



# Indefinite Linear MPC and Approximated Economic MPC for Nonlinear Systems

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- 1 Economic MPC and Stability Analysis
- 2 The Linear Quadratic Case
- 3 Approximated EMPC with stability guarantees

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## MPC

Optimal Control Problem

$$\min_{x_0, u_0, \dots, x_N}$$

s.t.

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$$\text{s.t. } x_0 - \bar{x}_i = 0,$$

Initial condition

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$$x_{k+1} - f(x_k, u_k) = 0,$$

System dynamics

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$$x_N - x_N^s = 0.$$

Initial condition

System dynamics

Terminal constraint

## MPC

### Optimal Control Problem

$$\begin{aligned} \min_{x_0, u_0, \dots, x_N} \quad & \sum_{k=0}^{N-1} l(x_k, u_k) && \text{(Quadratic) stage cost} \\ \text{s.t.} \quad & x_0 - \bar{x}_i = 0, && \text{Initial condition} \\ & x_{k+1} - f(x_k, u_k) = 0, && \text{System dynamics} \\ & x_N - x_N^s = 0. && \text{Terminal constraint} \end{aligned}$$



# MPC

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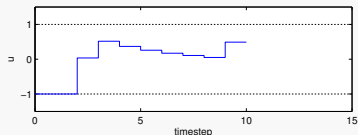
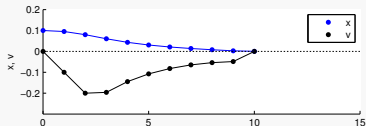
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(Quadratic) stage cost

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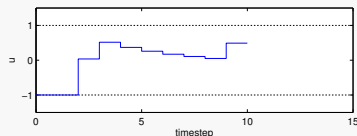
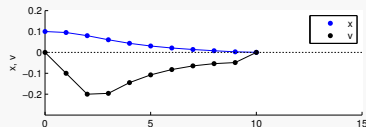
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At each sampling time  $i$ :

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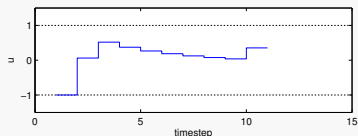
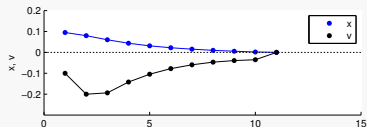
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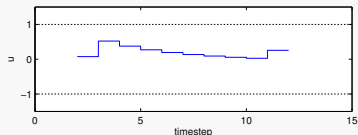
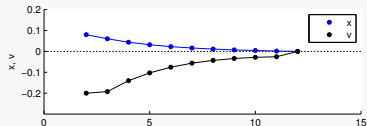
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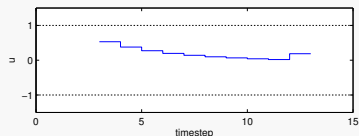
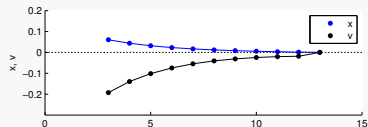
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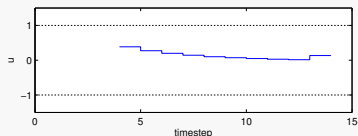
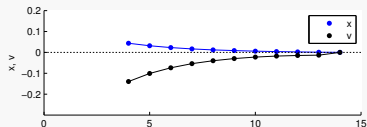
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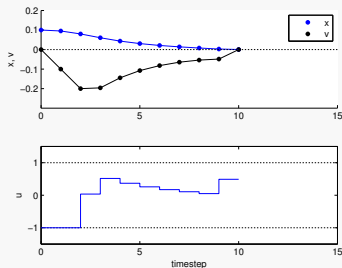


**Lyapunov stability**

Tracking MPC:  $l(x_s, u_s) = 0$  and  $\exists \alpha \in \mathcal{K}$  s.t.  $\alpha(x - x_s) \leq l(x, u), \forall u \in \mathbb{U}$

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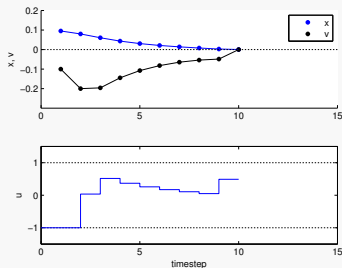


$$V_N(\bar{x}_i)$$



## Lyapunov stability

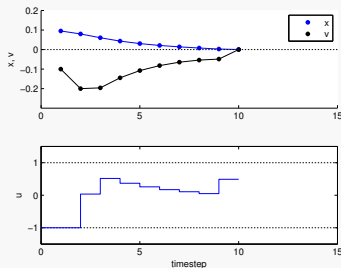
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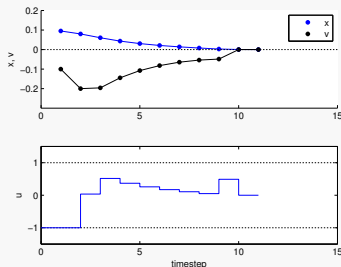


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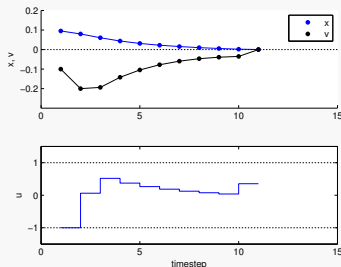
$$V_{N-1}(f(\bar{x}_i, u_0^*)) + l(x_s, u_s)$$

$$V_{N-1}(f(\bar{x}_i, u_0^*)) = V_N(\bar{x}_i) - l(\bar{x}_i, u_0^*)$$

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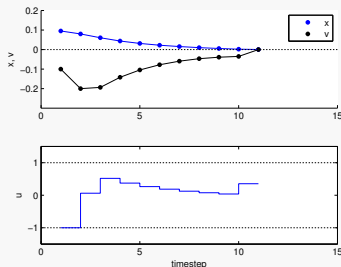


$$V_N(f(\bar{x}_i, u_0^*))$$

$$\begin{aligned}
 V_{N-1}(f(\bar{x}_i, u_0^*)) &= V_N(\bar{x}_i) - l(\bar{x}_i, u_0^*) \\
 V_N(f(\bar{x}_i, u_0^*)) &\leq V_N(\bar{x}_i) - l(\bar{x}_i, u_0^*) + \underbrace{l(x_s, u_s)}_{=0}
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$$V_N(f(\bar{x}_i, u_0^*)) - V_N(\bar{x}_i) \leq -l(\bar{x}_i, u_0^*)$$

**Do we always want to track?**

**Do we always want to track?**



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## Do we always want to track?



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**Then why do we track?**



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- We have been doing it since the 80s



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- Difficult to prove stability (2008-)





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**What about Economic MPC?**

- Difficult to prove stability (2008-)
- Increased “economic” gain



## **Economic vs Tracking**

## Economic vs Tracking

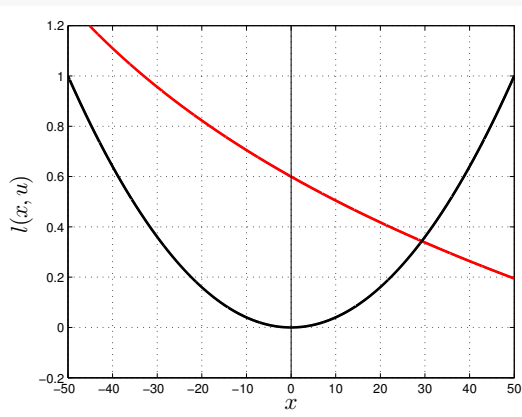
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## Economic vs Tracking

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- Stage cost: **Tracking** vs **Economic**

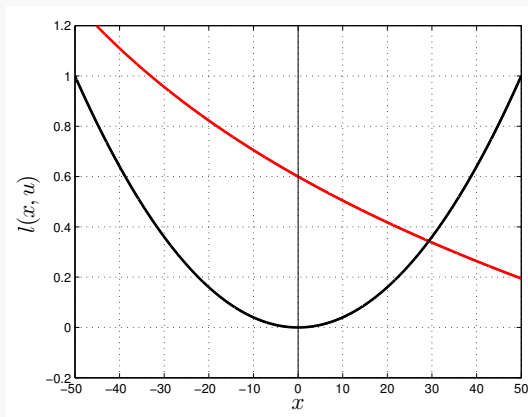
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**The classical stability theory does not apply!**

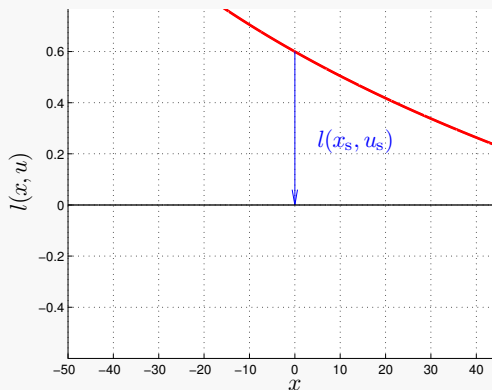
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$$l(x, u) \quad l(x_s, u_s)$$

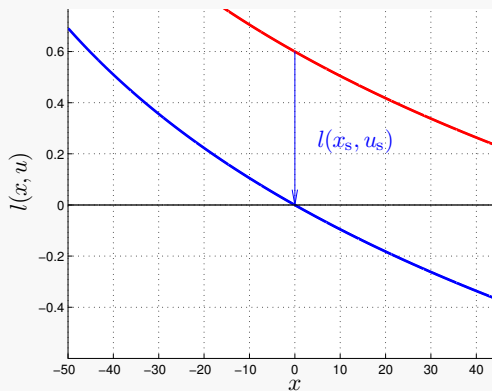




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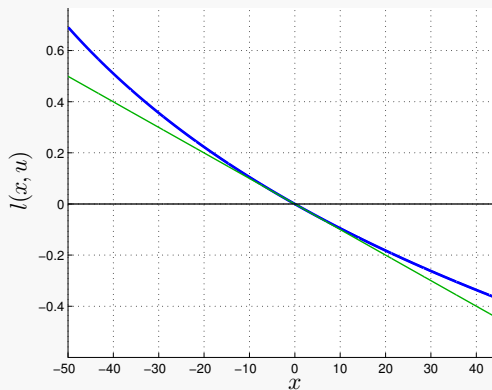
$$l(x, u) - l(x_s, u_s)$$



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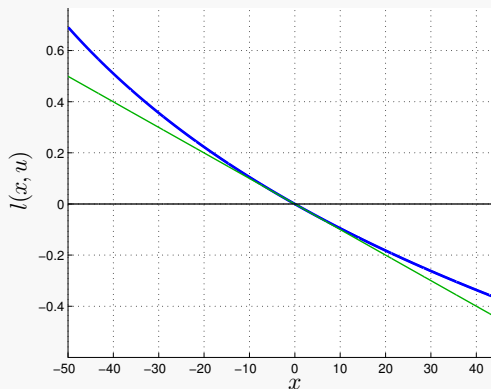
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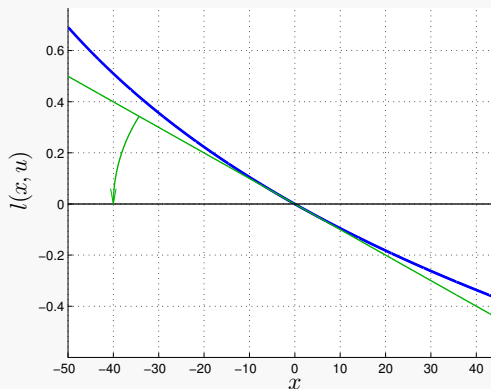
$$l(x, u) - l(x_s, u_s) \quad \underbrace{\lambda_s^T}_{\text{Lagrange multiplier}} (x - f(x, u))$$



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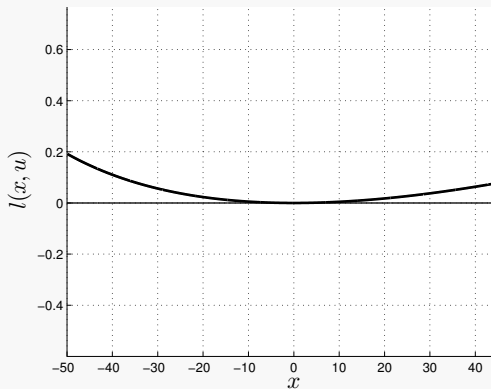
$$l(x, u) - l(x_s, u_s) + \underbrace{\lambda_s^T}_{\text{Lagrange multiplier}} (x - f(x, u))$$



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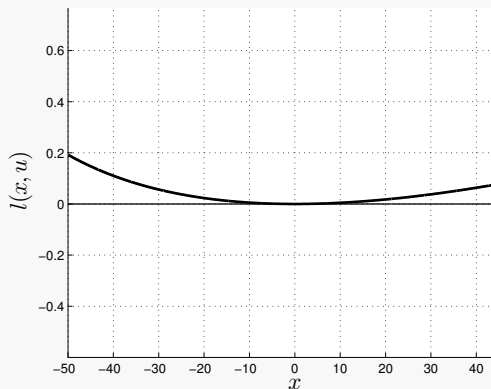
$$L(x, u) = \underbrace{l(x, u)}_{\text{Lagrange multiplier}} - \underbrace{l(x_s, u_s)}_{\text{Lagrange multiplier}} + \underbrace{\lambda_s^T}_{\text{Lagrange multiplier}} (x - f(x, u))$$



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**Rotated cost:**  $L(x, u) = \underbrace{l(x, u)}_{\text{[Diehl et al. 2011]}} - \underbrace{l(x_s, u_s)}_{\text{Lagrange multiplier}} + \underbrace{\lambda_s^T}_{\text{Lagrange multiplier}} (x - f(x, u))$



## Rotated MPC Problem

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Rotated Problem  $\equiv$  Original Problem

$$\sum_{k=0}^{N-1} L(x, u) = \sum_{k=0}^{N-1} l(x, u) + \underbrace{\lambda_s^T x_0 - \lambda_s^T x_N - (N-1) l(x_s, u_s)}_{\text{constant}}$$



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If

$$\alpha(x) \leq L(x, u), \quad \alpha \in \mathcal{K}$$

**the previous stability proof holds!** [Diehl et al. 2011]

## **Generalization** [Amrit et al. 2011]

Nonlinear rotating function:  $\lambda(x)$

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**What conditions on  $\lambda(x)$ ?****Strict Dissipativity**

System strictly dissipative wrt the supply rate  $s(x, u)$  if  $\exists \lambda(x) : \mathbb{X} \rightarrow \mathbb{R}$

$$\lambda(f(x, u)) - \lambda(x) \leq -\rho(x - x_s) + s(x, u),$$

$$\forall (x, u) \in \mathbb{X} \times \mathbb{U}$$

We are interested in  $s(x, u) = l(x, u) - l(x_s, u_s)$

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This entails

$$L(x, u) = l(x, u) - l(x_s, u_s) + \lambda(x) - \lambda(f(x, u)) \geq \rho(x - x_s)$$

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## LQ-EMPC

Consider a linear MPC problem

$$\begin{aligned} \mathcal{P}_N(A, B, Q, R, S, P_N) = \operatorname{argmin}_{x_0, u_0, \dots, x_N} & \sum_{k=0}^{N-1} \begin{bmatrix} x_k \\ u_k \end{bmatrix}^T H \begin{bmatrix} x_k \\ u_k \end{bmatrix} + x_N^T P_N x_N \\ \text{s.t.} & \quad x_0 - \bar{x}_i = 0, \\ & \quad x_{k+1} - A x_k - B u_k = 0. \end{aligned}$$

with

$$H = \begin{bmatrix} Q & S^T \\ S & R \end{bmatrix}$$



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with

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- If  $H \not\prec 0$  this is an **Economic MPC** problem

## LQ-EMPC

Consider a linear MPC problem

$$\begin{aligned} \mathcal{P}_N(A, B, Q, R, S, P_N) = \operatorname{argmin}_{x_0, u_0, \dots, x_N} & \sum_{k=0}^{N-1} \begin{bmatrix} x_k \\ u_k \end{bmatrix}^T H \begin{bmatrix} x_k \\ u_k \end{bmatrix} + x_N^T P_N x_N \\ \text{s.t.} & \quad x_0 - \bar{x}_i = 0, \\ & \quad x_{k+1} - A x_k - B u_k = 0. \end{aligned}$$

with

$$H = \begin{bmatrix} Q & S^T \\ S & R \end{bmatrix}$$

- If  $H \not\prec 0$  this is an **Economic MPC** problem
- When is it **stabilizing**?

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This is an (indefinite) LQR

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$$\exists \bar{P} \text{ s.t. } M = \begin{bmatrix} Q + A^T \bar{P} A - \bar{P} & S^T + A^T \bar{P} B \\ S + B^T \bar{P} A & R + B^T \bar{P} B \end{bmatrix} \succ 0$$

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One can enforce stability by adding  $\begin{bmatrix} x \\ u \end{bmatrix}^T T \begin{bmatrix} x \\ u \end{bmatrix}$  to the cost and solving

$$\min_{P, T} \|T\|^2 \quad \text{s.t. } M + T \succeq 0,$$

**One can modify the cost-to-go without changing the problem**

$$\mathcal{P}_{\infty}(A, B, Q, R, S) = \mathcal{P}_{\infty}(A, B, Q_{\bar{P}}, R_{\bar{P}}, S_{\bar{P}}),$$

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$$Q_{\bar{P}} = Q + A^T \bar{P} A - \bar{P}$$

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- $P_{\bar{P}} = 0$ , i.e. the cost-to-go can be zero!

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- $K_K = 0$
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- $R$  can be replaced by any  $R_K (\succ 0)$

## Positive Definite LQR Formulation

### Lyapunov Stability Theorem

If  $\rho(A_K) < 1$ , then

$$\forall Q_L \succ 0 \quad \exists P_L \succ 0 \text{ s.t.} \quad Q_L + A_K^T P_L A_K - P_L = 0$$



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Pos. def. is preserved when transforming back to  $(A, B)$

## What About MPC?

In the unconstrained case, the solution is given by the Discrete Riccati Equation (DRE)

$$\begin{aligned}\mathcal{R}_N(A, B, Q, R, S, P_N) = \{ & (P_0, P_1, \dots, P_N, K_0, \dots, K_{N-1}) \mid \\ & P_{k-1} = Q + A^T P_k A - (S^T + A^T P_k B) K_{k-1} \\ & K_{k-1} = (R + B^T P_k B)^{-1} (S + B^T P_k A)\}\end{aligned}$$

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## DRE equivalence

$$\mathcal{R}_N(A, B, Q, R, S, P_N) = \mathcal{R}_N(A, B, \tilde{Q}, \tilde{R}, \tilde{S}, \tilde{P}_N)$$

if

$$\begin{aligned}\tilde{P}_N - \tilde{P} &= P_N - P, \\ \tilde{R} + B^T \tilde{P} B &= R + B^T P B, \\ \tilde{S} + B^T \tilde{P} A &= S + B^T P A\end{aligned}$$

with  $P$  and  $\tilde{P}$  computed from  $\mathcal{D}(A, B, Q, R, S)$  and  $\mathcal{D}(A, B, \tilde{Q}, \tilde{R}, \tilde{S})$ .

## A Practical View on the Problem

Solve the following SDP

$$\begin{aligned} \min_{\tilde{P}, \tilde{Q}, \tilde{R}, \tilde{S}, \tilde{H}} \quad & \|\tilde{P} - I\|^2 + \|\tilde{H} - I\|^2 \\ \text{s.t.} \quad & \tilde{H} = \begin{bmatrix} \tilde{Q} & \tilde{S}^T \\ \tilde{S} & \tilde{R} \end{bmatrix} \\ & \tilde{H} \succeq 0 \\ & \tilde{P} \succeq 0 \\ & \tilde{Q} + A^T \tilde{P} A - \tilde{P} - (\tilde{S}^T + A^T \tilde{P} B) K = 0, \\ & (\tilde{R} + B^T \tilde{P} B) K - (\tilde{S} + B^T \tilde{P} A) = 0, \\ & \tilde{R} + B^T \tilde{P} B = R + B^T P B, \\ & \tilde{S} + B^T \tilde{P} A = S + B^T P A. \end{aligned}$$

This problem is convex!

- 1 Economic MPC and Stability Analysis
- 2 The Linear Quadratic Case
- 3 Approximated EMPC with stability guarantees



## Look at the Steady State Properties

Lagrangian of steady state problem

$$\mathcal{L} = l(x, u) - \lambda^T (x - f(x, u))$$

Lagrangian Hessian:

$$H = \begin{bmatrix} Q & S^T \\ S & R \end{bmatrix} = \frac{\partial^2 \mathcal{L}}{\partial (x, u)^2} \Big|_{x_S, u_S}$$

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$$A = \frac{\partial f(x, u)}{\partial x} \Big|_{x_S, u_S} \qquad B = \frac{\partial f(x, u)}{\partial u} \Big|_{x_S, u_S}$$

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- Formulate a tracking NMPC scheme using  $\tilde{H}$

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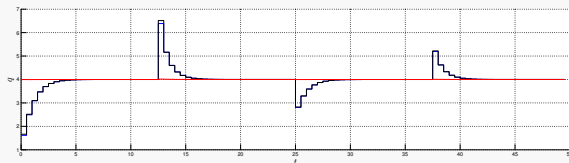
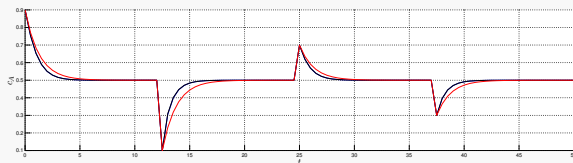
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- Approx. EMPC:  $l_{tr}^0(x, u) = \begin{bmatrix} x - x_s \\ u - u_s \end{bmatrix}^T \begin{bmatrix} 14.227 & 0.825 \\ 0.825 & 0.066 \end{bmatrix} \begin{bmatrix} x - x_s \\ u - u_s \end{bmatrix}$

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**Thank you for your attention!**