

Optimal Control

Lecture 1,2

Solmaz S. Kia

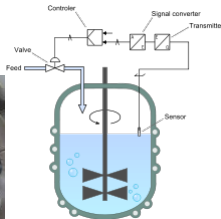
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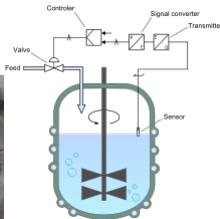
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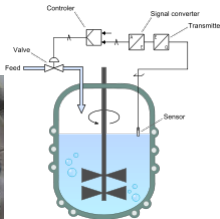


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- stabilization, regulation, tracking

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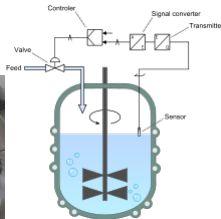


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- stabilization, regulation, tracking
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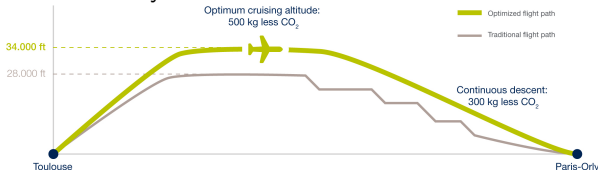
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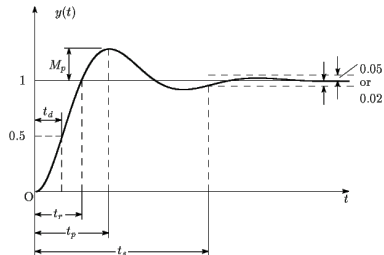
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- Performance measures considering step or ramp response:

- rise-time (t_r)
- settling time (t_s)
- peak overshoot (M_p)
- gain and phase margin and bandwidth
- steady state error

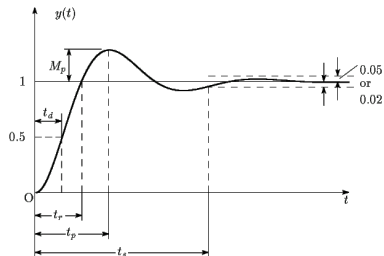
mostly for SISO systems



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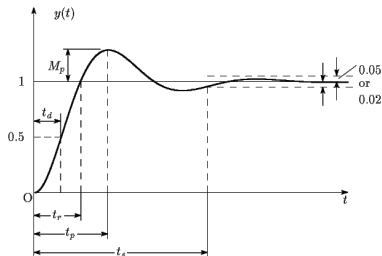
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- more complex performance measures, perhaps more closely related to the physical aspects of the system
 - minimum fuel
 - minimum control effort
 - minimum time

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- more complex performance measures, perhaps more closely related to the physical aspects of the system
 - minimum fuel
 - minimum control effort
 - minimum time
- satisfy some constraints on control and states of the system while optimizing performance measure

The objective of optimal control is to determine the control signals that will cause a process to satisfy the physical constraints and at the same time minimize (or maximize) some performance criterion.

The following three elements constitute the optimal control formulation|:

- model (a mathematical description) of the process/system to be controlled
- mathematical description of the (physical) constraints of the system
- a performance measure and its mathematical description

- **Minimum-time problem:** To transfer a system from arbitrary initial state $x(t_0) = x_0$ to a specified target set \mathcal{S} in minimum time

$$J = t_f - t_0 = \int_{t_0}^{t_f} dt, \quad (1)$$

where t_f is the first instant of time when $x(t)$ and \mathcal{S} intersect.

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For discrete-time systems, minimum-time performance can be cast as

$$J = N = \sum_{k=0}^{N-1} 1.$$

- **Terminal control problem:** to minimize the deviation of the final state of a system from its desired value $\mathbf{r}(\mathbf{t}_f) \in \mathbb{R}^n$

$$J = \sum_{i=1}^n (x_i(\mathbf{t}_f) - r_i(\mathbf{t}_f))^2 = (\mathbf{x}(\mathbf{t}_f) - \mathbf{r}(\mathbf{t}_f))^T (\mathbf{x}(\mathbf{t}_f) - \mathbf{r}(\mathbf{t}_f)) = \|\mathbf{x}(\mathbf{t}_f) - \mathbf{r}(\mathbf{t}_f)\|^2.$$

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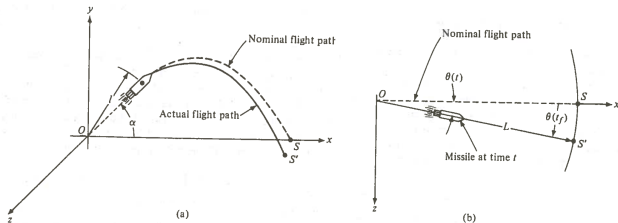
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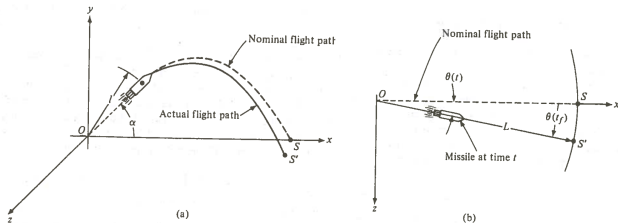


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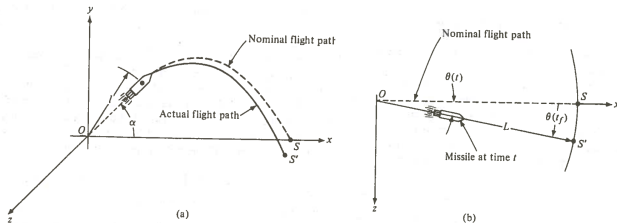
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For a discrete-time system:

$$J = \frac{1}{2} \sum_{k=0}^{N-1} u_k^T R u_k.$$

- **Tracking problem:** to maintain the system state $x(t)$ as close as possible to the desired state $r(t)$ in the interval $[t_0, t_f]$:

$$J = \int_{t_0}^{t_f} (x(t) - r(t))^T Q (x(t) - r(t)) dt = \int_{t_0}^{t_f} \|x(t) - r(t)\|_Q^2 dt, \quad Q \geq 0$$

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- **Regulation problem:** $r(t) = 0$ for all $t \in [t_0, t_f]$

All the performance measures discussed above are special cases of the general form

- Continuous-time

$$J = \underbrace{h(x(t_f), t_f)}_{\text{terminal cost}} + \underbrace{\int_{t_0}^{t_f} g(x(t), u(t), t) dt}_{\text{running cost}}.$$

- Discrete-time

$$J = \underbrace{\phi(x_N, N)}_{\text{terminal cost}} + \underbrace{\sum_{k=0}^{N-1} L^k(x_k, u_k)}_{\text{running cost}}.$$

Optimal Control Problem

Find admissible u^* which cause $\dot{x} = f(x(t), u(t), t)$ to follow admissible x^* that minimize

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- u^* : optimal control x^* : optimal trajectory

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 - Find all local minimum, and pick the smallest as global minimum

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 - **pro**: choose among multiple possibilities accounting for other measures

Parameter static optimization: when time is not a parameter in the problem

- Unconstrained optimization
- Constrained optimization

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$$\exists \epsilon > 0 \text{ s.t. } F(\mathbf{u}^*) \leq F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m, \quad \|\mathbf{u} - \mathbf{u}^*\| < \epsilon$$

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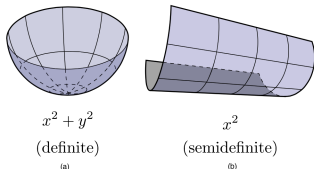
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(a) strong minimum, (b) weak minimum

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Global minimum: (weak) $F(\mathbf{u}^*) \leq F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m$, (strong) $F(\mathbf{u}^*) < F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m$

Unconstrained optimization

$$\mathbf{u}^* = \underset{\mathbf{u} \in \mathbb{R}^m}{\operatorname{argmin}} F(\mathbf{u}),$$

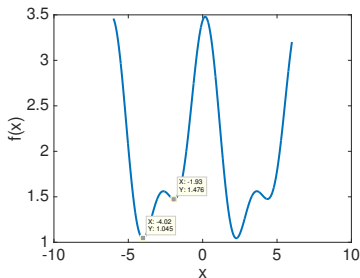
where $F : \mathbb{R}^m \rightarrow \mathbb{R}$ is differentiable

A point $\mathbf{u}^* \in \mathbb{R}^m$ is said to be a **Local (weak) minimum point** of F over \mathbb{R}^m if

$$\exists \epsilon > 0 \text{ s.t. } F(\mathbf{u}^*) \leq F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m, \quad \|\mathbf{u} - \mathbf{u}^*\| < \epsilon$$

Local (strong) minimum point: $\exists \epsilon > 0$ s.t. $F(\mathbf{u}^*) < F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m, \quad \|\mathbf{u} - \mathbf{u}^*\| < \epsilon$

Global minimum: (weak) $F(\mathbf{u}^*) \leq F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m$, (strong) $F(\mathbf{u}^*) < F(\mathbf{u}) \quad \forall \mathbf{u} \in \mathbb{R}^m$



$f(x) = 2 + \cos(x) + 0.5 \cos(2x - 0.5)$ has multiple local and global minimizer. 13 / 13