

Control of PDE Systems

Lecture 8 (Meetings 15 & 16)

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Motion Planning for PDEs

- Combined control solution: Feedforward (FF) + Feedback (FB)
- Trajectory generation, or motion planning $\rightarrow$ open-loop control for PDEs
- Reference trajectory + Combined FF+FB $\rightarrow$ Trajectory stabilization
- Trajectory tracking: state reference (relevant) $\rightarrow$ output reference (important)
 - Start from output reference trajectory, e.g. $u(0, t) = u^r(0, t)$
 - Generates the state trajectory $u^r(x, t)$ for all x
 - + Including $x = 1 \rightarrow$ control reference $u^r(1, t)$
 - Combine this FF results with FB control law
 - + Stabilize the trajectory $u^r(x, t)$
 - + Force $u(0, t) = u^r(0, t)$

Trajectory Generation

We present the ideas through several examples.

Consider the heat equation

$$\begin{aligned}u_t &= u_{xx} \\ u_x(0) &= 0 \\ u(0) &= \text{system output} \\ u(1) &= \text{system input}\end{aligned}$$

The objective is to follow the **output** trajectory

$$u^r(0,t) = 2 - (t-1)^2 = 1 + 2t - t^2$$

The first step is to construct the full state trajectory $u^r(x,t)$ which satisfies the PDE. Then add a [feedback law](#) that stabilizes that solution.

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We postulate the state trajectory in the form:

$$u^r(x, t) = \sum_{k=0}^{\infty} a_k(t) \frac{x^k}{k!}.$$

This is a Taylor series in x with time varying coefficients $a_k(t)$ that will be determined from the PDE, boundary condition, and desired trajectory.

From the desired trajectory we get

$$u^r(0, t) = a_0(t) = 1 + 2t - t^2.$$

The boundary condition gives

$$u_{\textcolor{red}{x}}^r(0, t) = a_1(t) = 0.$$

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Substituting $u^r(x, t)$ into the PDE we get:

$$\begin{aligned}\sum_{k=0}^{\infty} \dot{a}_k(t) \frac{x^k}{k!} &= \frac{\partial^2}{\partial x^2} \sum_{k=0}^{\infty} a_k(t) \frac{x^k}{k!} \\ &= \sum_{k=2}^{\infty} a_k(t) \frac{k(k-1)x^{k-2}}{k!} \\ &= \sum_{k=2}^{\infty} a_k(t) \frac{x^{k-2}}{(k-2)!} \\ &= \sum_{k=0}^{\infty} a_{k+2}(t) \frac{x^k}{k!}.\end{aligned}$$

We get the recursive relationship

$$a_{\textcolor{red}{k}+2}(t) = \dot{a}_{\textcolor{red}{k}}(t)$$

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The recursion yields

$$\begin{aligned}a_0 &= 1 + 2t - t^2, & a_1 &= 0 \\a_2 &= 2 - 2t, & a_3 &= 0 \\a_4 &= -2, & a_5 &= 0 \\a_6 &= 0, & a_i &= 0 \quad \text{for } i > 6.\end{aligned}$$

This gives the reference trajectory

$$u^r(x, t) = 1 + 2t + t^2 + (1 - t)x^2 - \frac{1}{12}x^4,$$

and the input signal

$$u^r(1, t) = \frac{23}{12} + t - t^2.$$

Remark. Perfect trajectory obtained only if the initial condition of the plant agrees with the initial condition of the trajectory, that is, $u(x, 0) = 1 + x^2 - \frac{1}{12}x^4$.

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Example 2. Reaction-diffusion equation

$$\begin{aligned}u_t &= u_{xx} + \lambda u \\ u_x(0) &= 0\end{aligned}$$

Desired output reference signal

$$u^r(0,t) = e^{\alpha t}.$$

From the boundary condition we have

$$a_1(t) = 0,$$

and from the PDE

$$a_{k+2}(t) = \dot{a}_k(t) + \lambda a_k(t).$$

These conditions give

$$\begin{aligned}a_{2k+1} &= 0 \\ a_{2k+2} &= \dot{a}_{2k} - \lambda a_{2k} \\ a_2 &= (\alpha - \lambda)e^{\alpha t} \\ a_4 &= (\alpha - \lambda)^2 e^{\alpha t} \\ a_{2k} &= (\alpha - \lambda)^k e^{\alpha t}\end{aligned}$$

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The state trajectory is

$$\begin{aligned}u^r(x,t) &= \sum_{k=0}^{\infty} (\alpha - \lambda)^k e^{\alpha t} \frac{x^{2k}}{2k!} \\&= e^{\alpha t} \sum_{k=0}^{\infty} \frac{(\sqrt{\alpha - \lambda}x)^{2k}}{2k!} \\&= e^{\alpha t} \begin{cases} \cosh(\sqrt{\alpha - \lambda}x) & \alpha \geq \lambda \\ \cos(\sqrt{\alpha - \lambda}x) & \alpha < \lambda \end{cases}\end{aligned}$$

The reference input is

$$u^r(1,t) = e^{\alpha t} \cosh(\sqrt{\alpha - \lambda}).$$

Useful formulae when calculating trajectories for sinusoidal outputs:

$$\begin{aligned}\cosh(a) &= \sum_{k=0}^{\infty} \frac{a^{2k}}{(2k)!}, & \sinh(a) &= \sum_{k=0}^{\infty} \frac{a^{2k+1}}{(2k+1)!} \\ \cosh(ja) &= \cos(a), & \sinh(ja) &= j \sin(a), & \sin(ja) &= j \sinh(a).\end{aligned}$$

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Example 8. First order hyperbolic PDE

$$\begin{aligned}u_t &= u_x + gu(0) \\u^r(1,t) &= \text{control} \\u^r(0,t) &= \sin(\omega t) = \text{Im}\left\{e^{j\omega t}\right\} = a_0(t)\end{aligned}$$

Since this is a first order PDE, the only boundary condition is the one that is available for control.

From the PDE we get

$$\begin{aligned}a_1 &= \dot{a}_0 - ga_0 \\&= \text{Im}\left\{(j\omega - g)e^{j\omega t}\right\}\end{aligned}$$

$$\begin{aligned}a_{i+1} &= \dot{a}_i \\a_k(t) &= \text{Im}\left\{(j\omega - g)(j\omega)^{k-1}e^{j\omega t}\right\} \\&= \text{Im}\left\{\left(1 - \frac{g}{j\omega}\right)(j\omega)^k e^{j\omega t}\right\}\end{aligned}$$

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State reference

$$\begin{aligned}u^r(x,t) &= \operatorname{Im} \left\{ \left[1 + \left(1 - \frac{g}{j\omega} \right) \sum_{k=1}^{\infty} \frac{(j\omega x)^k}{k!} \right] e^{j\omega t} \right\} \\&\quad \text{add and subtract } \frac{g}{j\omega} \\&= \operatorname{Im} \left\{ \left[\frac{g}{j\omega} + \left(1 - \frac{g}{j\omega} \right) e^{j\omega x} \right] e^{j\omega t} \right\} \\&= \operatorname{Im} \left\{ \frac{g}{j\omega} e^{j\omega t} + \frac{j\omega - g}{j\omega} e^{j\omega(t+x)} \right\} \\[1em]u^r(x,t) &= -\frac{g}{\omega} [\cos(\omega t) - \cos(\omega(t+x))] + \sin(\omega(t+x))\end{aligned}$$

Input reference

$$u^r(\mathbf{1}, t) = \frac{g}{\omega} [\cos(\omega(t+1)) - \cos(\omega t)] + \sin(\omega(t+1)).$$

Trajectory Tracking

Trajectory Tracking = stabilization of reference trajectory with feedback control.

Consider the previous example

$$\begin{aligned}\text{plant:} \quad u_t &= u_x + gu(0) \\ \text{trajectory:} \quad u^r(x, t) &= \frac{g}{\omega} [\cos(\omega(t+x)) - \cos(\omega t)] + \sin(\omega(t+x))\end{aligned}$$

Stabilizing controller

$$u(1, t) - u^r(1, t) = \int_0^1 k(1, y) [u(y, t) - u^r(y, t)] dy$$

$$\begin{aligned}\text{transformation:} \quad w(x, t) &= u(x, t) - u^r(x, t) - \int_0^x k(x, y) [u(y, t) - u^r(y, t)] dy \\ \text{kernel:} \quad k(x, y) &= -ge^{g(x-y)} \\ \text{target system:} \quad w_t &= w_x \quad (\text{unit delay with zero input}) \\ w(1) &= 0\end{aligned}$$

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Stabilizing controller

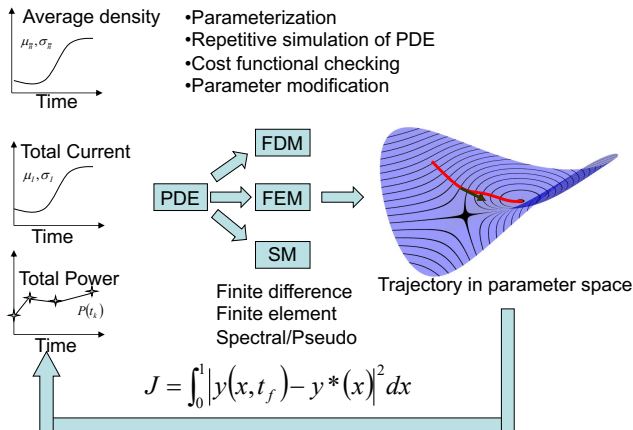
$$\begin{aligned}u(1,t) - u^r(1,t) &= \int_0^1 k(1,y)[u(y,t) - u^r(y,t)]dy \\u(1,t) &= u^r(1,t) + \int_0^1 k(1,y)[u(y,t) - u^r(y,t)]dy \\&= \underbrace{u^r(1,t) - \int_0^1 k(1,y)u^r(y,t)dy}_{\text{feedforward (fcn of } t)}} + \underbrace{\int_0^1 k(1,y)u(y,t)dy}_{\text{feedback}}\end{aligned}$$

$$\begin{aligned}\text{Ffwd} &= \frac{g}{\omega}[\cos(\omega(t+1)) - \cos(\omega t)] + \sin(\omega(t+1)) \\&\quad + \int_0^1 g e^{g(1-y)} \left\{ \frac{g}{\omega}[\cos(\omega(t+y)) - \cos(\omega t)] + \sin(\omega(t+x)) \right\} dy \\&= \frac{g}{\omega}[\cos(\omega(t+1)) - \cos(\omega t)] + \sin(\omega(t+1)) - \frac{g}{\omega}[\cos(\omega(t+1)) - \cos(\omega t)] \\&= \sin(\omega(t+1))\end{aligned}$$

which is $u^r(0,t) = \sin(\omega t)$ advanced by one time unit!

Thus, it suffices to determine the reference trajectory for the target system (rather than for the complicated original system). **This is true in general.**

Motion Planning for PDEs



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Motion Planning for PDEs



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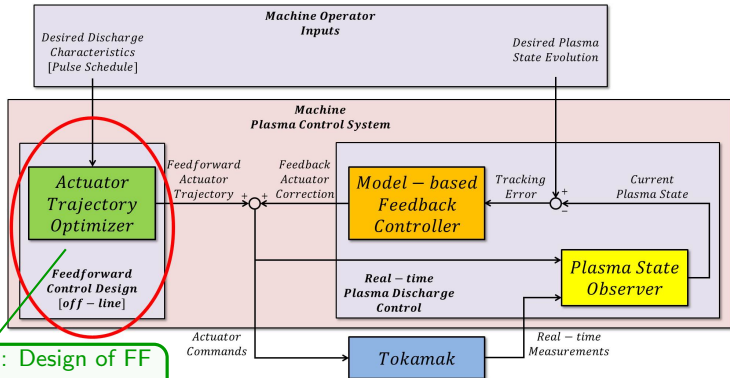
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Feedforward (FF) Control Optimization Problem Defined as Tradeoff Between Multiple Objectives

- Control Synthesis: feedforward controller, feedback controllers, state observers.



STEP 1: Design of FF actuator trajectories to drive plasma close to desired target state

Figure 1:

Feedforward (FF) Control Optimization Problem Defined as Tradeoff Between Multiple Objectives

- **Objective:** Reach **target plasma state** at some time t_{targ} by designing **actuator waveforms** subject to **plasma dynamics** and **constraints**.
 - Defines nonlinear, constrained optimization problem.
- **Target state:** Defined in terms of q profile and β_N .
 - Proximity of achieved state to target formulated into cost functional (J).
 - To-be-minimized cost function is weighted sum of three objectives

$$J = k_q J_q(q(t_{\text{targ}})) + k_{ss} J_{ss}(\dot{\psi}(t_{\text{targ}})) + k_{\beta_N} J_{\beta_N}(\beta_N(t_{\text{targ}}))$$

- Target q -profile objective

$$J_q(q(t_{\text{targ}})) = \int_0^1 W_q(\hat{\rho}) [q_{\text{targ}}(\hat{\rho}) - q(\hat{\rho}, t_{\text{targ}})]^2 d\hat{\rho}$$

- Stationarity objective

$$J_{ss}(\dot{\psi}(t_{\text{targ}})) = \int_0^1 W_{ss}(\hat{\rho}) [g_{ss}(\hat{\rho}, t_{\text{targ}})]^2 d\hat{\rho}$$

$$g_{ss}(\hat{\rho}, t) = -2\pi \frac{\partial U_p}{\partial \hat{\rho}} \quad U_p = \frac{\partial \psi}{\partial t} = \text{loop voltage}$$

- Target β_N objective

$$J_{\beta_N}(\beta_N(t_{\text{targ}})) = [\beta_{N_{\text{targ}}} - \beta_N(t_{\text{targ}})]^2$$

Solution of Feedforward (FF) Control Optimization Problem Requires Minimization under Constraints

- An open-loop (feedforward) control policy u_{FF} is obtained via nonlinear optimization subject to constraints. Returns target trajectory ψ_{FF} (q_{FF}).

$$\min_{\alpha} \quad J(\psi_{FF}, \dot{\psi}_{FF}, \beta_N) \quad \left. \vphantom{\min} \right\} \text{Cost Function (Optimization Objective)}$$

$$\text{s.t.} \quad \dot{\psi}_{FF} = f_{\psi}(\psi_{FF}, u_{FF}), \psi_{FF}(t_0) = \psi_0 \quad \left. \vphantom{\text{s.t.}} \right\} \text{MDE}$$

$$\dot{W}_{FF} = f_W(W_{FF}, u_{FF}) \quad \left. \vphantom{\dot{W}_{FF}} \right\} \text{Energy Balance}$$

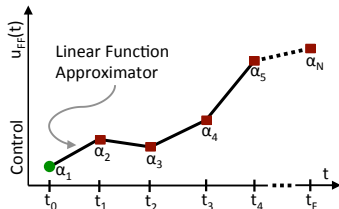
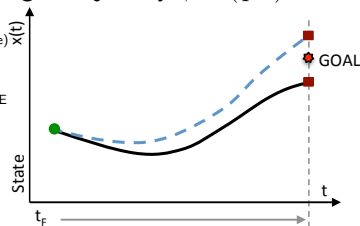
$$\beta_N(t) \leq \beta_{N_{\max}}, q \geq 1 \quad \left. \vphantom{\beta_N(t)} \right\} \begin{array}{l} \text{State Constraint,} \\ \text{MHD Stability Limit} \end{array}$$

$$\bar{n}_e|_{20} \leq I_p / \pi a^2 \quad \left. \vphantom{\bar{n}_e|_{20}} \right\} \begin{array}{l} \text{State Constraint,} \\ \text{Density Limit} \end{array}$$

$$P_{\text{tot}}(t) \geq P_{\text{tot}_{\min}} \quad \left. \vphantom{P_{\text{tot}}(t)} \right\} \begin{array}{l} \text{State Constraint,} \\ \text{Prevent H} \rightarrow \text{L Transition} \end{array}$$

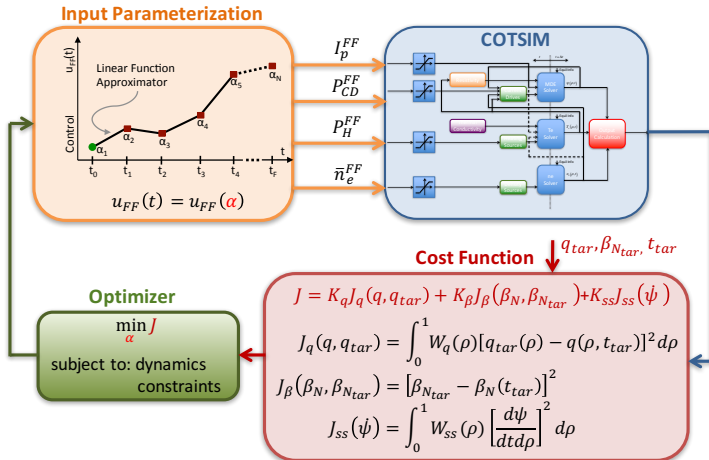
$$u_{FF}(t) \in \mathcal{U} \quad \left. \vphantom{u_{FF}(t)} \right\} \begin{array}{l} \text{Input Constraint,} \\ \text{Saturation / Rate Limit} \end{array}$$

$$u_{FF}(t) = u_{FF}(\alpha) \quad \left. \vphantom{u_{FF}(t)} \right\} \begin{array}{l} \text{Linear Function} \\ \text{Approximator} \end{array}$$



Solution of Feedforward (FF) Control Optimization Problem Requires Minimization under Constraints

- COTSIM enables systematic model-based scenario planning based on nonlinear constrained optimization with arbitrary cost function.



- FF Design (offline): Arbitrary model complexity (COTSIM $\rightarrow$ TRANSP)