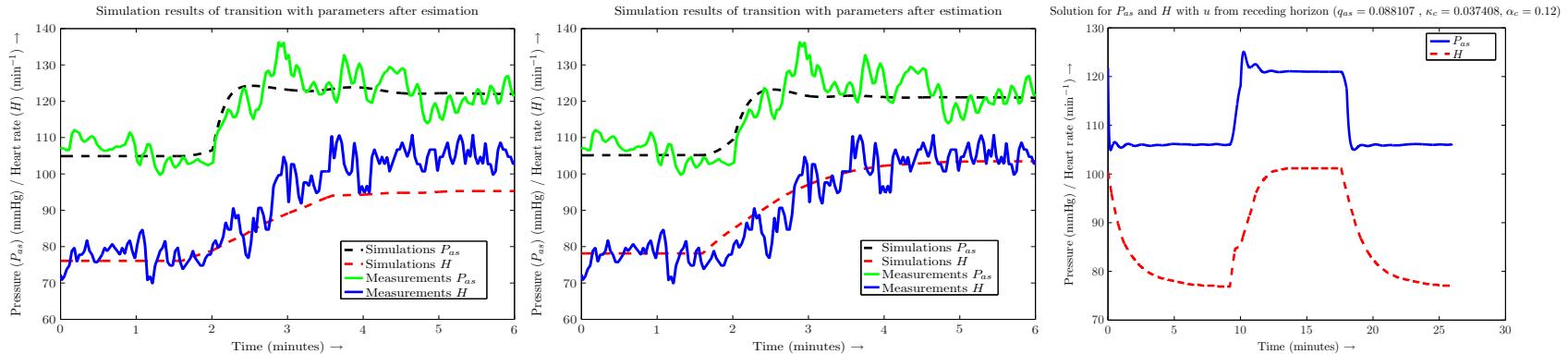
i.e., we obtain the uniquely solvable linear (saddlepoint) system

$$\begin{pmatrix} Q & A^\top \\ A & 0 \end{pmatrix} \begin{pmatrix} \bar{x} \\ \bar{p} \end{pmatrix} = \begin{pmatrix} q \\ b \end{pmatrix}$$

**Second-Order Sufficient Optimality Condition:**  $\mathcal{L}_{xx}(x, p) = Q$  positive definite on  $\ker A$

## 2 Optimization of Linear Dynamical Systems

# 2 Optimization of Linear Dynamical Systems



## References:

- [4] Gerdts: *Optimal Control of ODEs and DAEs*, De Gruyter, 2011

## Linear-Quadratic Problem

**Consider:**

$$\min_{(y,u)} J(y,u) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt \quad \text{s.t.} \quad \begin{cases} \dot{y}(t) = Ay(t) + Bu(t) \text{ for } t \in (0, T] \\ y(0) = y_0 \end{cases} \quad (\mathbf{P}_2)$$

with infinite-dimensional state  $y \in \mathcal{Y} = H^1(0, T; \mathbb{R}^n)$  and control  $u \in \mathcal{U} = L^2(0, T; \mathbb{R}^m)$

**Equality Constraints:** For  $\mathcal{X} = \mathcal{Y} \times \mathcal{U}$  and  $\mathcal{Z} = L^2(0, T; \mathbb{R}^n) \times \mathbb{R}^n$  let  $e : \mathcal{X} \rightarrow \mathcal{Z}$  be given as

$$e(x) = \begin{pmatrix} e_1(x) \\ e_2(x) \end{pmatrix} = \begin{pmatrix} \dot{y} - Ay - Bu \\ y(0) - y_0 \end{pmatrix} \in \mathcal{Z} \quad \text{for } x = (y, u) \in \mathcal{X}$$

**Constrained Optimization Problem:**

$$\min_x J(x) \quad \text{s.t.} \quad x \in \mathcal{X} \text{ satisfies } e(x) = 0 \quad (\mathbf{P}_2)$$

**Problem Setting:**  $T > 0$ ,  $Q \in \mathbb{R}^{n \times n}$  symmetric and positive semidefinite,  $R \in \mathbb{R}^{m \times m}$  symmetric positive definite,  $A \in \mathbb{R}^{n \times n}$ ,  $B \in \mathbb{R}^{n \times m}$ ,  $y_0 \in \mathbb{R}^n$

## Lagrange Functional

**Consider:**

$$\min_{(y,u)} J(y,u) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt \quad \text{s.t.} \quad \begin{cases} \dot{y}(t) = Ay(t) + Bu(t) \text{ for } t \in (0, T] \\ y(0) = y_0 \end{cases} \quad (\mathbf{P}_2)$$

**Equality Constraint:** For  $\mathcal{X} = \mathcal{Y} \times \mathcal{U}$  and  $\mathcal{Z} = L^2(0, T; \mathbb{R}^n) \times \mathbb{R}^n$  let  $e : \mathcal{X} \rightarrow \mathcal{Z}$  be given as

$$e(x) = \begin{pmatrix} e_1(x) \\ e_2(x) \end{pmatrix} = \begin{pmatrix} \dot{y} - Ay - Bu \\ y(0) - y_0 \end{pmatrix} \in \mathcal{Z} \quad \text{for } x = (y, u) \in \mathcal{X}$$

**Lagrange Functional:** For  $x = (y, u) \in \mathcal{X}$  and  $p = (p_1, p_2) \in \mathcal{Z}$  we set

$$\begin{aligned} \mathcal{L}(x, p) &= J(x) + \langle e(x), p \rangle_{\mathcal{Z}} = J(x) + \langle e_1(x), p_1 \rangle_{L^2(0, T; \mathbb{R}^n)} + \langle e_2(x), p_2 \rangle_{\mathbb{R}^n} \\ &= \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt + \int_0^T (\dot{y}(t) - Ay(t) - Bu(t))^\top p_1(t) dt + (y(0) - y_0)^\top p_2 \end{aligned}$$

## Constraint Qualification

**Equality Constraint:** For  $\mathcal{X} = \mathcal{Y} \times \mathcal{U}$  and  $\mathcal{Z} = L^2(0, T; \mathbb{R}^n) \times \mathbb{R}^n$  let  $e : \mathcal{X} \rightarrow \mathcal{Z}$  be given as

$$e(x) = \begin{pmatrix} e_1(x) \\ e_2(x) \end{pmatrix} = \begin{pmatrix} \dot{y} - Ay - Bu \\ y(0) - y_0 \end{pmatrix} \in \mathcal{Z} \quad \text{for } x = (y, u) \in \mathcal{X}$$

**Jacobian:** For  $x = (y, u) \in \mathcal{X}$  and direction  $x^\delta = (y^\delta, u^\delta) \in \mathcal{X}$  we obtain

$$e'(x)x^\delta = \begin{pmatrix} e'_1(x)x^\delta \\ e'_2(x)x^\delta \end{pmatrix} = \begin{pmatrix} \dot{y}^\delta - Ay^\delta - Bu^\delta \\ y^\delta(0) \end{pmatrix} \in \mathcal{Z}$$

**Constraint Qualification:** Let  $\mathcal{F} = (f, f_0) \in \mathcal{Z}$  be arbitrary. Then we consider

$$\begin{aligned} e'(x)x^\delta = \mathcal{F} \text{ in } \mathcal{Z} &\Leftrightarrow e'_1(x)x^\delta = f \text{ in } L^2(0, T; \mathbb{R}^n) \text{ and } e'_2(x)x^\delta = f_0 \text{ in } \mathbb{R}^n \\ &\Leftrightarrow \dot{y}^\delta - Ay^\delta - Bu^\delta = f \text{ in } L^2(0, T; \mathbb{R}^n) \text{ and } y^\delta(0) = f_0 \text{ in } \mathbb{R}^n \end{aligned}$$

For any  $u^\delta \in \mathcal{U}$  there exists a (unique) solution  $y^\delta \in \mathcal{Y} \Rightarrow e'(x) : \mathcal{X} \rightarrow \mathcal{Z}$  is surjective

## First-Order Optimality Conditions

**Consider:**

$$\min_{(y,u)} J(y, u) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt \quad \text{s.t.} \quad \begin{cases} \dot{y}(t) = Ay(t) + Bu(t) \text{ for } t \in (0, T] \\ y(0) = y_0 \end{cases} \quad (\mathbf{P}_2)$$

**Unique Optimal Solution:**  $\bar{x} = (\bar{y}, \bar{u}) \in \mathcal{X}$

**Lagrange Functional:** For  $x = (y, u) \in \mathcal{X}$  and  $p = (p_1, p_2) \in \mathcal{Z}$  we set

$$\mathcal{L}(x, p) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt + \int_0^T (\dot{y}(t) - Ay(t) - Bu(t))^\top p_1(t) dt + (y(0) - y_0)^\top p_2$$

**Optimality Conditions:** There exists a unique  $\bar{p} = (\bar{p}_1, \bar{p}_2) \in \mathcal{Z}$  satisfying

$$\mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}) \text{ in } \mathcal{Y}', \quad \mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}) \text{ in } \mathcal{U}', \quad \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}) = 0 \text{ in } \mathcal{Z}'$$

## State Equation

**Lagrange Functional:** For  $x = (y, u) \in \mathcal{X}$  and  $p = (p_1, p_2) \in \mathcal{Z}$  we set

$$\mathcal{L}(x, p) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt + \int_0^T (\dot{y}(t) - A y(t) - B u(t))^\top p_1(t) dt + (y(0) - y_\circ)^\top p_2$$

**Optimality Conditions:** There exists a unique  $\bar{p} = (\bar{p}_1, \bar{p}_2) \in \mathcal{Z}$  satisfying

$$\mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}) \text{ in } \mathcal{Y}', \quad \mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}) \text{ in } \mathcal{U}', \quad \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}) = 0 \text{ in } \mathcal{Z}'$$

**State/Primal Equation:**  $\mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}) = 0$  in  $\mathcal{Z}' \Leftrightarrow \langle \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}), p \rangle_{\mathcal{Z}', \mathcal{Z}} = 0$  for all  $p = (p_1, p_2) \in \mathcal{Z}$

$$\begin{aligned} 0 &= \langle \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}), p \rangle_{\mathcal{Z}', \mathcal{Z}} = \int_0^T (\dot{\bar{y}}(t) - A \bar{y}(t) - B \bar{u}(t))^\top p_1(t) dt + (\bar{y}(0) - y_\circ)^\top p_2 \\ &\Leftrightarrow \dot{\bar{y}} = A \bar{y} + B \bar{u} \text{ in } L^2(0, T; \mathbb{R}^n) \text{ and } \bar{y}(0) = y_\circ \text{ in } \mathbb{R}^n \end{aligned}$$

## Adjoint/Dual Equation

**Lagrange Functional:** For  $x = (y, u) \in \mathcal{X}$  and  $p = (p_1, p_2) \in \mathcal{Z}$  we set

$$\mathcal{L}(x, p) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt + \int_0^T (\dot{y}(t) - A y(t) - B u(t))^\top p_1(t) dt + (y(0) - y_0)^\top p_2$$

**Adjoint/Dual Equation:**  $\mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}) = 0$  in  $\mathcal{Y}' \Leftrightarrow \langle \mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}), y \rangle_{\mathcal{Y}', \mathcal{Y}} = 0$  for all  $y \in \mathcal{Y}$

$$0 = \langle \mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}), y \rangle_{\mathcal{Y}', \mathcal{Y}} = \int_0^T \bar{y}(t)^\top Q y(t) dt + \int_0^T (\dot{y}(t) - A y(t))^\top \bar{p}_1(t) dt + y(0)^\top \bar{p}_2$$

**Variational arguments:**

$$\begin{aligned} & \int_0^T \dot{y}(t)^\top \bar{p}_1(t) dt = - \int_0^T \dot{\bar{p}}_1(t)^\top y(t) dt \text{ for all } y \in C_0^\infty(0, T; \mathbb{R}^n) \hookrightarrow \mathcal{Y} \hookrightarrow L^2(0, T; \mathbb{R}^n) \\ \Rightarrow \quad & 0 = \int_0^T (- \dot{\bar{p}}_1(t) - A^\top \bar{p}_1(t) + Q \bar{y}(t))^\top y(t) dt \text{ for all } y \in C_0^\infty(0, T; \mathbb{R}^n) \hookrightarrow L^2(0, T; \mathbb{R}^n) \\ \Rightarrow \quad & 0 = - \dot{\bar{p}}_1 - A^\top \bar{p}_1 + Q \bar{y} \text{ in } L^2(0, T; \mathbb{R}^n) \\ \Rightarrow \quad & 0 = \langle \mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}), y \rangle_{\mathcal{Y}', \mathcal{Y}} = (y(t) \bar{p}_1(t))|_{t=0}^{t=T} + y(0)^\top \bar{p}_2 \quad \Rightarrow \quad \bar{p}_1(T) = 0 \text{ and } \bar{p}_2 = \bar{p}_1(0) \end{aligned}$$

## Optimality Condition

**Lagrange Functional:** For  $x = (y, u) \in \mathcal{X}$  and  $p = (p_1, p_2) \in \mathcal{Z}$  we set

$$\mathcal{L}(x, p) = \frac{1}{2} \int_0^T y(t)^\top Q y(t) + u(t)^\top R u(t) dt + \int_0^T (\dot{y}(t) - A y(t) - B u(t))^\top p_1(t) dt + (y(0) - y_\circ)^\top p_2$$

**Optimality Condition:**  $\mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}) = 0$  in  $\mathcal{U}' \Leftrightarrow \langle \mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}), u \rangle_{\mathcal{U}', \mathcal{U}} = 0$  for all  $u \in \mathcal{U}$

$$\begin{aligned} 0 &= \langle \mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}), u \rangle_{\mathcal{U}', \mathcal{U}} = \int_0^T \bar{u}(t)^\top R u(t) dt + \int_0^T (-B u(t))^\top \bar{p}_1(t) dt \\ &= \int_0^T (R \bar{u}(t) - B^\top \bar{p}_1(t))^\top u(t) dt \quad \Rightarrow \quad \bar{u} = R^{-1} B^\top \bar{p}_1 \text{ in } \mathcal{U} = L^2(0, T; \mathbb{R}^m) \end{aligned}$$

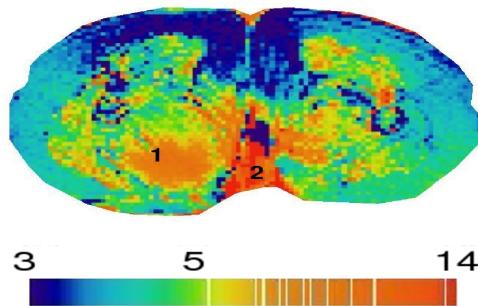
**KKT System:** coupled ODE system

$$\dot{\bar{y}}(t) = A \bar{y}(t) + B \bar{u}(t) \quad \text{for } t \in (0, T], \quad \bar{y}(0) = y_\circ \quad (\text{state equation})$$

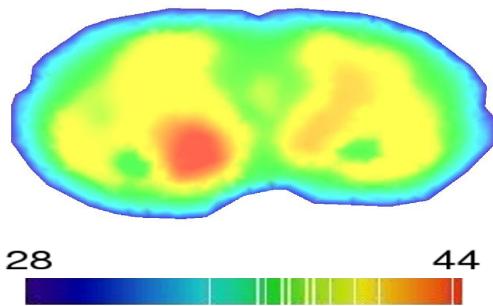
$$-\dot{\bar{p}}_1(t) = A^\top \bar{p}_1(t) - Q \bar{y}(t) \quad \text{for } t \in [0, T), \quad \bar{p}_1(T) = 0, \quad \bar{p}_2 = \bar{p}_1(0) \quad (\text{adjoint equation})$$

$$\bar{u}(t) = R^{-1} B^\top \bar{p}_1(t) \quad \text{for } t \in (0, T) \quad (\text{optimality condition})$$

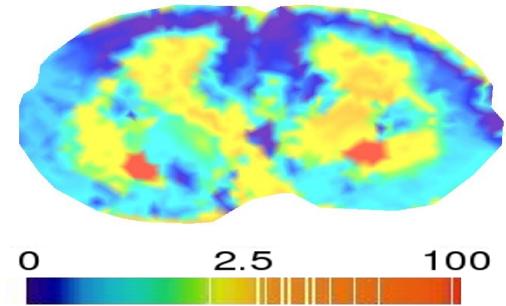
## 3 Optimization of Linear Elliptic PDEs



Messwerte



identifizierte Temperatur



berechnete Perfusion

### References:

- [05] Hinze/Pinnau/Ulbrich/Ulbrich: *Optimization with PDE Constraints*, Springer, 2009
- [06] Lions: *Optimal Control of Systems Governed by Partial Differential Equations*, Springer-Verlag, 1971
- [07] Tröltzsch: *Optimal Control of Partial Differential Equations*, AMS, 2010

## Infinite-Dimensional Optimization

**Consider:**  $\Omega \subset \mathbb{R}^d$  bounded ( $d \in \{1, 2, 3\}$ ),  $y_d \in L^2(\Omega)$ ,  $\sigma > 0$ ,  $V = H^1(\Omega)$ ,  $\mathcal{U} = L^2(\Omega)$

$$\min_{(y,u)} J(y, u) = \frac{1}{2} \int_{\Omega} |y - y_d|^2 + \sigma |u|^2 \, d\mathbf{x} \quad \text{s.t.} \quad -\Delta y + y = u \text{ in } \Omega, \quad \frac{\partial y}{\partial \mathbf{n}} = 0 \text{ on } \Gamma = \partial\Omega \quad (\mathbf{P}_3)$$

**Setting:**  $\mathcal{X} = V \times \mathcal{U}$ , cost functional  $J : \mathcal{X} \rightarrow \mathbb{R}$ , constraint operator  $e : \mathcal{X} \rightarrow V'$  with

$$\langle e(x), \varphi \rangle_{V', V} = \int_{\Omega} \nabla y \cdot \nabla \varphi + y \varphi - u \varphi \, d\mathbf{x} \quad \text{for } x = (y, u) \in \mathcal{X}, \varphi \in V$$

i.e.,  $e(x) = 0$  in  $V' \Leftrightarrow x = (y, u)$  satisfies  $\int_{\Omega} \nabla y \cdot \nabla \varphi + y \varphi \, d\mathbf{x} = \int_{\Omega} u \varphi \, d\mathbf{x}$  for all  $\varphi \in V$ .

**Optimization Problem with Equality Constraints:**

$$\min J(x) \quad \text{s.t.} \quad x \in \mathcal{X} \text{ satisfies } e(x) = 0 \text{ in } V' \quad (\mathbf{P}_3)$$

## Unconstrained Reduced Problem

**Neumann Problem:**  $V = H^1(\Omega)$ ,  $\mathcal{U} = L^2(\Omega)$

$$\min_{(y,u)} J(y, u) = \frac{1}{2} \int_{\Omega} |y - y_d|^2 + \sigma |u|^2 \, dx \quad \text{s.t.} \quad \int_{\Omega} \nabla y \cdot \nabla \varphi + y \varphi \, dx = \int_{\Omega} u \varphi \, dx \text{ for all } \varphi \in V \quad (\mathbf{P}_3)$$

**Control-to-State Mapping:** For  $u \in \mathcal{U}$  let  $y(u) = \mathcal{S}u \in V$  be the unique solution to

$$\langle e(y(u), u), \varphi \rangle_{V', V} = \int_{\Omega} \nabla y(u) \cdot \nabla \varphi + y(u) \varphi - u \varphi \, dx \quad \text{for all } \varphi \in V$$

Then,  $e(y(u), u) = 0$  in  $V'$  holds. Moreover,  $\mathcal{S}$  is linear and bounded ( $\|y(u)\|_V \leq \|u\|_{\mathcal{U}}$ )

**Reduced Cost Functional:**  $\hat{J}(u) = J(y(u), u)$  for  $u \in \mathcal{U}$

**Reduced Problem:**

$$\min_u \hat{J}(u) = \frac{1}{2} \int_{\Omega} |\mathcal{S}u - y_d|^2 + \sigma |u|^2 \, dx \quad (\hat{\mathbf{P}}_3)$$

## Existence of Optimal Controls

**Constrained Optimization:**  $\min_{(y,u)} J(y,u) = \frac{1}{2} \int_{\Omega} |y - y_d|^2 + \sigma |u|^2 \, dx$  s.t.  $e(y,u) = 0$   $(P_3)$

**Unconstrained Reduced Problem:**  $\min_u \hat{J}(u) = \frac{1}{2} \int_{\Omega} |\mathcal{S}u - y_d|^2 + \sigma |u|^2 \, dx$   $(\hat{P}_3)$

**Existence of a unique Optimal Control:**  $\mathcal{U} = L^2(\Omega)$

- $\{u^k\}_{k \in \mathbb{N}}$  minimizing sequence for  $(\hat{P}_3)$ , i.e.,  $\lim_{k \rightarrow \infty} \hat{J}(u^k) = \inf\{\hat{J}(u) \mid u \in \mathcal{U}\} \geq 0$
- $\hat{J}$  radially unbounded, i.e.,  $\hat{J}(u) \rightarrow \infty$  for  $\|u\|_{\mathcal{U}} \rightarrow \infty \Rightarrow \|u^k\|_{\mathcal{U}}$  bounded
- $\bar{u}$  solution to  $(\hat{P}_3)$ , because  $u^k \rightharpoonup \bar{u}$  in  $\mathcal{U}$  and weakly lower semicontinuity of  $\hat{J}$  imply

$$\infty > \inf\{\hat{J}(u) \mid u \in \mathcal{U}\} = \lim_{k \rightarrow \infty} \hat{J}(u^k) = \liminf_{k \rightarrow \infty} \hat{J}(u^k) \geq \hat{J}(\bar{u})$$

- $\hat{J}$  quadratic  $\Rightarrow (\hat{P}_3)$  convex  $\Rightarrow$  unique optimal solution  $\bar{u}$
- $\bar{x} = (\bar{y}, \bar{u})$  unique solution to  $(P_3)$  with  $\bar{y} = \mathcal{S}\bar{u}$
- Utilized facts: linear, bounded control-to-state mapping  $\mathcal{S}$ , reflexivity of  $\mathcal{U}$ ,  $\sigma > 0$

## First-Order Sufficient Optimality Conditions

**Neumann Problem:**  $V = H^1(\Omega)$ ,  $\mathcal{U} = L^2(\Omega)$ ,  $\mathcal{X} = V \times \mathcal{U}$

$$\min_{(y,u)} J(y, u) = \frac{1}{2} \int_{\Omega} |y - y_d|^2 + \sigma |u|^2 \, dx \quad \text{s.t.} \quad \int_{\Omega} \nabla y \cdot \nabla \varphi + y \varphi \, dx = \int_{\Omega} u \varphi \, dx \text{ for all } \varphi \in V \quad (\mathbf{P}_3)$$

**Lagrange Functional for  $(\mathbf{P}_3)$ :**

$$\mathcal{L}(y, u, p) = J(y, u) + \langle e(y, u), p \rangle_{V', V} = \int_{\Omega} \left( \frac{1}{2} |y - y_d|^2 + \frac{\sigma}{2} |u|^2 + \nabla y \cdot \nabla p + y p - u p \right) dx$$

**Optimality System:**  $\bar{x} = (\bar{y}, \bar{u}) \in \mathcal{X}$  optimal solution. Then there exists  $\bar{p} \in V$  satisfying

$$\mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}) = 0 \text{ in } V', \quad \mathcal{L}_u(\bar{y}, \bar{u}, p) = 0 \text{ in } \mathcal{U}', \quad \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}) = 0 \text{ in } V'$$

since a constrained qualification condition holds ( $e'(\bar{x}) : \mathcal{X} \rightarrow V'$  is surjective)

**Note:** derivatives are functionals!

## State Equation

**Lagrange Functional for  $(P_3)$ :**  $\mathcal{L}(y, u, p) = \int_{\Omega} \left( |y - y_d|^2 + \frac{\sigma}{2} |u|^2 + \nabla y \cdot \nabla p + yp - up \right) dx$

**State/Primal Equation:**  $\mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}) = 0$  in  $V'$   $\Leftrightarrow \langle \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}), p \rangle_{V', V} = 0$  for all  $p \in V$

$$0 = \langle \mathcal{L}_p(\bar{y}, \bar{u}, \bar{p}), p \rangle_{V', V} = \int_{\Omega} (\nabla \bar{y} \cdot \nabla p + \bar{y}p - \bar{u}p) dx \quad \text{for all } p \in V$$

i.e.,  $\bar{y} = y(\bar{u}) \in V$  is the weak solution to  $-\Delta \bar{y} + \bar{y} = \bar{u}$  in  $\Omega$ ,  $\frac{\partial \bar{y}}{\partial \mathbf{n}} = 0$  on  $\Gamma$  (state equation)

**Stationarity:** From

$$\int_{\Omega} \nabla y(u) \cdot \nabla \varphi + y(u) \varphi dx = \int_{\Omega} u \varphi dx \quad \text{for all } \varphi \in V'$$

we infer  $\mathcal{L}_p(y(u), u, p) = 0$  in  $V'$  for any  $(u, p) \in \mathcal{U} \times V$ , because

$$\langle \mathcal{L}_p(y(u), u, p), \varphi \rangle_{V', V} = \int_{\Omega} (\nabla y(u) \cdot \nabla \varphi + y(u) \varphi - u \varphi) dx = 0 \quad \text{for all } \varphi \in V$$

## Adjoint Equation

**Lagrange Functional for  $(P_3)$ :**  $\mathcal{L}(y, u, p) = \int_{\Omega} \left( |y - y_d|^2 + \frac{\sigma}{2} |u|^2 + \nabla y \cdot \nabla p + yp - up \right) dx$

**Adjoint/Dual Equation:**  $\mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}) = 0$  in  $V'$   $\Leftrightarrow \langle \mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}), y \rangle_{V', V} = 0$  for all  $y \in V$

$$\begin{aligned} 0 &= \langle \mathcal{L}_y(\bar{y}, \bar{u}, \bar{p}), y \rangle_{V', V} = \int_{\Omega} \left( (\bar{y} - y_d)y + \nabla y \cdot \nabla \bar{p} + y\bar{p} \right) dx \\ &= \int_{\Omega} \left( \nabla \bar{p} \cdot \nabla y + \bar{p}y - (y_d - \bar{y})y \right) dx \quad \text{for all } y \in V \end{aligned}$$

i.e.,  $\bar{p} \in V$  is the weak solution to  $-\Delta \bar{p} + \bar{p} = y_d - \bar{y}$  in  $\Omega$ ,  $\frac{\partial \bar{p}}{\partial \mathbf{n}} = 0$  on  $\Gamma$  (adjoint equation)

**Stationarity:** From

$$\int_{\Omega} \nabla p(u) \cdot \nabla \varphi + p(u)\varphi dx = \int_{\Omega} (y_d - y(u))\varphi dx \text{ for all } \varphi \in V'$$

we infer  $\mathcal{L}_y(y(u), u, p(u)) = 0$  in  $V'$  for any  $u \in \mathcal{U}$

## Optimality Condition

**Lagrange Functional for  $(P_3)$ :**  $\mathcal{L}(y, u, p) = \int_{\Omega} \left( |y - y_d|^2 + \frac{\sigma}{2} |u|^2 + \nabla y \cdot \nabla p + yp - up \right) d\mathbf{x}$

**Optimality:**  $\mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}) = 0$  in  $\mathcal{U}' \Leftrightarrow \langle \mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}), u \rangle_{\mathcal{U}', \mathcal{U}} = 0$  for all  $u \in \mathcal{U}$

$$0 = \langle \mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}), u \rangle_{\mathcal{U}', \mathcal{U}} = \int_{\Omega} (\sigma \bar{u} u - u \bar{p}) d\mathbf{x} = \int_{\Omega} (\sigma \bar{u} - \bar{p}) u d\mathbf{x} = \langle \sigma \bar{u} - \bar{p}, v \rangle_{\mathcal{U}} \quad \text{for all } v \in \mathcal{U}$$

$\Rightarrow \bar{u} = \bar{p}/\sigma$  in  $\mathcal{U}$ ; moreover,  $\bar{u} \in V$  follows from  $\bar{p} \in V$

**Gradient:** Riesz representant  $\nabla_u \mathcal{L}(\bar{y}, \bar{u}, \bar{p}) \in \mathcal{U}$  of  $\mathcal{L}_u(\bar{y}, \bar{u}, \bar{p}) \in \mathcal{U}'$  is given as

$$\nabla_u \mathcal{L}(\bar{y}, \bar{u}, \bar{p}) = \sigma \bar{u} - \bar{p} \in \mathcal{U}$$

## Relation to the Reduced Cost Functional

**Reduced Cost:** For a chosen  $u \in \mathcal{U}$  we infer from  $\hat{J}(u) = J(y(u), u)$  and  $e(y(u), u) = 0$  in  $V'$

$$\hat{J}(u) = J(y(u), u) = J(y(u), u) + \underbrace{\langle e(y(u), u), p \rangle_{V', V}}_{=0} = \mathcal{L}(y(u), u, p) \text{ for any } p \in V$$

**Chain Rule:** For every direction  $v \in \mathcal{U}$  we have

$$\langle \hat{J}'(u), v \rangle_{\mathcal{U}', \mathcal{U}} = \langle \mathcal{L}_y(y(u), u, p), y'(u)v \rangle_{V', V} + \langle \mathcal{L}_u(y(u), u, p), v \rangle_{\mathcal{U}', \mathcal{U}} \quad \text{for any } p \in V \quad (2)$$

**Recall:**  $\mathcal{L}_y(y(u), u, p(u)) = 0$  in  $V'$

**Gradient of the Reduced Cost:** Choosing  $p = p(u) \in V$  in (2) imply for all  $v \in \mathcal{U}$

$$\langle \hat{J}'(u), v \rangle_{\mathcal{U}', \mathcal{U}} = \langle \mathcal{L}_u(y(u), u, p(u)), v \rangle_{\mathcal{U}', \mathcal{U}} = \int_{\Omega} (\sigma u - p(u))v \, dx = \langle \sigma u - p(u), v \rangle_{\mathcal{U}} = \langle \nabla \hat{J}(u), v \rangle_{\mathcal{U}}$$

## First-Order Optimality System / KKT-System

**Optimality system:**

$$\begin{aligned}
 -\Delta \bar{y} + \bar{y} &= \bar{u} & \text{in } \Omega, & \frac{\partial \bar{y}}{\partial \mathbf{n}} = 0 & \text{on } \Gamma & \text{(state equation)} \\
 \sigma \bar{u} - \bar{p} &= 0 & \text{in } \Omega, & & & \text{(optimality condition)} \\
 -\Delta \bar{p} + \bar{p} &= y_d - \bar{y} & \text{in } \Omega, & \frac{\partial \bar{p}}{\partial \mathbf{n}} = 0 & \text{on } \Gamma & \text{(adjoint equation)}
 \end{aligned}$$

**Reduction:**

$$\begin{aligned}
 -\Delta \bar{y} + \bar{y} + \frac{\bar{p}}{\sigma} &= 0 & \text{in } \Omega, & \frac{\partial \bar{y}}{\partial \mathbf{n}} = 0 & \text{on } \Gamma & \text{(state equation)} \\
 -\Delta \bar{p} + \bar{p} + \bar{y} &= y_d & \text{in } \Omega, & \frac{\partial \bar{p}}{\partial \mathbf{n}} = 0 & \text{on } \Gamma & \text{(adjoint equation)}
 \end{aligned}$$

## Numerical Solution Methods / Optimize-then-Discretize

**Reduced Problem:**  $\min_u \hat{J}(u) = \frac{1}{2} \|\mathcal{S}u - y_d\|_{L^2(\Omega)}^2 + \sigma \|u\|_{L^2(\Omega)}^2 \, d\mathbf{x}$   $(\hat{\mathbf{P}}_1)$

### Iteration of the Gradient Method:

- 1: Compute state  $y^k = y(u^k)$  and adjoint  $p^k = p(u^k)$ ;
- 2: Set  $\nabla J(u^k) = \sigma u^k - p^k$ ;
- 3: Determine appropriate step size  $t_k > 0$  (e.g., satisfying Armijo or Powell-Wolfe rule);
- 4:  $u^{k+1} = u^k - t_k \nabla \hat{J}(u^k)$ ;

**Note:**  $\|\mathcal{S}u - y_d\|_{L^2(\Omega)}^2 = \underbrace{\langle \mathcal{S}u, \mathcal{S}u \rangle_{L^2(\Omega)}}_{= \langle \mathcal{S}^* \mathcal{S}u, u \rangle_{L^2(\Omega)}} + 2 \underbrace{\langle \mathcal{S}u, y_d \rangle_{L^2(\Omega)}}_{= \langle \mathcal{S}^* y_d, u \rangle_{L^2(\Omega)}} + \|y_d\|_{L^2(\Omega)}^2$ ,  $\mathcal{S}^* : V \rightarrow \mathcal{U}$  adjoint of  $\mathcal{S}$

**Conjugate Gradient Method:** Let  $g^0 = \sigma u^0 - p(u^0)$  and  $d^0 = -g^0$  we compute for each  $k$

- 1: Set  $p^k = (\mathcal{S}^* \mathcal{S})d^k$ ,  $t_k = \|g^k\|_{L^2(\Omega)}^2 / \langle p^k, d^k \rangle_{L^2(\Omega)}$  and  $u^{k+1} = u^k + t_k d^k$ ;
- 2: Determine  $g^{k+1} = g^k + t_k d^k$ ;
- 3: Define  $\beta_k = \|g^{k+1}\|_{L^2(\Omega)}^2 / \|g^k\|_{L^2(\Omega)}^2$  and  $d^{k+1} = -g^{k+1} + \beta_k d^k$ ;