Distributed MPC: a comprehensive overview and some recent advances

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Model Predictive Control: motivations for its success

Fundamental features

- ☑ MPC is the most successful advanced control technique applied in the process industries
- ☑ MPC can ensure (for linear and nonlinear multivariable systems)
  - closed-loop stability
  - constraint satisfaction
  - robustness against modeling errors and disturbances
  - setpoint tracking (often hierarchically)
- ☑ MPC enhances the process profitability

Large scale systems: some examples

Large industrial plants

Power generation networks

Systems of Systems

MPC for large scale systems: different approaches

One or more MPCs?

☑ One **centralized MPC**

- Pros: global (plant-wide) optimality, stability
- Cons: limited flexibility, high computational cost

☑ Several **decentralized MPCs**

- Pros: lower computational cost, high modularity
- Cons: global suboptimality, stability issues

Middle field…

☑ Distributed **MPC**

- Pros: high modularity, stability
- Pros/Cons: global optimality (high computational cost)

Outline

1. Comprehensive overview of (linear) distributed MPC algorithms
   - Models
   - Decentralized, Cooperative and Non-Cooperative MPC
   - Design and properties of Cooperative MPC
   - Cooperative MPC for tracking
2. Advances in cooperative MPC for tracking
   - Proposed approaches
   - Application results
3. Conclusions

Part I
A comprehensive overview of distributed MPC

Models for distributed MPC - I

Overall DLTI system

$$x^+ = A\,x + B\,u$$
$$y = C\,x$$

$x \in \mathbb{R}^n$: current state

$x^+ \in \mathbb{R}^n$: successor state

$u \in \mathbb{R}^m$: manipulated input

$y \in \mathbb{R}^p$: controlled output

Local DLTI subsystems

$$x_i^+ = A_i\,x_i + B_i\,u_i + \sum_{j \in \mathcal{N}_i} B_{ij}\,u_j$$

$$y_i = C_i\,x_i$$

M: number of subsystems

$\mathcal{N}_i$: set of neighbors of subsystem i

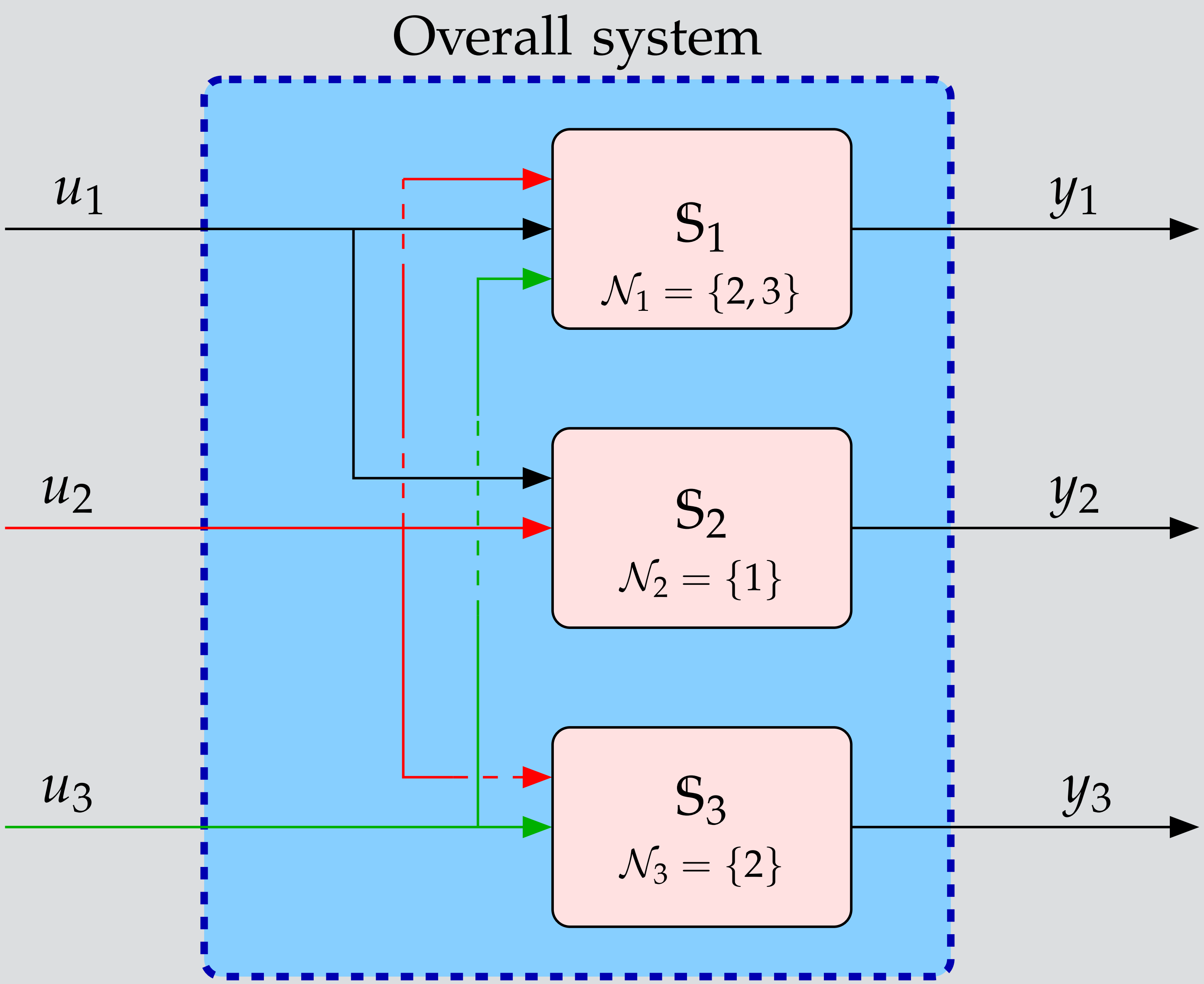
$x_i, x_i^+ \in \mathbb{R}^{n_i}$: current/successor i−th state

$u_i \in \mathbb{R}^{m_i}$: manipulated i−th input

$y_i \in \mathbb{R}^{p_i}$: controlled i−th output

Models for distributed MPC - II

Interconnected systems and neighbors definition



Models for distributed MPC - III

Why not coupling through states?

- The state of each subsystem includes all modes from local and neighboring **inputs** to local **output**

- An example of 2 subsystems "**coupled by states**":

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^+ = \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} B_{11} & 0 \\ 0 & B_{22} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} C_{11} & 0 \\ 0 & C_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

- Equivalent subsystems **coupled by inputs**:

$$\text{Subsystem 1:}\ x_1 \leftarrow \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad A_1 \leftarrow \begin{bmatrix} A_{11} & A_{12} \\ 0 & A_{22} \end{bmatrix}, \quad B_1 \leftarrow \begin{bmatrix} B_{11} \\ 0 \end{bmatrix}, \quad B_{12} \leftarrow \begin{bmatrix} 0 \\ B_{22} \end{bmatrix}, \quad C_1 \leftarrow \begin{bmatrix} C_{11} & 0 \end{bmatrix}$$

$$\text{Subsystem 2:}\ x_2 \leftarrow \begin{bmatrix} x_2 \end{bmatrix}, \quad A_2 \leftarrow \begin{bmatrix} A_{22} \end{bmatrix}, \quad B_2 \leftarrow \begin{bmatrix} B_{22} \end{bmatrix}, \quad B_{21} \leftarrow [\,], \quad C_2 \leftarrow \begin{bmatrix} C_{22} \end{bmatrix}$$

- Models obtained from **ID** naturally have input couplings

Taxonomy

Based on dynamics and objective of local controllers

- **Centralized MPC**: a single MPC computes all inputs to optimize a global objective
- **Decentralized MPC**: each MPC computes its local input, disregarding interacting dynamics, to optimize a local objective
- **Non-cooperative MPC**: each MPC computes its local input, considering interacting dynamics, to optimize a local objective
- **Cooperative MPC**: each MPC computes its local input, considering interacting dynamics, to optimize a global objective

Decentralized MPC

Model (decentralized)

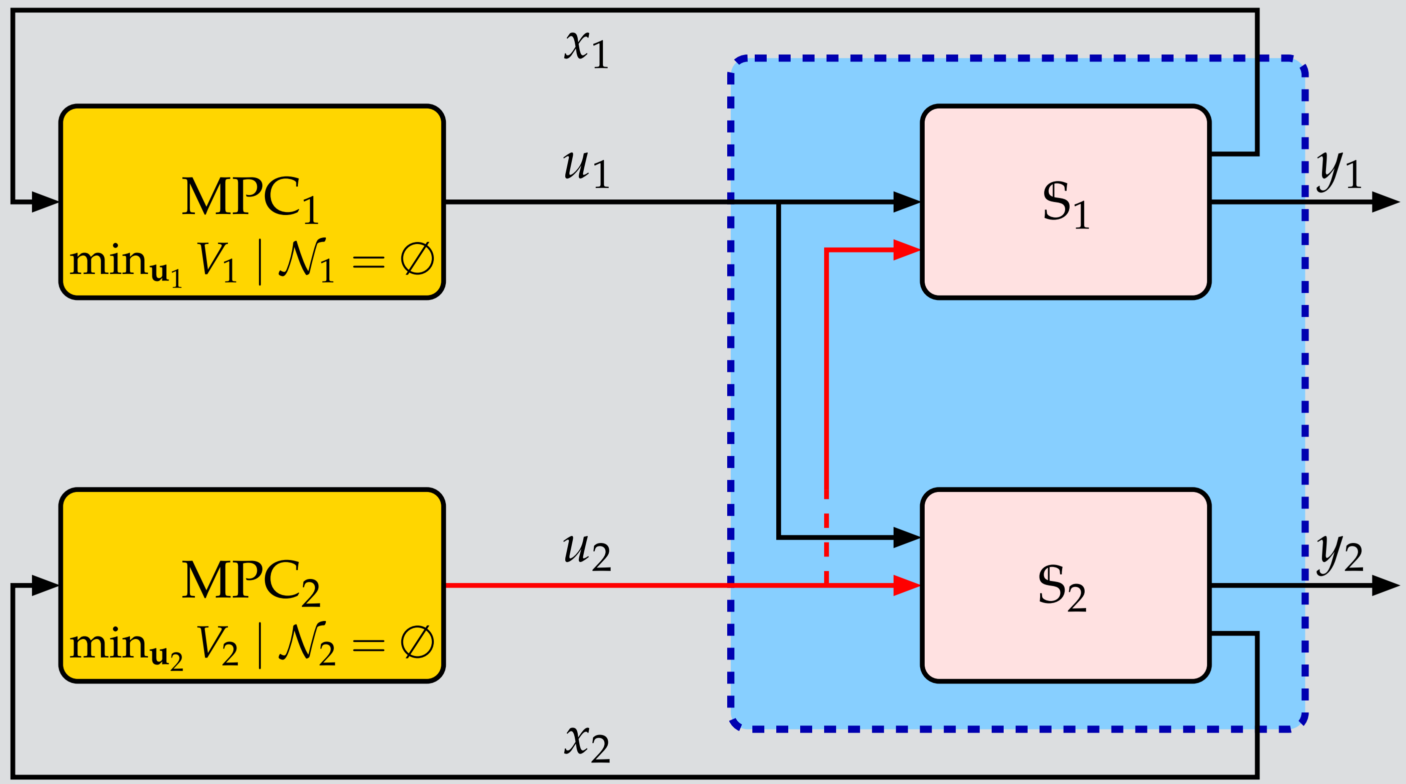
$$x_i^+ = A_i\, x_i + B_i\, u_i + \cancel{\sum_{j \in \mathcal{N}_i} B_{ij}\, u_j}$$

$$y_i = C_i\, x_i$$

Cost (local)

$$V_i = \sum_{k=0}^{N-1} \left(x_i(k)^T Q_i x_i(k) + u_i(k)^T R_i u_i(k) \right) + x_i(N)^T P_i x_i(N)$$

Reference Scheme



Non-cooperative Distributed MPC

Model (interacting)

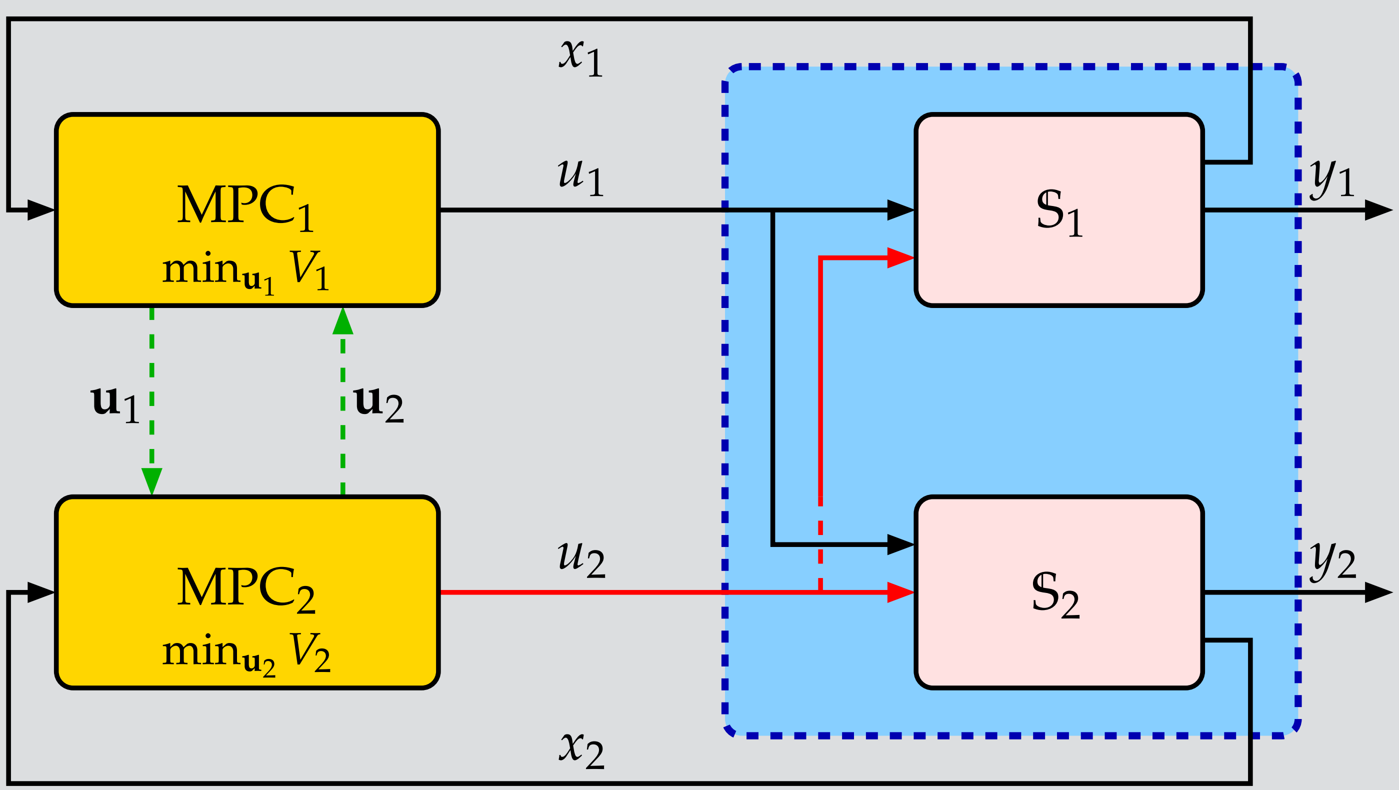
$$x_i^+ = A_i\, x_i + B_i\, u_i + \sum_{j \in \mathcal{N}_i} B_{ij}\, u_j$$

$$y_i = C_i\, x_i$$

Cost (local)

$$V_i = \sum_{k=0}^{N-1} \left(x_i(k)^T Q_i x_i(k) + u_i(k)^T R_i u_i(k) \right) + x_i(N)^T P_i x_i(N)$$

Reference Scheme



Cooperative Distributed MPC

Model (interacting)

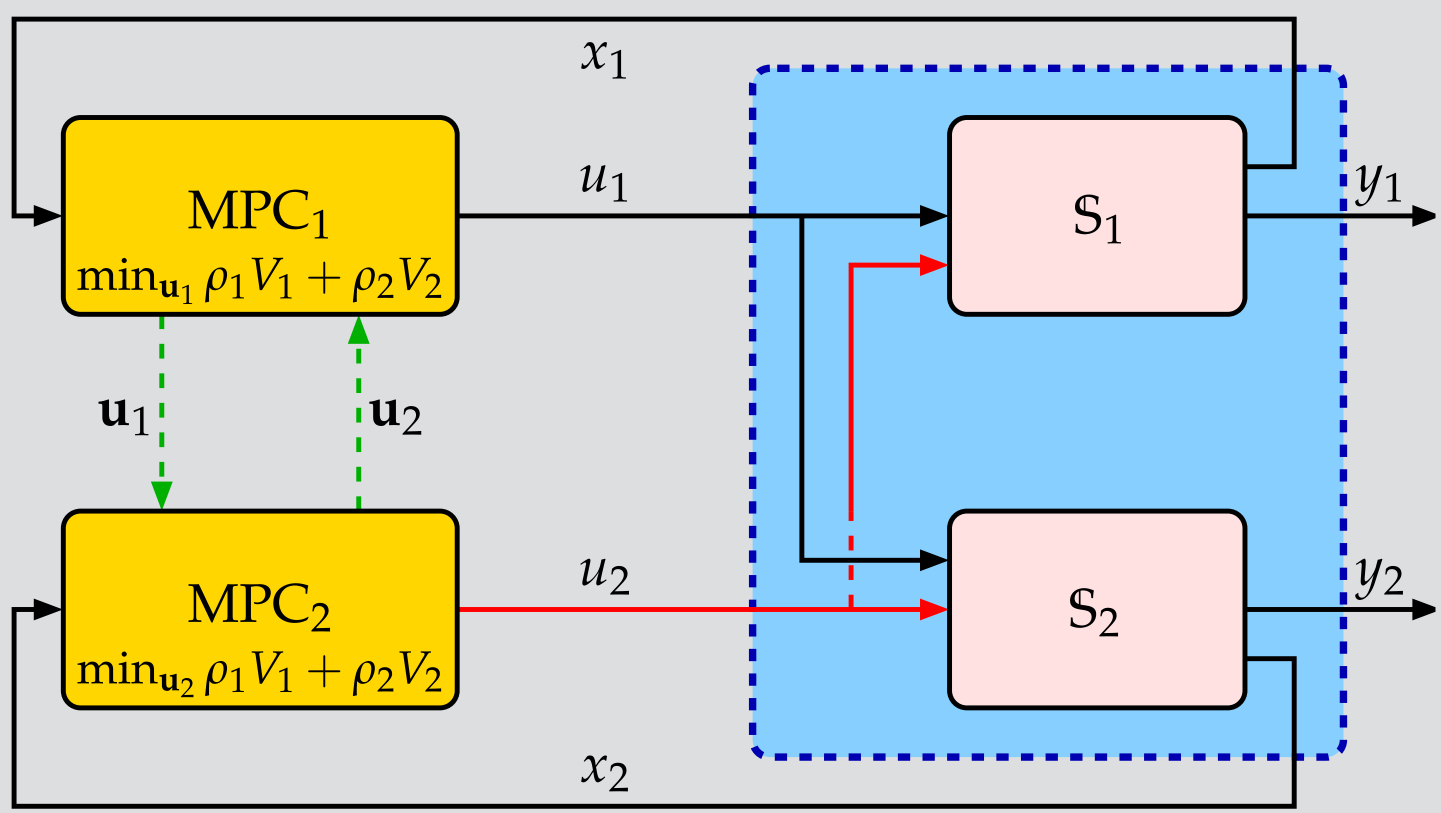
$$x_i^+ = A_i\, x_i + B_i\, u_i + \sum_{j \in \mathcal{N}_i} B_{ij}\, u_j$$

$$y_i = C_i\, x_i$$

Cost (global)

$$V = \sum_{j=1}^{M} \rho_i V_i = \sum_{k=0}^{N-1} \left(x(k)^T Q x(k) + u(k)^T R u(k) \right) + x(N)^T P x(N)$$

Reference Scheme



Properties of different architectures

- **Decentralized** MPC
  - Due to neglected dynamics, stability (as well feasibility, tracking, etc.) are not guaranteed
  - Possible remedies are based on robust (tube) MPC paradigms [Alessio et al., 2011; Riverso et al., 2013]
- **Noncooperative** distributed MPC
  - Due to local objectives, convergence of iterations and stability is not guaranteed
  - When convergence occurs, Nash equilibrium is reached. Still, stability may not hold [Rawlings and Mayne, 2009]
- **Cooperative** distributed MPC
  - Convergence of iterations and stability is guaranteed [Rawlings and Mayne, 2009]
  - Global optimality can be guaranteed [Stewart et al., 2011]

Cooperative distributed MPC - I

FHOCP and cooperative iterations

- Each local MPC, knowing **candidate sequences** of all other MPCs, solves the FHOCP

$$\mathbb{P}_i\left(x, \{\mathbf{u}_j\}_{j\neq i}\right): \quad \min_{\mathbf{u}_i} V(x, \mathbf{u}) \quad \text{s.t.}$$

$$\mathbf{u}_i \in \mathcal{U}_i\left(x, \{\mathbf{u}_j\}_{j\neq i}\right), \qquad x(N) \in \mathbb{X}_f$$

Keep track of overall state dynamics

- Input **feasibility** space

$$\mathcal{U}_i\left(x, \{\mathbf{u}_j\}_{j\neq i}\right) = \{\mathbf{u}_i \mid u_i(k) \in \mathbb{U}_i \,,\, x(k) \in \mathbb{X}\}$$

- **Cooperative** iterations, given $\mathbf{u}_i^0$: solution to $\mathbb{P}_i\left(x, \left\{\mathbf{u}_j^{[q-1]}\right\}_{j\neq i}\right)$

$$\mathbf{u}_i^{[q]} = w_i \mathbf{u}_i^0 + (1 - w_i)\mathbf{u}_i^{[q-1]}$$

Cooperative distributed MPC - II

Main properties

- **Feasibility** of each iterate

$$\mathbf{u}_i^{[q-1]} \in \mathcal{U}_i^N \Rightarrow \mathbf{u}_i^{[q]} \in \mathcal{U}_i^N, \text{ for all } i = 1, \dots, M \text{ and } q \in \mathbb{I}_{\geq 0}$$

- Cost **decrease** at each iteration

$$V(x(0), \mathbf{u}^{[q]}) \leq V(x(0), \mathbf{u}^{[q-1]}) \text{ for all } q \in \mathbb{I}_{\geq 0}$$

- Cost **convergence** to centralized optimum

$$\lim_{q \to \infty} V(x(0), \mathbf{u}^{[q]}) = \min_{\mathbf{u} \in \mathcal{U}^N} V(x(0), \mathbf{u})$$

- **Stability**, for any finite q, is proved via **suboptimal MPC** arguments

Can reduce computational requirements

Tracking in centralized MPC

Equilibrium target

- Any **equilibrium** solves: $\begin{bmatrix} A-I & B & 0 \\ C & 0 & -I \end{bmatrix} \begin{bmatrix} x_s \\ u_s \\ y_s \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$
- Given **desired setpoint** y_t, the optimal equilibrium is:

$$\min_{x_s, u_s, y_s} \quad V_{ss}(y_s, y_t) \quad \text{s.t. above constraint and } x_s \in \mathbb{X}, \quad u_s \in \mathbb{U}$$

Tracking MPC problem

- **Deviation** variables: $\tilde{x} = x - x_s^0, \;\; \tilde{u} = u - u_s^0$

$$\mathbb{P}(\tilde{x}) : \qquad V^0(\tilde{x}) = \min_{\tilde{\mathbf{u}}} \left\{ V(\tilde{x}(0), \tilde{\mathbf{u}}) \,\middle|\, \tilde{\mathbf{u}} \in \tilde{\mathcal{U}}_N(\tilde{x}) \right\}$$

- **Single step** approaches are also possible [Limon et al., 2008]

Distributed cooperative MPC for tracking - I

Single step approach [Ferramosca et al., 2013]

☑ **Centralized** cost function, including centralized **target**

$$V_t\left(x,\, \mathbf{u},\, x_s,\, u_s,\, y_s\right) = \sum_{k=0}^{N-1} \ell(x(k) - x_s, u(k) - u_s) + V_f(x(N) - x_s)$$

$$+V_{ss}\left(y_s,\, y_t\right)$$

$$\text{s.t.} \qquad x(0) = x$$

$$x\left(k+1\right) = A\,x\left(k\right) + B\,u\left(k\right)$$

$$\begin{bmatrix} A - I & B & 0 \\ C & 0 & -I \end{bmatrix} \begin{bmatrix} x_s \\ u_s \\ y_s \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Distributed cooperative MPC for tracking - II

FHOCP and cooperative iterations

- Each local MPC, knowing **candidate** sequences of all other MPCs, solves the FHOCP

$$\mathbb{P}_i\left(x, \{\mathbf{u}_j\}_{j\neq i}\right) : \quad \min_{\mathbf{u}_i,\, x_s,\, u_s,\, y_s} \; V_t\left(x,\, \mathbf{u},\, x_s,\, u_s,\, y_s\right) \quad \text{s.t.}$$

$$\mathbf{u}_i \in \mathcal{U}_i\left(x, \{\mathbf{u}_j\}_{j\neq i}\right), \qquad (x(N), y_s) \in \Omega$$

- Ω is an **invariant set** for tracking [Ferramosca et al. 2013]

- **Cooperative** iterations, given $\mathbf{u}_i^0$: so ... $-1]\}_{j\neq i}\Big)$

$$\mathbf{u}_i^{[q]} = w_i \mathbf{u}_i^0 + (1 - w_i) \ldots$$

Need to keep track of centralized state dynamics

Part II
Advances in cooperative MPC for tracking

Some reminders of graph theory

Useful definitions

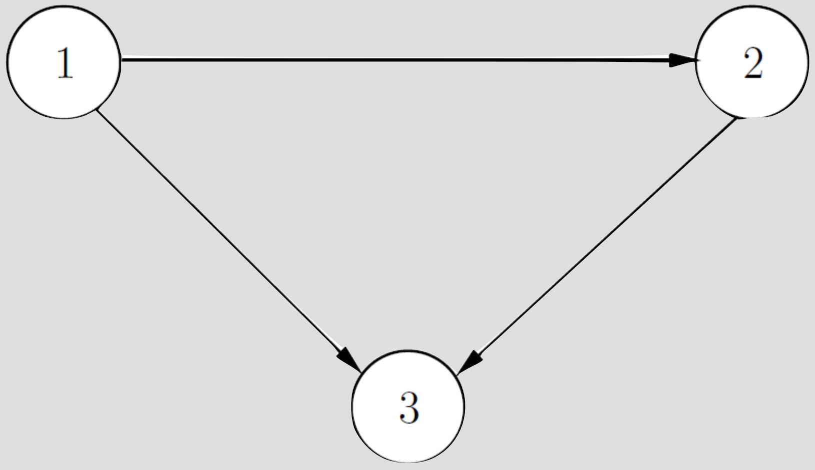
- A graph $\mathcal{G} = (\mathcal{V},\mathcal{E})$: set of vertices $\mathcal{V}$ and edges $\mathcal{E}$
- A directed graph is composed by oriented edges
- **Inlet** star: $S_i^{IN} = \{v_j \in \mathcal{V} \,|\, (v_j, v_i) \in \mathcal{E}\}$
- **Outlet** star: $S_i^{OUT} = \{v_j \in \mathcal{V} \,|\, (v_i, v_j) \in \mathcal{E}\}$

An example

$$x_1^+ = A_1\, x_1 + B_1\, u_1$$

$$x_2^+ = A_2\, x_2 + B_2\, u_2 + B_{21}\, u_1$$

$$x_3^+ = A_3\, x_3 + B_3\, u_3 + B_{31}\, u_1 + B_{32}\, u_2$$



$$S_1^{IN} = \emptyset,\ S_1^{OUT} = \{2,3\},\ S_2^{IN} = \{1\},\ S_2^{OUT} = \{3\},\ S_3^{IN} = \{1,2\},\ S_3^{OUT} = \emptyset$$

The augmented system - I

Key observations

- The evolution of *i-th* subsystem is **influenced** by inputs of subsystems in its **inlet star**
- The input of *i-th* subsystem **influences** evolution of subsystems in its **outlet star**

$$x_i^+ = A_i\, x_i + B_i\, u_i + \sum_{k \in S_i^{IN}} B_{ik}\, u_k$$

$$x_j^+ = A_j\, x_j + B_{ji}\, u_i + \left(B_j\, u_j + \sum_{k \in S_j^{IN} \setminus \{i\}} B_{jk}\, u_k \right), \quad j \in S_i^{OUT}$$

- Other subsystems are **not affected** by the *i*-th subsystem input

$$x_j^+ = A_j\, x_j + \left(B_j\, u_j + \sum_{k \in S_j^{IN}} B_{jk}\, u_k \right), \quad j \notin S_i^{OUT}$$

The augmented system - II

Augmented i-th subsystem

- Augmented inlet star

$$\mathbb{S}_i^{IN} \leftarrow S_i^{IN} \cup S_i^{OUT} \cup \left(\bigcup_{j \in S_i^{OUT}} S_j^{IN} \setminus \{i\} \right)$$

- Augmented local variables and matrices

$$\bar{x}_i = \begin{bmatrix} x_i \\ \left[x_j\right]_{j \in S_i^{OUT}} \end{bmatrix}, \quad \bar{u}_i = \left[u_k\right]_{k \in \mathbb{S}_i^{IN}}, \quad \bar{y}_i = \begin{bmatrix} y_i \\ \left[y_j\right]_{j \in S_i^{OUT}} \end{bmatrix}$$

$$\bar{A}_i = \text{diag}\left\{A_i, \, \{A_j\}_{j \in S_i^{OUT}}\right\}, \quad \bar{B}_i = \begin{bmatrix} B_i \\ \left[B_{ji}\right]_{j \in S_i^{OUT}} \end{bmatrix}, \quad \bar{B}_i^{IN} = \left[\text{hor}\{B_{ik}\}_{k \in \mathbb{S}_i^{IN}}, \; \text{hor}\{B_{jk}\}_{j \in S_i^{OUT}, \, k \in \mathbb{S}_i^{IN}}\right]$$

- Final augmented dynamics

$$\bar{x}_i^+ = \bar{A}_i \, \bar{x}_i + \bar{B}_i \, u_i + \bar{B}_i^{IN} \, \bar{u}_i$$

$$\bar{y}_i = \bar{C}_i \, \bar{x}_i$$

Augmented system based cooperative MPC for tracking - I

Local (augmented system) cost function

- The global cost function can be **reduced** to a local (augmented) cost

$$V_{ti}(\cdot) = \sum_{k=0}^{N-1} \bar{\ell}_i(\bar{x}_i(k) - \bar{x}_{si}, u_i(k) - u_{si}) + \bar{V}_{fi}(\bar{x}_i(k) - \bar{x}_{si}) + \|y_s - y_t\|_T^2$$

s.t.

$$\bar{x}_i(0) = \bar{x}_i$$

$$\bar{x}_i(k+1) = \bar{A}_i \, \bar{x}_i(k) + \bar{B}_i \, u_i(k) + \bar{B}_i^{IN} \, \bar{u}_i($$

Local (augmented) cost functions

$$\bar{\ell}_i(\bar{x}_i, u_i) = \frac{1}{2}\left(\bar{x}_i^T \bar{Q}_i \bar{x}_i + u_i^T R_i \right. \quad \ldots \quad 2 \, \bar{x}_i^T \bar{P}_i \bar{x}_i$$

The solution is the same as considering the global cost

- Discarded terms in the global function are **not affected** by u_i

Augmented system based cooperative MPC for tracking - II

FHOCP and cooperative iterations

- Each local MPC, knowing **candidate** sequences of all MPCs in its **inlet star**, solves the FHOCP

$$\mathbb{P}_i\left(\bar{x}_i, \{\mathbf{u}_j\}_{j\in\mathbb{S}_i^{IN}}\right) : \quad \min_{\mathbf{u}_i, x_s, u_s, y_s} V_{ti}(\mathbf{u}_i, x_s, u_s, y_s) \text{ s.t.}$$

$$\mathbf{u}_i \in \bar{\mathcal{U}}_i\left(\bar{x}_i, \{\mathbf{u}_j\}_{j\in\mathbb{S}_i^{IN}}\right), \quad (\bar{x}_i(N), \bar{y}_{si}) \in \bar{\Omega}_i$$

$$\begin{bmatrix} A-I & B & 0 \\ C & 0 & -I \end{bmatrix} \begin{bmatrix} x_s \\ \vdots \end{bmatrix}$$

Need to keep track of augmented state dynamics only

- Input **feasibility** space

$$\bar{\mathcal{U}}_i\left(\bar{x}_i, \{\mathbf{u}_j\}_{j\in\mathbb{S}_i^{IN}}\right) = \{\mathbf{u}_i \mid u_i(k) \in \mathbb{U}_i, \; \bar{x}_i(k) \in \bar{\mathbb{X}}_i\}$$

- Cooperative iterations: $\mathbf{u}_i^{[q]} = w_i \mathbf{u}_i^0 + (1 - w_i)\mathbf{u}_i^{[q-1]}$

Overall algorithm

Require: Augmented subsystems, $\mathbb{S}_i^{IN}\ \forall i = 1 \dots M$, tolerance ϵ, maximum no. cooperative iterations q_{max}, convex combination weights $w_i > 0$, such that $\sum_{i=1}^{M} w_i = 1$.

Set $q \leftarrow 0$ and $e_i \leftarrow 2\epsilon$.

while $q < q_{max}$ and $\exists\, i$ such that $e_i > \epsilon$ **do**

  $q \leftarrow q + 1$

  for $i = 1$ **to** M **do**

    Solve problem $\mathbb{P}_i$ to obtain the optimal input sequence $\mathbf{u}_i^0(x)$ and the centralized state-steady triple $(x_s,\ u_s,\ y_s)$.

    if $q = 1$ **then**

      $\mathbf{u}_i^{[q-1]} = \begin{bmatrix} u_{s_i}^T & \cdots & u_{s_i}^T \end{bmatrix}^T$

    end if

    Define new iterate: $\mathbf{u}_i^{[q]} = w_i \mathbf{u}_i^0 + (1 - w_i)\mathbf{u}_i^{[q-1]}$.

    Compute convergence error: $e_i = \frac{||\mathbf{u}_i^{[q]} - \mathbf{u}_i^{[q-1]}||}{1 + ||\mathbf{u}_i^{[q]}||}$

  end for

end while

return Overall solution $\mathbf{u} = \left(\mathbf{u}_1^{[q]},\ \mathbf{u}_2^{[q]},\ \dots,\ \mathbf{u}_M^{[q]}\right)$.

A two-step variant

Step 1

- Solve the centralized target problem to obtain (x_s, u_s, y_s)

Step 2

- Each local MPC, knowing **candidate** sequences of all MPCs in its **inlet star**, solves the FHOCP with known (x_s, u_s, y_s)
- Cooperative iterations: $\mathbf{u}_i^{[q]} = w_i \mathbf{u}_i^0 + (1 - w_i)\mathbf{u}_i^{[q-1]}$

Complexity of different methods

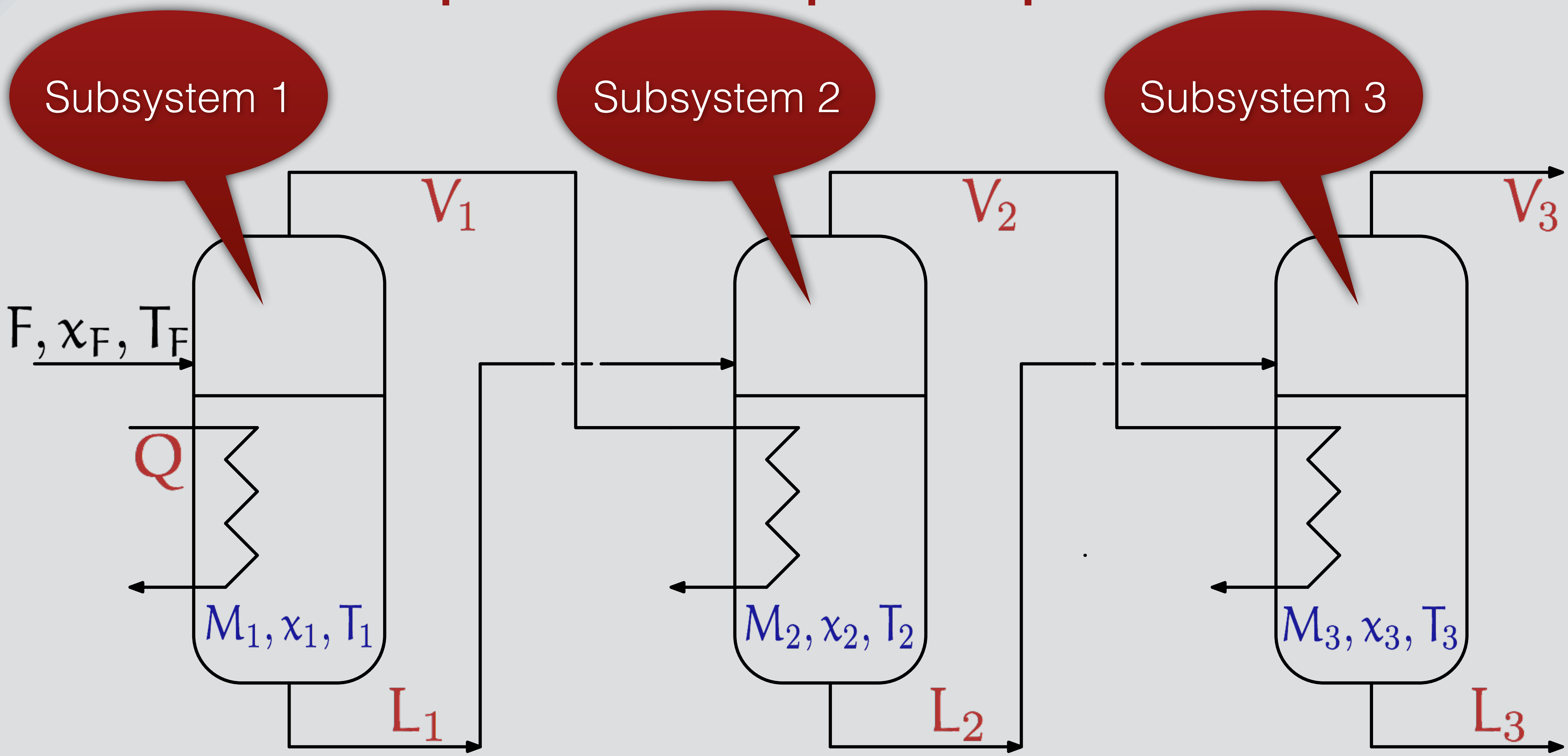
Three alternatives

- ☑ DMPC0: available method [Ferramosca et al., 2013]
- ☑ DMPC1: proposed method (single step)
- ☑ DMPC2: proposed method (two steps)

	DMPC0	DMPC1	DMPC2
Prediction model	Centralized	Augmented	Augmented
Target calc. (TC)	Embedded	Embedded	Separate
TC decision var.	–	–	(x_s, u_s, y_s)
OCP decision var.	$(\mathbf{u}_i, \mathbf{x}, x_s, u_s, y_s)$	$(\mathbf{u}_i, \bar{\mathbf{x}}_i, x_s, u_s, y_s)$	$(\mathbf{u}_i, \bar{\mathbf{x}}_i)$

Application example - I

A triple effect evaporator process



Application example - II

Identified linear model

	L_1	Q_1	V_1	L_2	V_2	L_3	V_3
M_1	$-\frac{0.04797}{z-2.717}$	-	$-\frac{0.0339}{z-2.717}$	-	-	-	-
T_1	-	$\frac{0.564}{z-2.509}$	$-\frac{0.1745}{z-2.509}$	-	-	-	-
χ_1	-	-	$\frac{0.009394}{z-2.549}$	-	-	-	-
M_2	$\frac{0.05726}{z-2.716}$	-	-	$-\frac{0.07207}{z-2.716}$	$-\frac{0.09465}{z-2.716}$	-	-
T_2	$\frac{0.008029z-0.01856}{z^2-4.913z+6.029}$	$\frac{0.089z-0.02579}{z^2-4.913z+6.029}$	$\frac{0.2431z-0.6396}{z^2-4.913z+6.029}$	-	$\frac{-0.6057z+1.451}{z^2-4.913z+6.029}$	-	-
χ_2	$-\frac{0.01418}{z-2.604}$	-	$\frac{0.01038}{z-2.604}$	-	$\frac{0.02976}{z-2.604}$	-	-
M_3	-	-	-	$\frac{0.07503}{z-2.712}$	-	$-\frac{0.08504}{z-2.712}$	$-\frac{0.1255}{z-2.712}$
T_3	$\frac{0.001138z+0.03875}{z^2-4.898z+5.986}$	$\frac{-0.02526z+0.3423}{z^2-4.898z+5.986}$	$\frac{0.06671z-0.127}{z^2-4.898z+5.986}$	$\frac{0.09903z-0.2557}{z^2-4.898z+5.986}$	$\frac{2.472z-6.521}{z^2-4.898z+5.986}$	-	$\frac{-2.895z+7.385}{z^2-4.898z+5.986}$
χ_3	$\frac{-0.01013z+0.01865}{z^2-5.241z+6.864}$	-	$\frac{0.004064z-0.005355}{z^2-5.241z+6.864}$	$\frac{-0.2224z+0.6029}{z^2-5.241z+6.864}$	$\frac{0.01244z-0.02893}{z^2-5.241z+6.864}$	-	$\frac{0.464z-1.249}{z^2-5.241z+6.864}$

Neighbors and local (augmented) systems

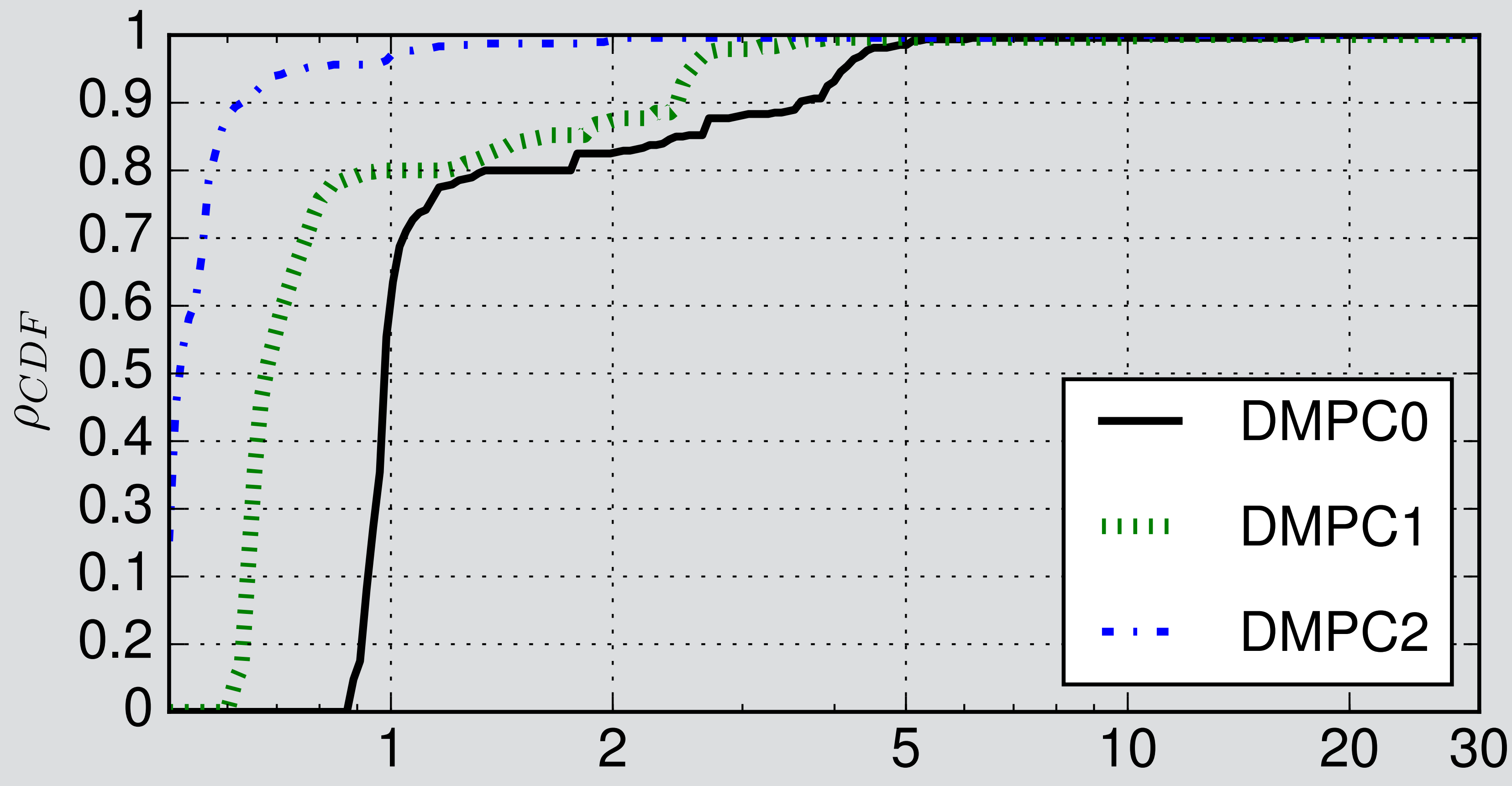
- ☑ Neighbors sets: $\mathcal{N}_1 = \emptyset,\ \mathcal{N}_2 = \{1\},\ \mathcal{N}_3 = \{1,2\}$
- ☑ Augmented systems:

$$\bar{x}_1 = (x_1, x_2, x_3),\ \bar{x}_2 = (x_2, x_3),\ \bar{x}_3 = x_3$$

$$\mathbb{S}_1^{IN} = \{2,3\},\ \mathbb{S}_2^{IN} = \{1,3\},\ \mathbb{S}_3^{IN} = \{1,3\}$$

Application example - III

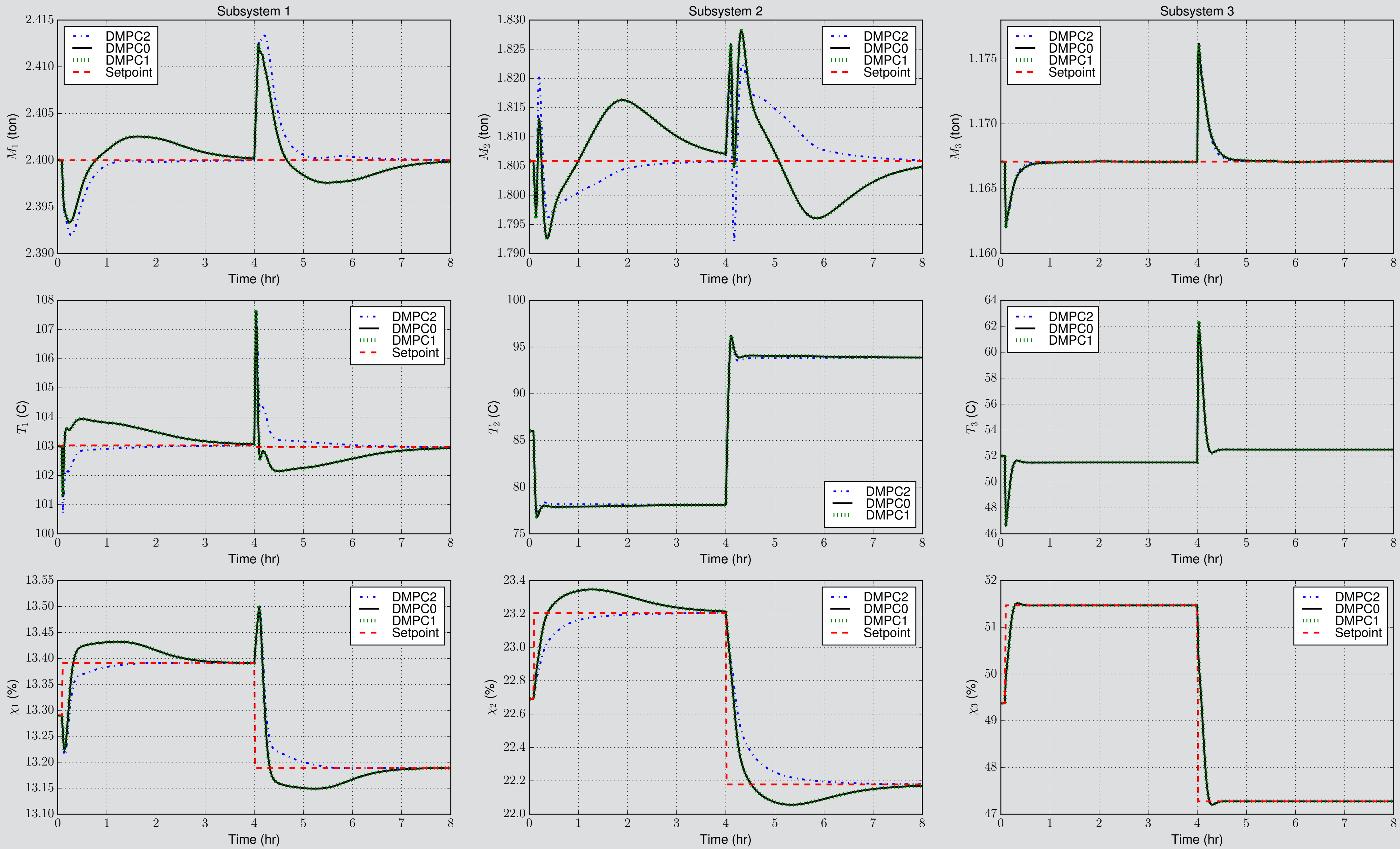
Comparison of computation time



- Simulations performed in Matlab, MacBook Pro (3 GHz Intel Core i7, 16 GB RAM)
- Horizon N=100, QP solved (non condensed form) using quadprog (interior-point)
- Tested for 8 hours (480 samples) with two setpoint changes

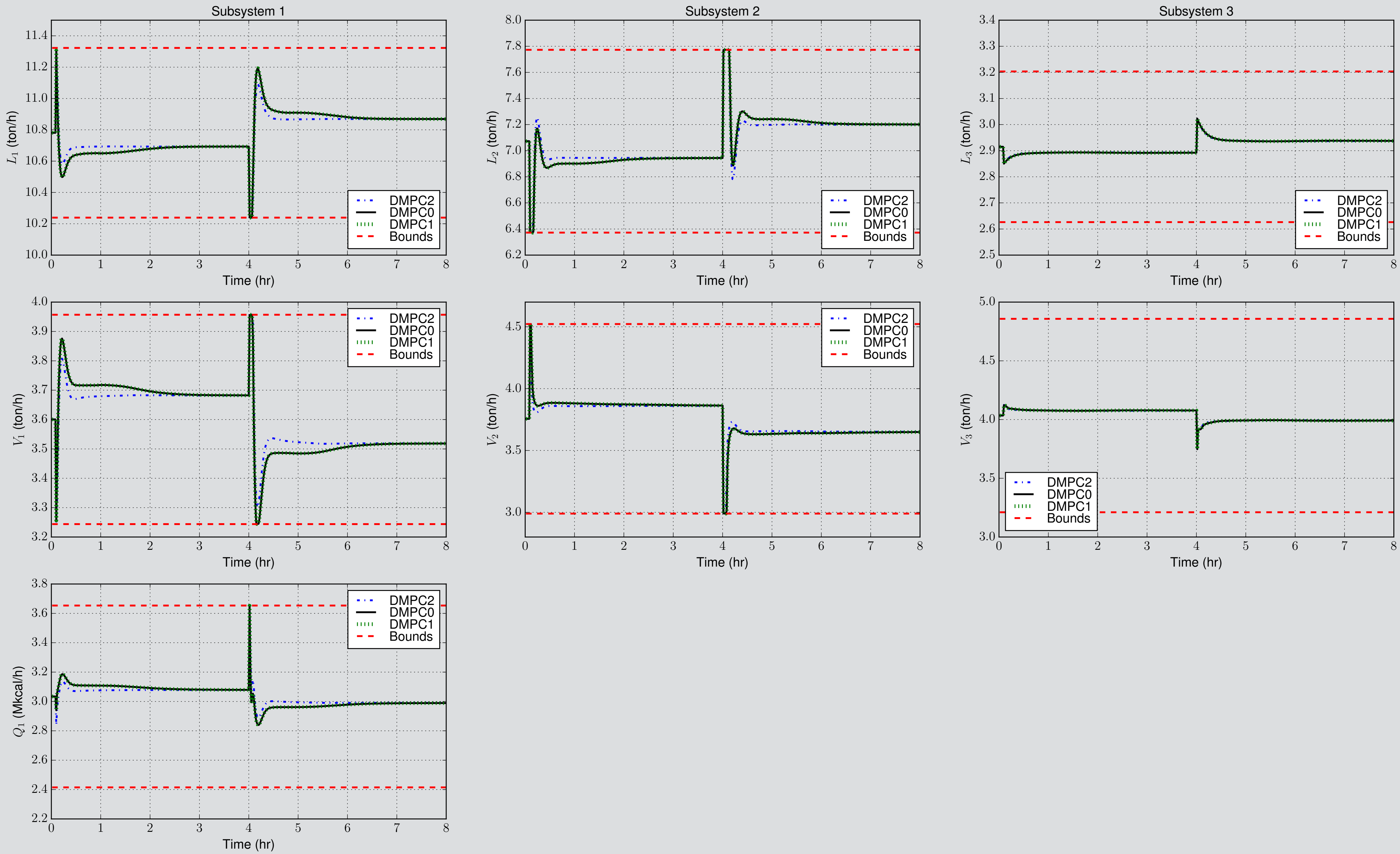
Application example - IV

Comparison of closed-loop outputs



Application example - V

Comparison of closed-loop inputs



Part III
Conclusions

Conclusions - I

Summary

- Presented a comprehensive overview on linear distributed MPC
- Focus on cooperative algorithms, which share compelling properties with centralized architectures
- Discussed available distributed MPC for tracking algorithms
- Proposed novel distributed MPC for tracking approaches that rely “as local as possible” information instead of plant-wide state

Conclusions - II

Take home messages

- Distributed MPC is a **solid** and reliable **alternative** to centralized MPC
- **Cooperative** architectures should be **preferred**
- Distributed MPC is preferable with respect to centralized MPC for **organizational** reasons, **not computational**

Research directions

- Nonlinear distributed MPC
- Reconfigurability and reliability with respect to communication disruptions
- Distributed economic MPC

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- **Matteo Razzanelli** (PhD student, University of Pisa)
- Prof. John Bagterp Jorgensen (DTU)
- Prof. James B. Rawlings (Univ. of Wisconsin)
- Prof. David Q. Mayne (Imperial College)

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