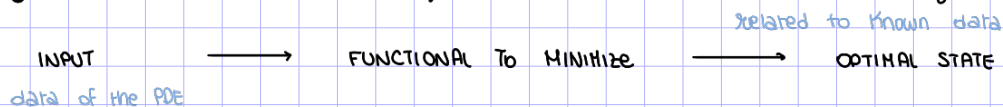


## 16 - OPTIMAL CONTROL PROBLEMS

In this setting the PDE is: a state system needs to be OPTIMIZED with some "external help", i.e. other variables called CONTROLS

The goal of OCP is minimize an objective functional to reach beneficial configuration



Then, our problem is: given a control  $u \in U$  with  $U$  a Hilbert space, the state variable  $y(u) \in Y$ , with  $Y$  an Hilbert space, verifies the strong form of the controlled PDE

①  $G(y(u), u; \mu) = 0$  in  $Y'$  with  $\mu :=$  physic or geometric parameter

The main goal is to minimize over  $Y \times U$

$J: Y \times U \times P \rightarrow \mathbb{R}$  defined as

$J(y(u), u; \mu) = \frac{1}{2} \|y(u) - y_d\|_{Y_d}^2 + \frac{\alpha}{2} \|u\|_U^2$  such that the strong form holds  $\rightarrow$  The function is quadratic to guarantee the uniqueness

where  $\rightarrow$  is bigger than  $Y$  because you required less property

- $y_d \in Y_d \supset Y$  is the observation
- $\alpha > 0$  is the penalization parameter  $\rightarrow \alpha := \text{small}$  big control,  $\alpha := \text{big}$  small control

In an abstract way, an OCP can be recast as

find  $u^* := \operatorname{argmin}_{u \in U} J(y(u), u; \mu)$   
st.  $G(y(u), u; \mu) = 0$

$u^* :=$  the optimal control

$y^*(u^*) :=$  the optimal state

fixing a parameter, if you change  $\mu$  you have to recompute everything

From now on, we work with linear PDEs:

$G(y(u), u; \mu) = K(\mu)y - C(\mu)u - f(\mu) = 0$

where  $\rightarrow C(\mu): U \rightarrow Y'$ , continuous

$\rightarrow K(\mu): Y \rightarrow Y'$ , continuous, positive definite coercive problem

$\rightarrow f(\mu) \in Y'$

The related bilinear form are

- $a: Y \times Y \rightarrow \mathbb{R}$
- $c: U \times Y \rightarrow \mathbb{R}$
- $f: Y \rightarrow \mathbb{R}$

and the weak formulation of ① is

②  $a(y, v; \mu) - c(u, v; \mu) - f(v; \mu) = 0 \quad \forall v \in Y$

But also the functional can be written in "weak form", rewriting the norm into integral

$J(y, u; \mu) = \frac{1}{2} m(y - y_d, y - y_d; \mu) + \frac{\alpha}{2} n(u, u; \mu)$

where  $\rightarrow m: Y_d \times Y_d \rightarrow \mathbb{R}$  is  $Y_d$ -norm product

$\rightarrow n: U \times U \rightarrow \mathbb{R}$  is  $U$ -inner product

Example.  $Y_d = L^2(\Omega_0)$   $\Omega_0 \subseteq \Omega$ ,  $U = L^2(\Omega_u)$   $\Omega_u \subseteq \Omega$

Then  $J$  in strong form is  $J(y, u; \mu) = \frac{1}{2} \|y - y_d\|_{L^2(\Omega_0)}^2 + \frac{\alpha}{2} \|u\|_{L^2(\Omega_u)}^2$

$\downarrow$   
 $(y - y_d, y - y_d)_{L^2(\Omega_0)}$   
 $\int_{\Omega_0} (y - y_d)(y - y_d) dx$

What happen if I add another term? Consider  $J(y, u; \mu) = \frac{1}{2} m(y - y_d, y - y_d; \mu) + \frac{\alpha}{2} n(u, u; \mu) - \frac{1}{2} m(y_d, y_d)$ , but the solution remain the same



Algebraically, in compact form

$$\begin{bmatrix} M_S(\mu) & 0 \\ 0 & \alpha N_S(\mu) \\ K_S(\mu) & -C_S(\mu) \end{bmatrix} \begin{bmatrix} y \\ u \\ p \end{bmatrix} = \begin{bmatrix} M_S(\mu) y_d \\ 0 \\ f_S \end{bmatrix}$$

↗ observation vector

Saddle-point structure. Consider the problem that is in this structure, we can write

$$\begin{bmatrix} A(\mu) & B^T(\mu) \\ B(\mu) & 0 \end{bmatrix} \begin{bmatrix} z \\ p \end{bmatrix} = \begin{bmatrix} g_S \\ f_S \end{bmatrix} \quad \text{where } z = \begin{bmatrix} y \\ u \end{bmatrix}, \quad g_S = \begin{bmatrix} M_S(\mu) y_d \\ 0 \end{bmatrix}$$

•  $A(\mu)$  is always well-posedness

• For  $B(\mu)$ , the well-posedness is related to the inf-sup stability and it is provable if  $p \in Y$

↓

ROM level. Collect three sets of snapshots and build three different basis matrices  $B_y, B_u, B_p$

•  $y_n$  spanned by  $B_y$

•  $u_n$  spanned by  $B_u$

•  $p_n$  spanned by  $B_p \neq B_y$  → How can I recover the inf-sup aggregated spaces?

We define  $B_{yp} = [B_y | B_p]$  the aggregated space and consider  $y_n, p_n$  spanned by  $B_{yp}$

↓

In order to guarantee well-posedness, we need SN basis wrt N basis without control!

Once we build the basis, assuming affinity, we can pre-compute

$$M_N = B_{yp}^T M_S B_{yp}$$

$$N_N = B_u^T N_S B_u$$

$$K_N = B_{yp}^T K_S B_{yp}$$

$$C_N = B_{yp}^T C_S B_u$$

and solve

$$\begin{pmatrix} M_N & 0 & K_N^T \\ 0 & \alpha N_N & C_N^T \\ K_N & C_N & 0 \end{pmatrix} \begin{pmatrix} y_N \\ u_N \\ p_N \end{pmatrix} = \begin{pmatrix} M_N y_d^N \\ 0 \\ f_N \end{pmatrix} \quad \text{where } \begin{matrix} y_d^N = B_{yp}^T y_d \\ f_N = B_{yp}^T f_S \end{matrix}$$

### 10.1 A very simple practice example

Consider  $\Omega = [0,1] \times [0,1]$ ,  $y_d \in L^2(\Omega)$ ,  $\Omega_0 \subseteq \Omega$ ,  $\mu \in P \subseteq \mathbb{R}$  d>0

Given  $a, \mu \in P$ , find  $(y, \mu) \in H^1_0(\Omega) \times L^1(\Omega)$  s.t. they verify

$$\min_{(y, \mu)} \frac{1}{2} \|y - y_d\|_{L^2(\Omega_0)}^2 + \frac{\alpha}{2} \|u\|_{L^2(\Omega)}^2$$

$$\text{s.t. } \begin{cases} -\mu \Delta y = u + f & \text{in } \Omega \\ y = 0 & \text{in } \partial\Omega \end{cases}$$

Let us define  $p \in H^1_0(\Omega)$  and the Lagrangian

$$\mathcal{L}(y, u, p; \mu) = \frac{1}{2} \int_{\Omega_0} (y - y_d)^2 dz + \frac{\alpha}{2} \int_{\Omega} u^2 dz + \underbrace{\mu \int_{\Omega} \nabla y \nabla p dz}_{a(y, p)} - \underbrace{\int_{\Omega} u p dz}_{-c(u, p)} - \int_{\Omega} f p dz$$

Now we have to differentiate

$$\partial_y \mathcal{L}(y, u, p; \mu)[q] = \int_{\Omega_0} (y - y_d) q dz + \underbrace{\mu \int_{\Omega} \nabla q \nabla p dz}_{\text{self adjoint}}$$

$$\partial_u \mathcal{L}(y, u, p; \mu)[v] = \alpha \int_{\Omega} u v dz - \int_{\Omega} p v dz \quad \text{self adjoint}$$

$$\partial_p \mathcal{L}(y, u, p; \mu)[z] = \mu \int_{\Omega} \nabla y \nabla z dz - \int_{\Omega} u z dz - \int_{\Omega} f z dz \quad \rightarrow \text{This is the variational formulation}$$

⚠ If you have an advection term  $a(y, z; \mu) = \int_{\Omega} \beta \nabla y \cdot z dz = \int_{\Omega} \text{div}(\beta y z) dz - \int_{\Omega} \beta \nabla y \cdot z dz = \int_{\partial\Omega} \beta y z n ds - \int_{\Omega} \beta \cdot \nabla y z dz = 0 \text{ b.c.} = a^*(z, y; \mu)$