Economic Model Predictive Control

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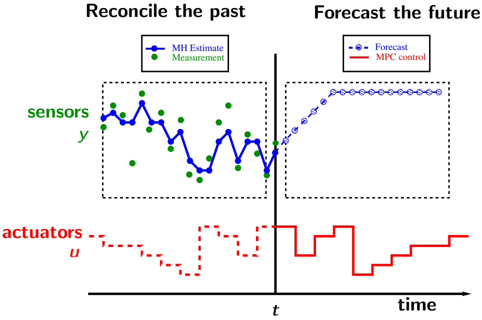
Outline

1. Introduction to Economic MPC
2. Problem Formulation and Properties
   - Asymptotic Average Performance
   - Dissipativity and Asymptotic Stability
3. Economic MPC with Periodic Constraints
4. Stanford Energy System Innovations (SESI) project
5. Conclusions and Open Research Issues

Optimizing process economics

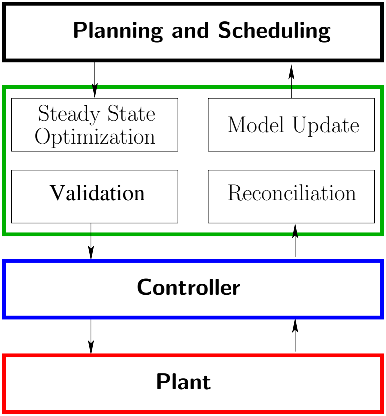
Model predictive control



$$\min_{u(t)} \int_0^T |y_{sp} - g(x,u)|_Q^2 + |u_{sp} - u|_R^2 \, dt$$

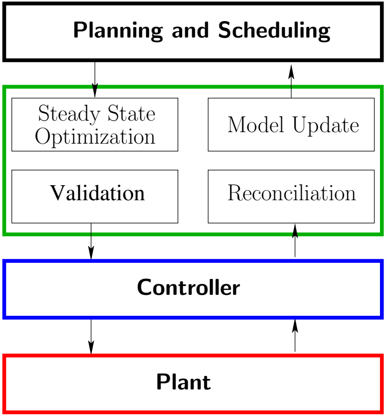
$$\dot{x} = f(x,u)$$
$$x(0) = x_0 \quad \text{(given)}$$
$$y = g(x,u)$$

Optimizing economics: current industrial practice



1. Two layer structure
   - Steady-state layer
     - ★ RTO optimizes steady state model
     - ★ Optimal setpoints passed to dynamic layer
   - Dynamic layer
     - ★ Controller tracks the setpoints
     - ★ Linear MPC

Optimizing economics: current industrial practice



1. Two layer structure
2. Drawbacks
   - Inconsistent models
   - Re-identify linear model as setpoint changes
   - Time scale separation may not hold
   - Economics unavailable in dynamic layer

Steady-state optimization problem definition

- Stage cost: $\ell(x, u)$
- Optimization:

$$\begin{aligned}(x_s, u_s) = \arg\min_{x,u} \quad & \ell(x, u) \\ \text{subject to:} \quad & x = f(x, u), \qquad (x, u) \in \mathbb{Z}\end{aligned}$$

Tracking MPC problem definition

- Stage cost:

$$\ell_t(x,u) = |x - x_s|_Q^2 + |u - u_s|_R^2 + \left|u - u^-\right|_S^2$$

- Optimization:

$$\min_{\boldsymbol{u}} \quad V_N(x, \boldsymbol{u}) = \sum_{k=0}^{N-1} \ell_t(x(k), u(k))$$

$$\text{subject to} \begin{cases} x^+ = f(x,u) \\ (x(k), u(k)) \in \mathbb{Z} \quad k \in \mathbb{I}_{0:N-1} \\ x(N) = x_s \quad x(0) = x \end{cases}$$

- Control law: $u = \kappa_N(x)$
- Admissible set: $\mathcal{X}_N$

Closed-loop stability of tracking MPC

Assumption: Model, cost and admissible set

1. The model $f(\cdot)$ and stage cost $\ell(\cdot)$ are continuous. The admissible set $\mathcal{X}_N$ contains x_s in its interior.
2. There exists a set $\mathbb{X}_f$ containing x_s in its interior and $\mathcal{K}_\infty$-function $\gamma(\cdot)$ such that $V_N^0(x) \leq \gamma(|x - x_s|)$ for $x \in \mathbb{X}_f$.

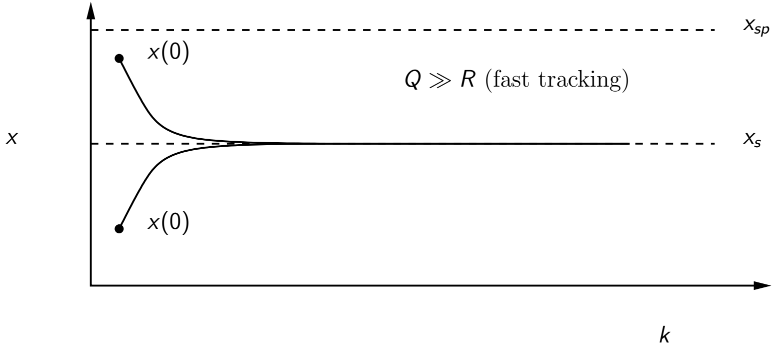
Theorem: Stability of tracking MPC with terminal constraint

The steady-state target (x_s, u_s) is an asymptotically stable equilibrium point of the closed-loop system

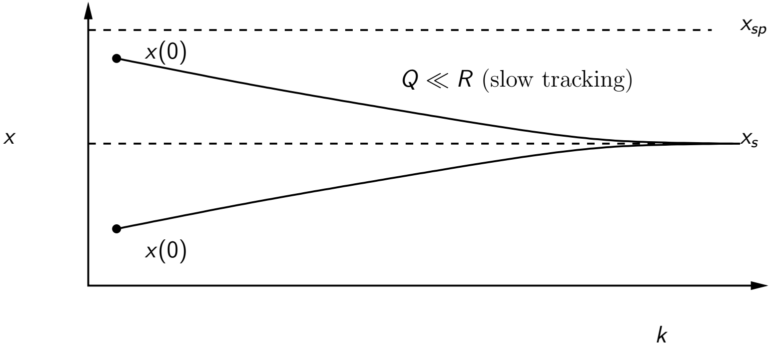
$$x^+ = f(x, \kappa_N(x))$$

with region of attraction $\mathcal{X}_N$.

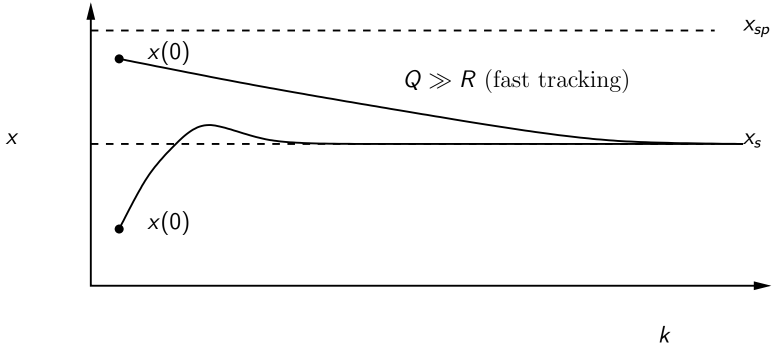
What closed-loop behavior is desirable? Fast tracking



What closed-loop behavior is desirable? Slow tracking



What closed-loop behavior is desirable? Asymmetric tracking



This desirable (profitable) asymmetric behavior is not a standard tracking problem

Economic MPC: motivating the idea

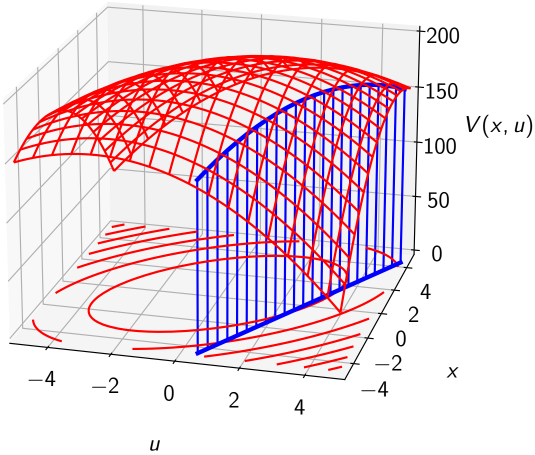


Figure 1: Cost function and steady-state slice.

Economic MPC definition (with terminal constraint)

- Economic stage cost: $\ell(x, u)$
- Optimization:

$$\min_{\boldsymbol{u}} \quad V_{N,e}(x, \boldsymbol{u}) = \sum_{k=0}^{N-1} \ell(x(k), u(k))$$

$$\text{subject to} \begin{cases} x^+ = f(x, u) \quad x(0) = x \\ (x(k), u(k)) \in \mathbb{Z} \quad k \in [0 : N-1] \\ x(N) = x_s \end{cases} \tag{1}$$

- Control law: $u = \kappa_{N,e}(x)$
- Admissible set: $\mathcal{X}_{N,e}$

Linear example

$$x^+ = Ax + Bu$$

$$A = \begin{bmatrix} 0.857 & 0.884 \\ -0.0147 & -0.0151 \end{bmatrix} \qquad B = \begin{bmatrix} 8.565 \\ 0.88418 \end{bmatrix}$$

Input constraint: $-1 \leq u \leq 1$

- $\ell(x, u) = \alpha' x + \beta' u$
- $\alpha = \begin{bmatrix} -3 & -2 \end{bmatrix}' \quad \beta = -2$

- $\ell_t(x, u) = |x - x_s|_Q^2 + |u - u_s|_R^2$
- $Q = 2I_2 \qquad R = 2$
- $x_s = \begin{bmatrix} 60 & 0 \end{bmatrix}' \qquad u_s = 1$

Cost contours and phase portrait

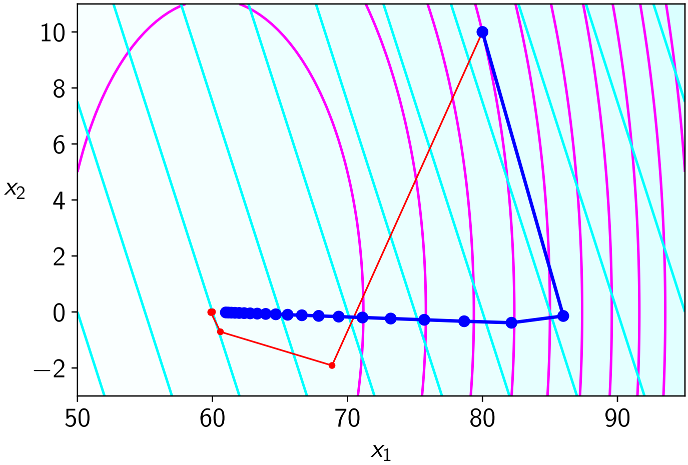


Figure 2: Cost contours and phase portrait for economic MPC (blue) vs. tracking MPC (red). Darker shading shows lower cost.

States and inputs versus time

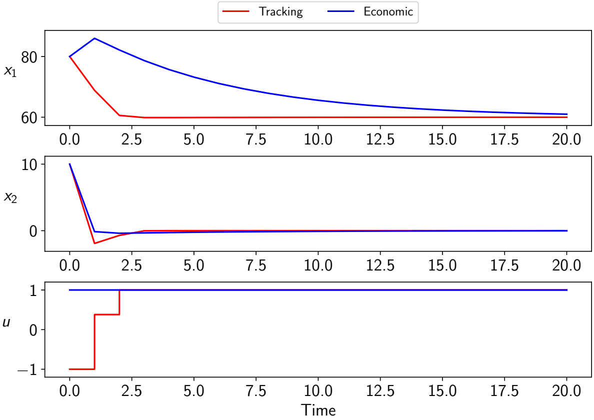


Figure 3: Economic MPC versus tracking MPC for a linear system.

Economic MPC Assumptions

Assumption 1 (Continuity of system and cost)

The functions $f : \mathbb{Z} \to \mathbb{R}^n$ and $\ell : \mathbb{Z} \to \mathbb{R}_{\geq 0}$ are continuous. $V_f(\cdot) = 0$. There exists at least one point $(x_s, u_s) \in \mathbb{Z}$ satisfying $x_s = f(x_s, u_s)$.

Assumption 2 (Properties of constraint sets)

The set $\mathbb{Z}$ is closed. If there are control constraints, the set $\mathbb{U}(x)$ is compact and is uniformly bounded in $\mathbb{X}$.

The economic stage cost

Thebiggest change is that we do not assume here that the stage cost $\ell(x, u)$ is positive definite with respect to the optimal steady state, only that it is lower bounded.

Assumption 3 (Cost lower bound)

1. The terminal set is a single point, $\mathbb{X}_f = \{x_s\}$.
2. The stage cost $\ell(x, u)$ is lower bounded for $(x, u) \in \mathbb{Z}$.

For clarity in this discussion, we do not assume that (x_s, u_s) has been shifted to the origin.

Asymptotic Average Performance

We already have enough structure in this simple problem to establish that the average cost of economic MPC is better, i.e., not worse, than any steady-state performance $\ell(x_s, u_s)$.

Proposition 4 (Asymptotic average performance)

Let Assumptions 1, 2, and 3 hold. Then for every $x \in \mathcal{X}_N$, the following holds

$$\limsup_{t \to \infty} \sum_{k=0}^{t-1} \frac{\ell(x(k), u(k))}{t} \leq \ell(x_s, u_s)$$

in which $x(k)$ is the closed-loop solution to $x^+ = f(x, \kappa_N(x))$ with initial condition x.

Why does this hold?

Proof.

Because of the terminal constraint, we have that

$$V_N^0\big(f(x,\kappa_N(x))\big) \leq V_N^0(x) - \ell(x,\kappa_N(x)) + \ell(x_s,u_s) \tag{2}$$

Performing a sum on this inequality gives (first telescoping sum)

$$\sum_{k=0}^{t=1} \frac{\ell(x(k),u(k))}{t} \leq \ell(x_s,u_s) + (1/t)(V_N^0(x(0)) - V_N^0(x(t)))$$

The left-hand side may not have a limit (why not?), so we take $\limsup$ of both sides.

Why does this hold?

Proof (cont.).

Note that from Assumption 3.2, $\ell(x, u)$ is lower bounded for $(x, u) \in \mathbb{Z}$, hence so is $V_N(x, u)$ for $(x, u) \in \mathbb{Z}$, and $V_N^0(x)$ for $x \in \mathcal{X}_N$.
Denote this bound by M, so $V_N^0(x) \geq M$. Then

$$\lim_{t \to \infty} (1/t) V_N^0(x(t)) \geq \lim_{t \to \infty} M/t = 0$$

and we have that

$$\limsup_{t \to \infty} \sum_{k=0}^{t=1} \frac{\ell(x(k), u(k))}{t} \leq \ell(x_s, u_s)$$

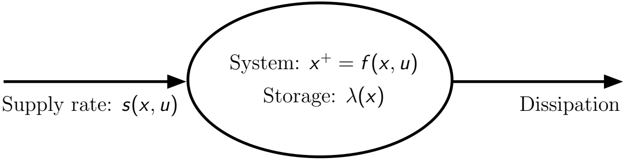
Comments

- This result does not imply that the economic MPC controller stabilizes the steady state (x_s, u_s), only that the *average* closed-loop performance is better than the best steady-state performance.
- There are many examples of nonlinear systems for which the time-average of an oscillation is better than the steady state.
- For such systems, we would expect an optimizing controller to destabilize even a stable steady state to obtain the performance improvement offered by cycling the system.
- Note also that the appearance in (2) of the term $-\ell(x, \kappa_N(x)) + \ell(x_s, u_s)$, which is sign indeterminate, destroys the cost decrease property of $V_N^0(\cdot)$ so it no longer can serve as a Lyapunov function in a closed-loop stability argument.
- We next examine the stability question.

Asymptotic stability and EMPC

- Steady operation often *desired* by practitioners
  - Equipment not designed for strongly unsteady operation
  - Operator acceptance issue for unsteady operation
- Stability analysis
  - Check that stability is consistent with the process model and control objectives
  - Or modify the control objectives (stage cost) given the process model

Stabilizing assumption for EMPC



Assumption: Dissipativity

The system $x^+ = f(x, u)$ is dissipative with respect to the supply rate $s : \mathbb{Z} \to \mathbb{R}$ if there exists a function $\lambda : \mathbb{X} \to \mathbb{R}$ such that:

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

for all $(x, u) \in \mathbb{Z}$. If $\rho : \mathbb{X} \to \mathbb{R}_{\geq 0}$ positive definite exists such that:

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

then the system is said to be strictly dissipative.

Stability theorem for EMPC

Theorem: Stability of EMPC Angeli, Amrit, and Rawlings (2012)

If the system

$$x^+ = f(x,u) \quad (x,u) \in \mathbb{Z}$$

is strictly dissipative with respect to the supply rate

$$s(x,u) = \ell(x,u) - \ell(x_s,u_s)$$

then x_s is an asymptotically stable equilibrium point of the closed-loop system with region of attraction $\mathcal{X}_{N,e}$.

- Nominal average asymptotic performance not worse than steady operation is always implied by stability

Sketch of proof

- Lyapunov-based proof, with rotated stage cost (Diehl, Amrit, and Rawlings, 2011):

$$\tilde{\ell}(x,u) := \ell(x,u) - \ell(x_s,u_s) + \lambda(x) - \lambda(f(x,u))$$

- Consider the rotated cost function

$$\begin{aligned}
\tilde{V}_N(x,\boldsymbol{u}) &= \sum_{k=0}^{N-1} \tilde{\ell}(x(k),u(k)) \\
&= \sum_{k=0}^{N-1} \underbrace{\ell(x(k),u(k)) - \ell(x_s,u_s)}_{V_N(x,\boldsymbol{u}) - N\ell(x_s,u_s)} + \sum_{k=0}^{N-1} \underbrace{\lambda(x(k)) - \lambda(x(k+1))}_{\text{telescoping sum}}
\end{aligned}$$

Optimal cost

- (Second) telescoping sum

$$\sum_{k=0}^{N-1} \lambda(x(k)) - \lambda(x(k+1)) =$$

$$\left[\lambda(x(0)) - \lambda(x(1))\right] + \left[\lambda(x(1)) - \lambda(x(2))\right] + \left[\cdots\right] + \left[\lambda(x(N-1)) - \lambda(x(N))\right.$$

$$= \lambda(x(0)) - \lambda(x(N))$$

$$\tilde{V}_N(x, \boldsymbol{u}) = V_N(x, \boldsymbol{u}) \underbrace{-N\ell(x_s, u_s) + \lambda(x(0)) - \lambda(x_s)}_{\text{does not depend on } \boldsymbol{u}}$$

- Optimal control is unaffected by cost rotation!

$$\arg\min_{\boldsymbol{u}} \tilde{V}_N(x, \boldsymbol{u}) = \arg\min_{\boldsymbol{u}} V_N(x, \boldsymbol{u})$$

Sketch of proof (cont.)

- Under dissipativity assumption rotated cost fulfills standard MPC conditions (positive semi-definite):

$$\begin{aligned}\tilde{\ell}(x,u) &:= \ell(x,u) - \ell(x_s,u_s) + \lambda(x) - \lambda(f(x,u)) \\ &= s(x,u) + \lambda(x) - \lambda(f(x,u)) \\ &\geq 0\end{aligned}$$

  In addition, under strict dissipativity, the rotated cost is positive definite:

$$\tilde{\ell}(x,u) \geq \rho(x)$$

- Rotated optimal cost can be used as a candidate Lyapunov function

$$\tilde{V}_N^0(x) := \min_{\boldsymbol{u}} \sum_{k=0}^{N-1} \tilde{\ell}(x(k),u(k))$$

  subject to initial, terminal and dynamic model constraints.

Check cost decrease

- Consider optimal solution at state x with cost $\tilde{V}_N^0(x)$ and first stage cost $\tilde{\ell}(x, \kappa_{N,e}(x))$.
- Define the candidate control sequence for successor state x^+

$$\tilde{\boldsymbol{u}} = (u(1; x), u(2; x), \ldots, u(N-1; x), u_s)$$

  This candidate is *feasible* since it satisfies the terminal constraint $f(x_s, u_s) = x_s$.
- Therefore

$$\tilde{V}_N(x^+, \tilde{\boldsymbol{u}}) = \tilde{V}_N^0(x) - \tilde{\ell}(x, \kappa_{N,e}(x)) + \tilde{\ell}(x_s, u_s)$$

- Note that by construction $\tilde{\ell}(x_s, u_s) = 0$, and optimize to obtain

$$\begin{aligned} \tilde{V}_N^0(x^+) &\leq \tilde{V}_N^0(x) - \tilde{\ell}(x, \kappa_{N,e}(x)) \\ &\leq \tilde{V}_N^0(x) - \rho(x) \end{aligned}$$

  establishing the cost decrease for the rotated cost function.

Exercise: CSTR

Consider an isothermal CSTR with $A \rightarrow B$ first order (rate $r = kc_A$). The continuous-time model is (Diehl et al., 2011):

$$\frac{dc_A}{dt} = \frac{Q}{V}(c_{Af} - c_A) - kc_A$$
$$\frac{dc_B}{dt} = \frac{Q}{V}(c_{Bf} - c_B) + kc_A$$

We define two stage costs:

$$\ell_{\text{econ}}(c_A, c_B, Q) = -(2Qc_B - 0.5Q)$$
$$\ell_{\text{regularized}}(c_A, c_B, Q) = -(2Qc_B - 0.5Q) + |c_A - 0.5|^2_{Q_A} + |c_B - 0.5|^2_{Q_B} + |Q - 12|^2_R$$

$\ell_{\text{regularized}}$ is strongly-dual, while ℓ_{normal} is not.

Duality Check

We can check strong duality by looking at contours of the Lagrangian for the steady-state problem.

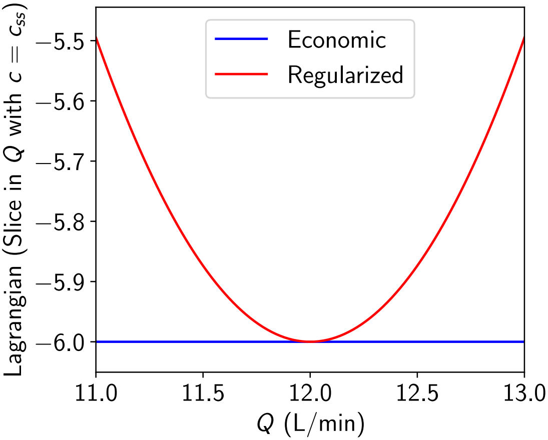


Figure 4: Slice of regularized objective is consistent with strong duality, while slice of normal objective shows lack of strong duality.

Continuous vs. Discrete Objective

- Economic cost function:

$$\ell_{\text{econ}}(x, u) = -(2Qc_B - 0.5Q)$$

- Discrete objective (not strongly dual):

$$V_{\text{discrete}} = \sum_{k=0}^{N-1} \ell_{\text{econ}}(x_k, u_k)$$

- Continuous objective (strongly dual):

$$\begin{aligned} V_{\text{continuous}} &= \int_0^{N\Delta} \ell_{\text{econ}}(x(t), u(t))\, dt \\ &= \sum_{k=0}^{n-1} \left(\int_0^{\Delta} \ell_{\text{econ}}(\phi(t; x_k, u_k), u_k)\, dt \right) \end{aligned}$$

Regularized Objective

With the regularized objective, rotated cost is a Lyapunov function.

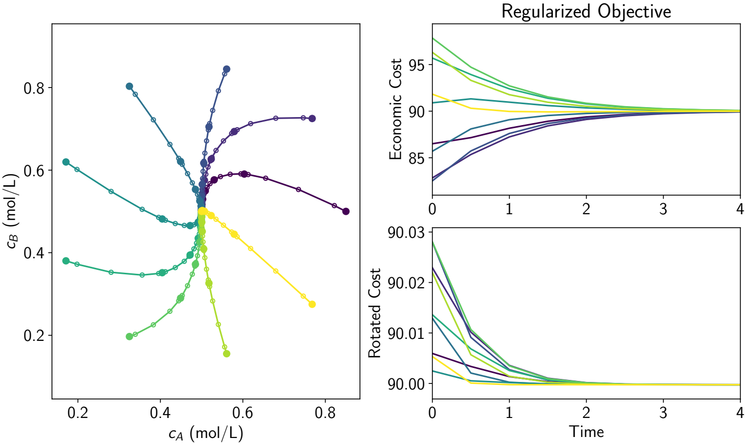


Figure 5: Closed-loop trajectories using regularized (strongly dual) objective.

Economic Objective

Without regularization, system is still asymptotically stable, but rotated cost is *not* a Lyapunov function.

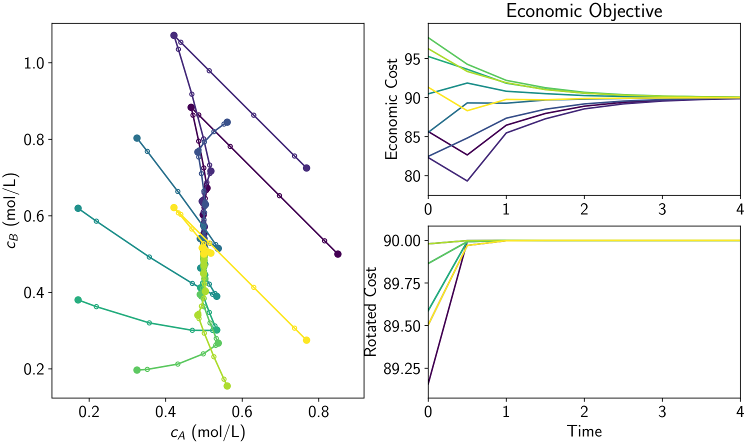


Figure 6: Closed-loop trajectories using normal economic (not strongly dual) objective.

Outperforming the best steady operation

- Terminal constraint instrumental in:
  1. guaranteeing recursive feasibility
  2. providing bound to asymptotic performance
- Any feasible trajectory may be used as a terminal constraint

Idea:

Replace best equilibrium by **best feasible periodic solution** with chosen period

EMPC with periodic constraint

Let the sequences $(\boldsymbol{x}_p, \boldsymbol{u}_p)$ denote a given q-periodic solution to a periodic nonlinear system

$$x_p(i+1) = f(x_p(i), u_p(i), i)$$
$$x_p(i+q) = x_p(i), \quad u_p(i+q) = u_p(i)$$

- In this problem, we assume a periodic solution is available, but change the controller's goal from stabilization of the periodic solution (tracking) to optimization of economic performance.
- The periodic solution then serves as a useful end constraint for the economic optimization problem.
- The stage cost $\ell(x, u)$ is free to be chosen as an economic profit function and has no connection to distance from (x_p, u_p) as in the tracking case.

Setup for economic MPC with periodic constraint

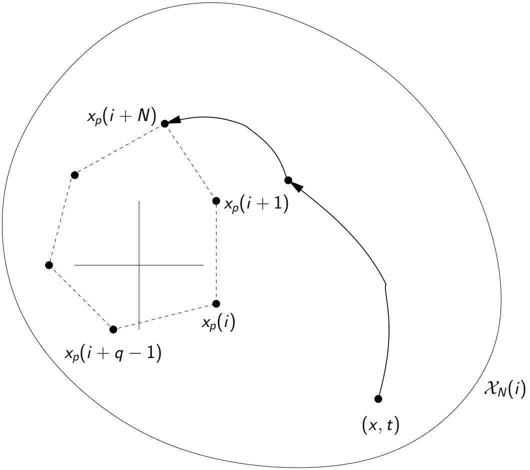


Figure 7: The periodic solution $x_p(i)$ as end constraint for economic MPC problem for a system with initial condition (x, t), $i = t \mod q$, and $N = 2$.

Average performance with periodic end constraint

- Let $V_N^0(x,t)$ be the optimal cost to go (note: time-varying Lyapunov function now)

$$V_N^0(x, t) = \min_{\boldsymbol{u}} \sum_{k=0}^{N-1} \ell(x(k), u(k))$$

subject to:

$$x^+ = f(x,u), \quad x(0) = x, \quad x(N) = x_s(t \bmod q)$$
$$(x(k), u(k)) \in \mathbb{Z}, \quad k \in \{0, 1, \dots, N-1\}$$

- Along closed-loop solution

$$V_N^0(x(t+1), t+1) \leq V_N^0(x(t), t) \\ - \ell(x(t), u(t)) + \ell(x_s(t \bmod q), u_s(t \bmod q))$$

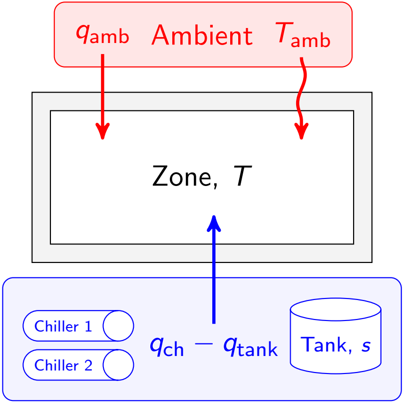
Average performance with periodic end constraint

- Taking sums between 0 and $T-1$ (third telescoping sum) and dividing by T yields:

$$\limsup_{T\to+\infty} \frac{\sum_{k=0}^{T-1} \ell(x(k), u(k))}{T} \leq \frac{\sum_{k=0}^{q-1} \ell(x_s(k), u_s(k))}{q}$$

- Average performance at least as good as optimal q-periodic solution
- q and N may be different from each other and unrelated
- The closed-loop system need not be asymptotically stable to the optimal q-periodic solution
- The optimal q-periodic solution need not be an equilibrium of the closed-loop system

Example: Simplified Building Cooling



$$\frac{dT}{dt} = -k(T - T_{\text{amb}}) + q_{\text{amb}} + q_{\text{ch}} - q_{\text{tank}}$$

$$\frac{ds}{dt} = -\sigma s + q_{\text{tank}}$$

$$v q_{\text{min}} \leq q \leq v q_{\text{max}}$$

$$q_{\text{tank}} \leq q_{\text{ch}}, \quad v \in \{0, 1, 2\}$$

$$x := (T, s)$$
$$u := (q_{\text{ch}}, q_{\text{tank}}, v)$$
$$d := (T_{\text{amb}}, q_{\text{amb}})$$

- Temperature must be maintained within preset bounds.
- Each chiller can be on or off.
- When on, chillers have minimum and maximum capacity.

Parameters

Stage Costs

$$\ell_{\text{econ}}(x, u, t) := \rho(t)q(t)$$
$$\ell_{\text{track}}(x, u, t) := |x(t) - x_p(t)|_Q^2 + |u(t) - u_p(t)|_R^2$$

- Horizon $N = 24$
- Periodic ρ, T_{amb}, q_{amb}
- Weights $Q = R = I$

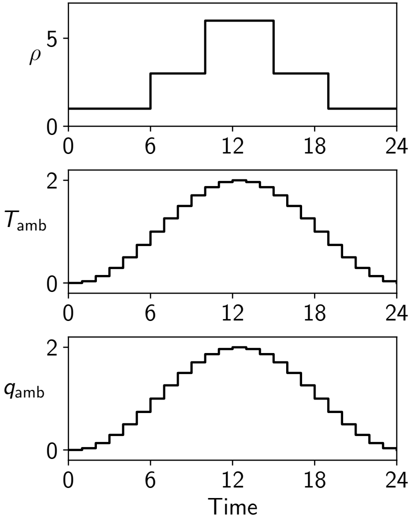


Figure 8: Parameters for building cooling example

Optimal Periodic Solution

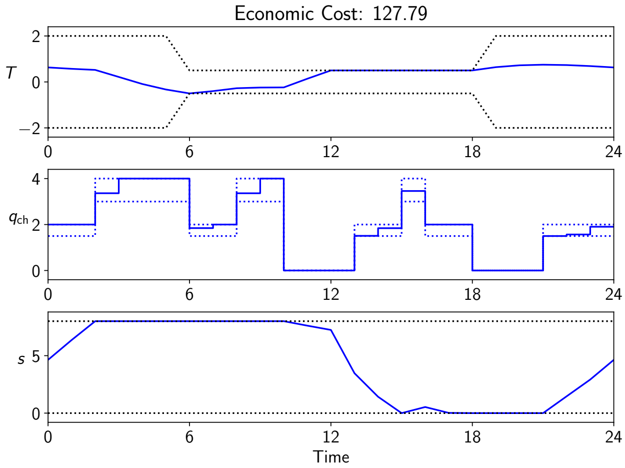


Figure 9: Periodic solution for building cooling that can serve as end constraint

- Precooling reduces cooling during peak price hours.
- “Bounds” on q are determined by the (integral) value of v.

Tracking MPC

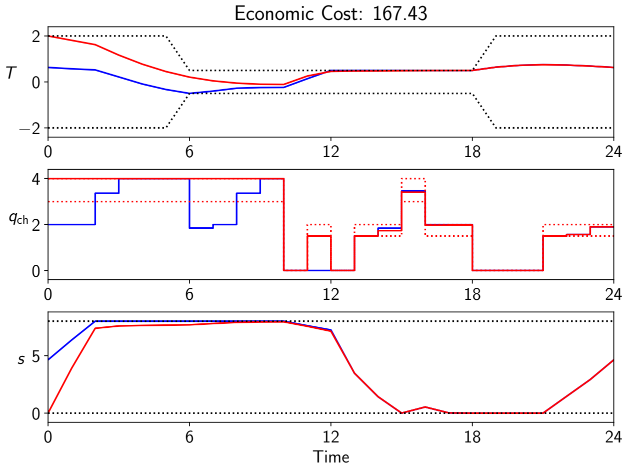


Figure 10: Closed-loop tracking MPC using optimal periodic solution

- Initial condition $T(0) = 2$, $s(0) = 0$.
- Stage cost penalizes changes in T, s, q_{ch}, q_{tank}, and v.

Economic MPC

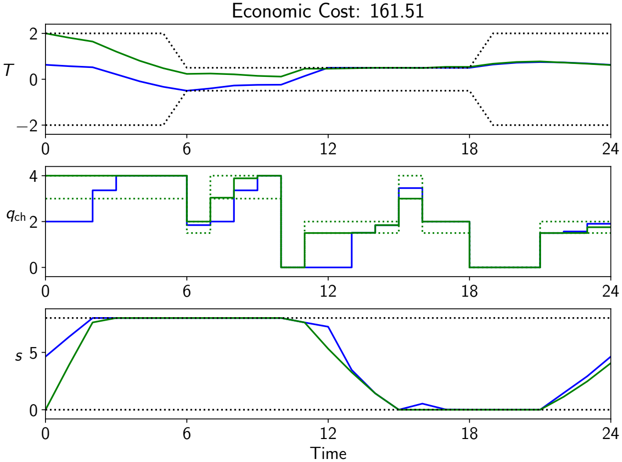
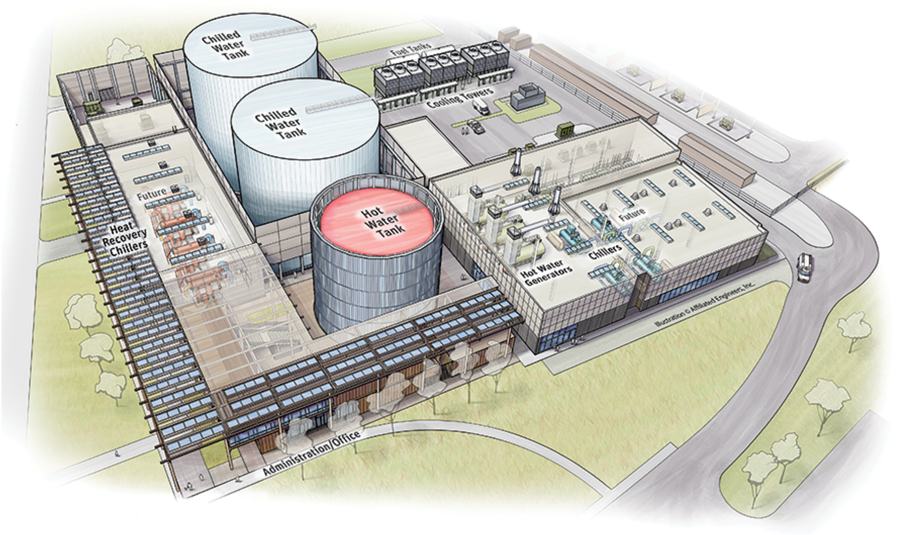


Figure 11: Closed-loop economic MPC with optimal periodic solution as the terminal constraint

- Controller aggressively pursues lower cost
- Deviation in u is not penalized

Moving the needle on total national energy use—Buildings

- In 2009, energy use in buildings accounted for 41% of total primary energy consumption and 18% of carbon emissions in the US.
- Commercial buildings consumed 19×10^{18} J of primary energy in 2009, accounting for roughly $200 billion a year in primary energy expenditures.
- Large, complex control problem usually decomposed into water side (chilling) and air side (temperature control) subproblems. Discrete decisions (chillers on/off) are critical in this application.
- Bob Turney of Johnson Controls convinced me to take a look at this problem. "If MPC can control chemical plants, why not buildings..."
- We're combining discrete actuators with economic MPC for this class of applications.
- First large-scale implementation: Stanford Energy System Innovations (SESI) project (completed 2015).



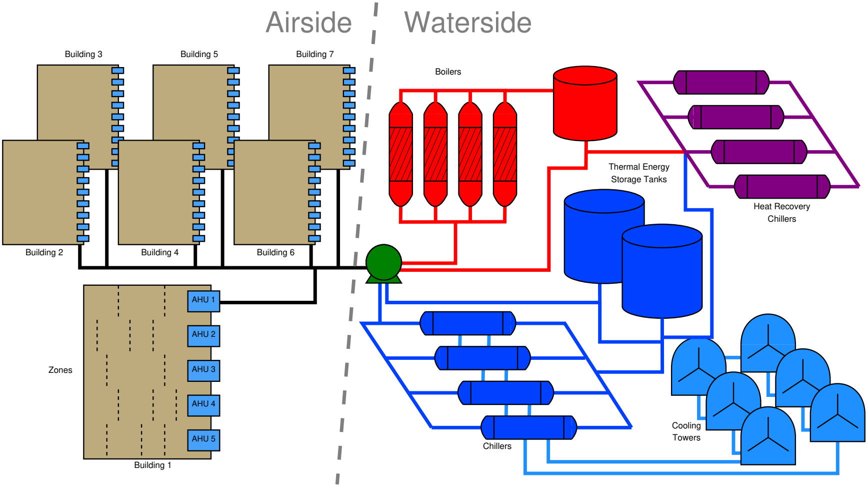
The $485-million Stanford Energy System Innovations (SESI) project; replaced an aging 50-MW natural-gas-fired cogeneration plant with a new heat-recovery system to provide heating and cooling to the campus.

A new 80-megavolt-ampere electrical substation brings electricity from the grid. Crews also converted 155 campus buildings from steam to hot-water distribution and installed a 22-mile-long network of new pipe.

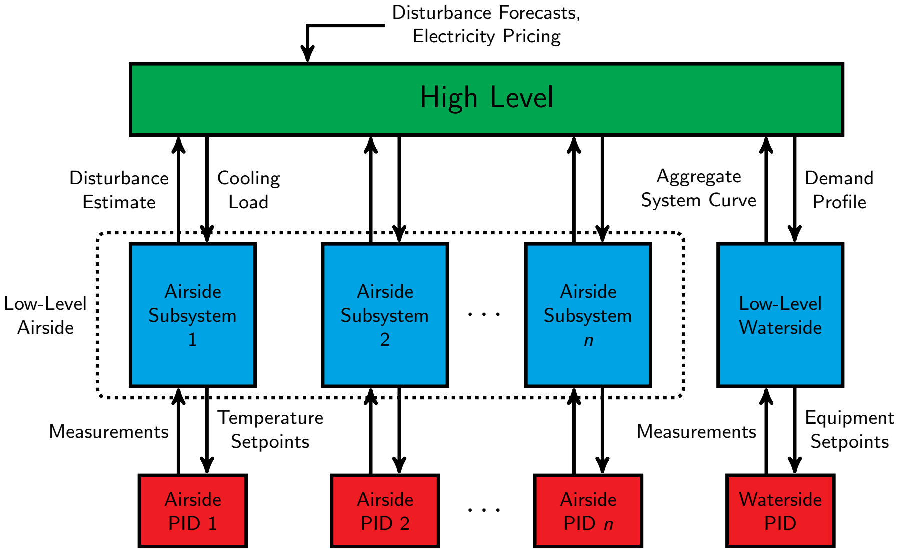
The star of the show: three heat-recovery chillers—the largest in the U.S.—that strip waste heat from 155 campus buildings.

Johnson Controls developed the Central Energy Plant Optimization Model (CEPOM); the algorithm optimizes a 10-day forecast every 15 minutes, considering campus loads, weather patterns, price of electricity, available equipment and many other factors.

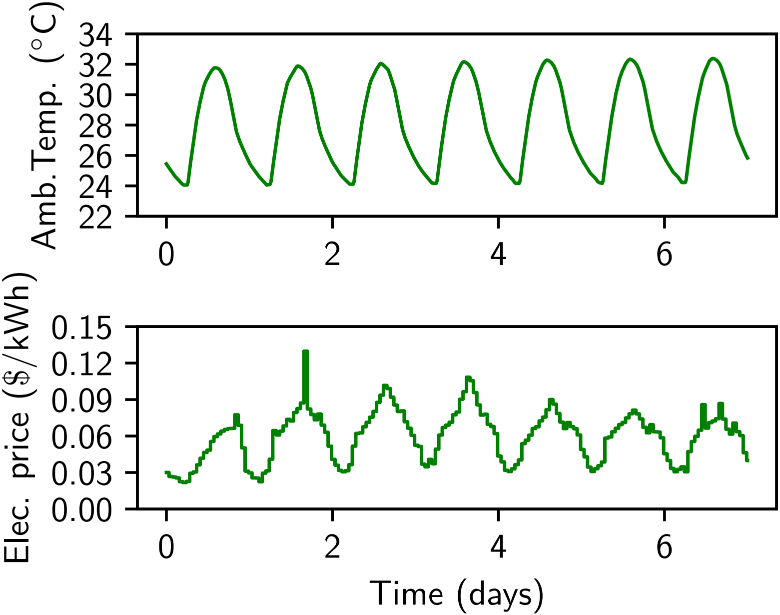
Large-scale commercial application



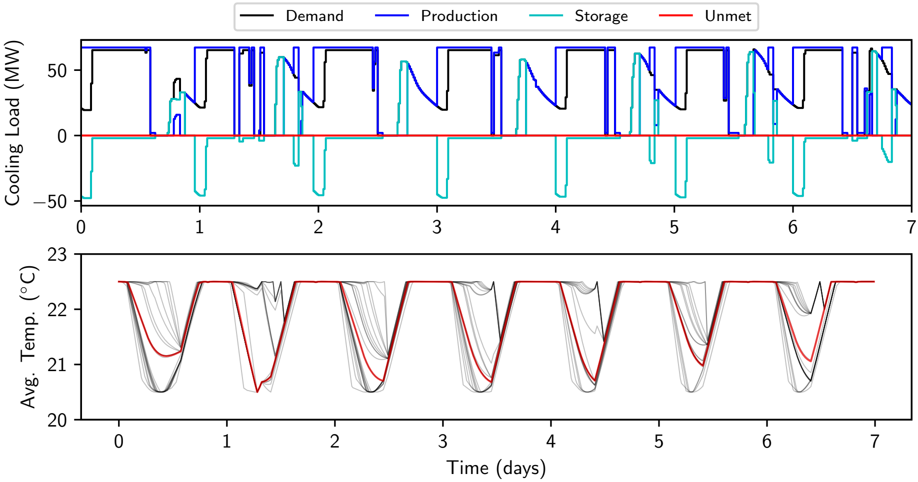
Control Decomposition



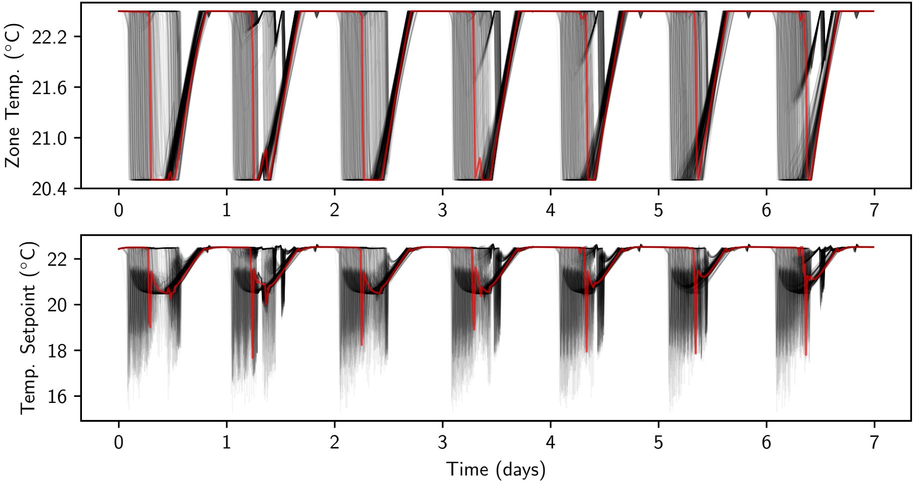
The disturbance forecast: weather and electricity prices



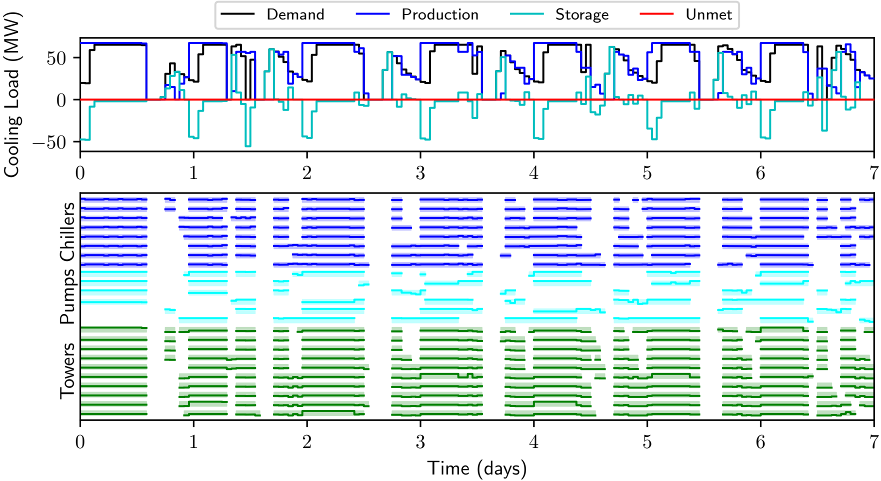
High-level problem: Optimal production and average building temperatures



Low level airside: Optimal zone temperatures and setpoints



Low level waterside: Gantt chart for central plant equipment



Real-time computational requirements

- The optimizations were solved using Gurobi 6.0 via MATLAB R2016b on a machine with 8GB RAM and 2.66GHz Intel Core 2 Quad Processor Q8400.
- The high-level problem took 35 seconds to solve.
- The low-level airside subproblems took about 15 seconds each to solve.
- The low-level waterside subproblem was given two minutes of computation time, after which the incumbent solution (with an optimality gap of 0.2%) was accepted.
- Since control executions occur every 15 minutes, this decomposition can easily be implemented online.
- Solution times can be further decreased by using a horizon shorter than one week (Risbeck, Maravelias, Rawlings, and Turney, 2016).

SESI operation summary

- In operation since December 2015 (Wenzel, Turney, and Drees, 2016).
- The central plant was run in autonomous mode about 90% of the time (including time off-line for plant maintenance).
- Achieved 10% to 15% additional savings in operating costs compared to control by the best team of trained human operators (Stagner, 2016).
- This large-scale implementation demonstrates the significant potential benefits to applying model-based optimization to large HVAC systems

Conclusions

- The economic objective function of EMPC causes novel behavior
  - EMPC may be unstable where MPC is stable
  - Using a terminal penalty or terminal equality constraint guarantees asymptotic average profit not worse than best steady state
  - Stability of EMPC requires dissipativity of process/stage cost
- Many techniques from MPC can be applied to EMPC
  - Terminal penalty formulation
  - Average constraints
  - Periodic terminal constraints

Open research issues

- Remove terminal constraints and costs by choosing sufficient N. See Grüne (2012, 2013) for recent results in this direction.
- Generalized terminal state constraint. Terminate on the steady-state *manifold* and move the end location dynamically to the best steady state (Fagiano and Teel, 2012; Ferramosca, Limon, Alvarado, Alamo, and Camacho, 2009)
- Analyzing closed-loop performance
  - What can be proven about net closed-loop performance of tracking MPC relative to EMPC?
  - What is observed about differences in net closed-loop performance in simulations?
  - What model, stage cost and disturbance characteristics cause large performance differences between MPC and EMPC?

Open research issues

- Tuning EMPC and robustness
  - For nondissipative process/stage costs, how should the stage cost be modified?
  - How robust is EMPC to model errors and disturbances?
  - How can economic risk be incorporated into the controller?
- Computational methods for implementing EMPC; strategies for adapting existing control hierarchies

Further reading I

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A. Ferramosca, D. Limon, I. Alvarado, T. Alamo, and E. Camacho. MPC for tracking of constrained nonlinear systems. In *IEEE Conference on Decision and Control (CDC)*, pages 7978–7983, Shanghai, China, 2009.

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