Security of distributed Model Predictive Control under False Data Injection

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Seminar
École Centrale de Lyon / Laboratoire Ampère
26/05/2023 @ Écully

https://bit.ly/3g3S6X4

About me

Rafael Accácio Nogueira

Postdoctoral researcher at LAAS/CNRS

Garanteed relative localisation and anticollision scenario for autonomous vehicles

Project AutOCampus (GIS neOCampus)

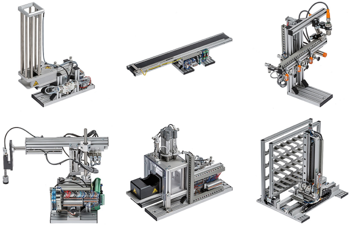
Advised by Soheib Fergani

About me

Bachelor Thesis at Escola Politécnica/UFRJ

Identification of DES for fault-diagnosis

Advised by Marcos Vicente de Brito Moreira



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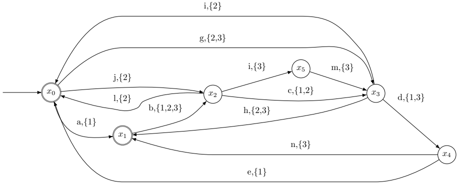


About me

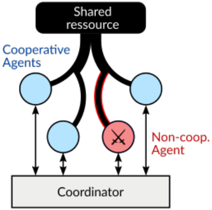
Doctoral Thesis at CentraleSupélec/IETR

Security of dMPC under False Data Injection

Advised by Hervé Guéguen and Romain Bourdais

CentraleSupélec

IETR



Context

Smart(er) Cities

Multiple systems interacting

Context

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- Distribution:

Context

Smart(er) Cities

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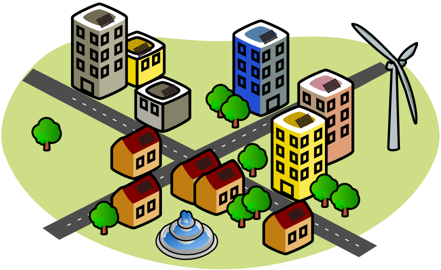
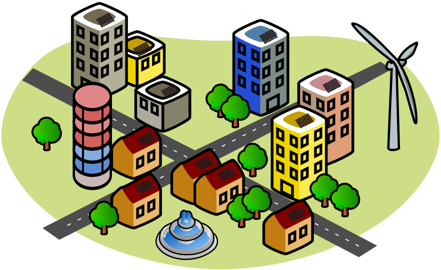


- Distribution:
    - Electricity

Smart(er) Cities

Multiple systems interacting



- Distribution:
  - Electricity
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- Distribution:
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Multiple systems interacting

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Multiple systems interacting under

- Technical/Comfort Constraints

Context

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- We also want

Context

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- We also want
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- We also want
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Smart(er) Cities

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- Solution → MPC

Model-based Predictive Control

Brief recap

Model-based Predictive Control

Brief recap

Find best control sequence using predictions based on a model.

Model-based Predictive Control

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Model-based Predictive Control

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Model-based Predictive Control

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- We need an optimization problem

$$\underset{\boldsymbol{u}[0:N-1|k]}{\text{minimize}} \quad J(\boldsymbol{x}[0|k], \boldsymbol{u}[0:N-1|k])$$

Model-based Predictive Control

Brief recap

Find optimal control sequence using predictions based on a model.

- We need an optimization problem
  - Decision variable is the control sequence

$$\underset{\boldsymbol{u}[0:N-1|k]}{\text{minimize}} \quad J(\boldsymbol{x}[0|k], \boldsymbol{u}[0:N-1|k])$$

Model-based Predictive Control

Brief recap

Find optimal control sequence using predictions based on a model.

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Model-based Predictive Control

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Find optimal control sequence using predictions based on a model.

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Model-based Predictive Control

Brief recap

Find optimal control sequence using predictions based on a model.

- We need an optimization problem
  - Decision variable is the control sequence calculated over horizon N
  - Objective function to optimize
  - System's Model

$$\begin{aligned} \underset{\boldsymbol{u}[0:N-1|k]}{\text{minimize}} \quad & J(\boldsymbol{x}[0|k], \boldsymbol{u}[0:N-1|k]) \\ \text{subject to} \quad & \left.\begin{aligned} \boldsymbol{x}[\xi|k] = f(\boldsymbol{x}[\xi-1|k], \boldsymbol{u}[\xi-1|k]) \\ \\ \end{aligned}\right\} \forall \xi \in \{1, \dots, N\} \end{aligned}$$

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\end{aligned}$$

Find optimal control sequence using predictions based on a model.

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  - Decision variable is the control sequence calculated over horizon N
  - Objective function to optimize
  - System's Model
  - Other constraints to respect (QoS, technical restrictions, ...)

$$
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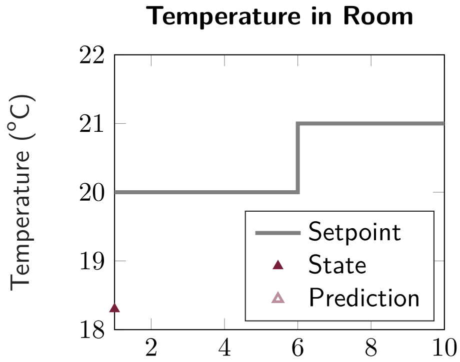
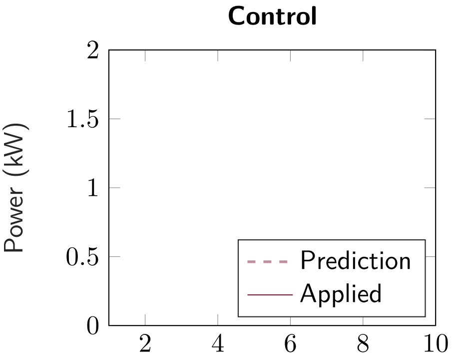
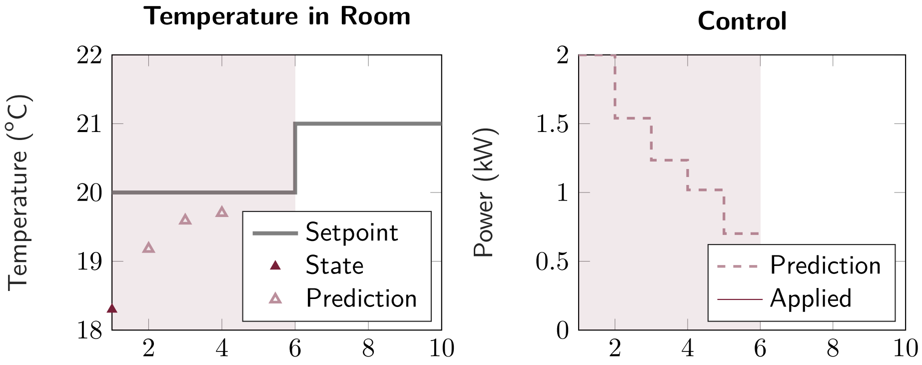
Model Predictive Control

In a nutshell





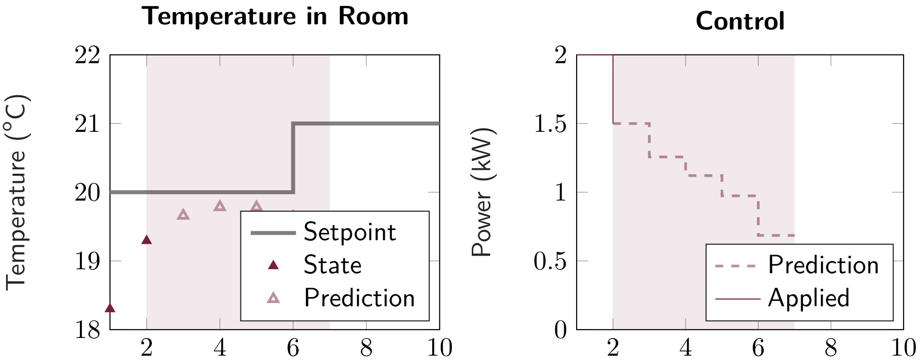
Find optimal control sequence



Model Predictive Control

In a nutshell

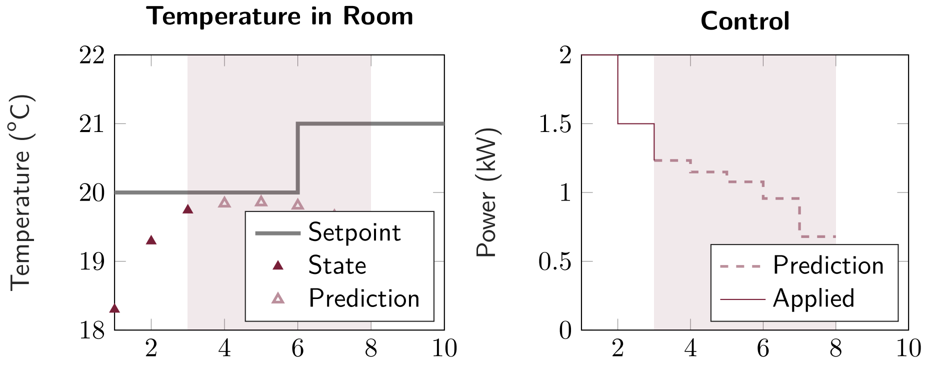
Find optimal control sequence, apply first element



Model Predictive Control

In a nutshell

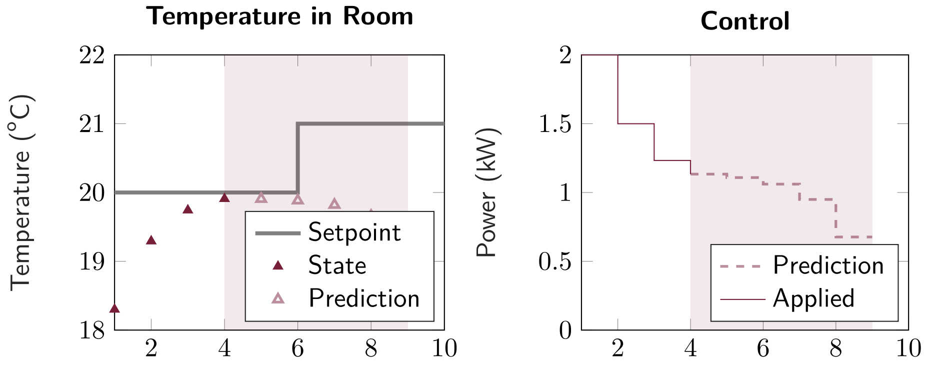
Find optimal control sequence, apply first element, rinse repeat



Model Predictive Control

In a nutshell

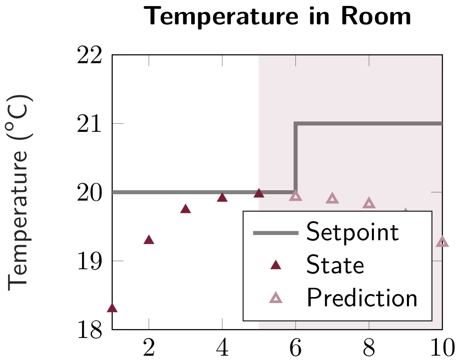
Find optimal control sequence, apply first element, rinse repeat → Receding Horizon

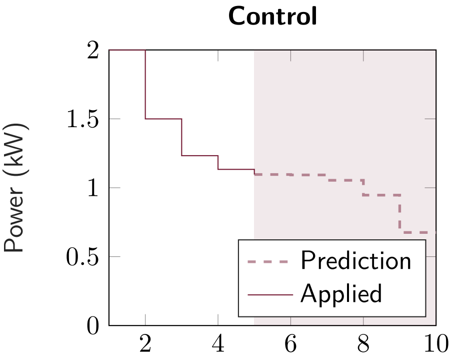


Model Predictive Control

In a nutshell

Find optimal control sequence, apply first element, rinse repeat → Receding Horizon





Model Predictive Control

Nothing is perfect

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- Problems

Model Predictive Control

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- Problems
    - Topology (Geographical distribution)

Model Predictive Control

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  - Privacy (RGPD)

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  - Privacy (RGPD)
- Solution: Divide and Conquer (distributed MPC)

Outline

1. Decomposing the MPC

Outline

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Distributed Model Predictive Control

Distributed Model Predictive Control

- We break the MPC optimization problem

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In other words

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In other words

- Agents solve local problems

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- Exchange some variables

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Until Convergence

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Until Convergence

Remark

If agents exchange same variable → consensus problem

Distributed Model Predictive Control

Optimization Frameworks

Usually based on optimization decomposition methods[1]:

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Distributed Model Predictive Control

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Distributed Model Predictive Control

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Security/privacy properties

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Distributed Model Predictive Control

It is about communication

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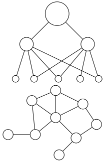
    - Many flavors to choose from
        - Hierarchical/Anarchical



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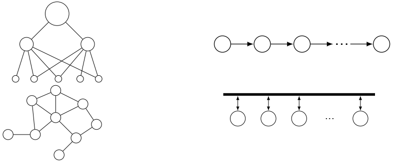

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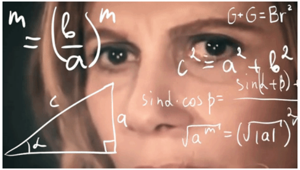

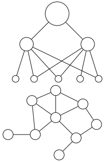

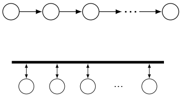

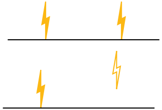

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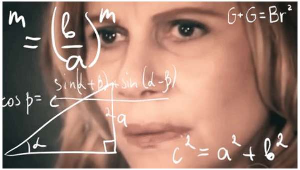

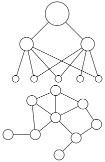

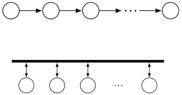

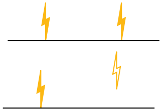

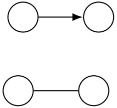

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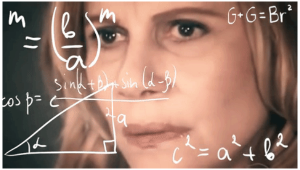

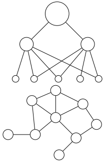

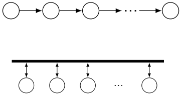

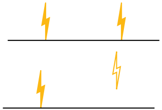

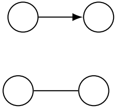

[4] José M Maestre, Negenborn, et al., Distributed Model Predictive Control made easy

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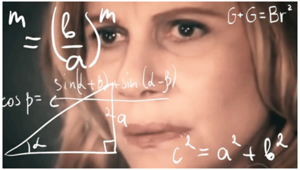

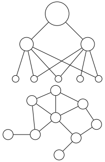

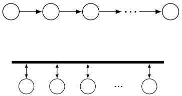

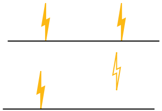

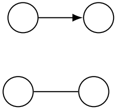

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Distributed Model Predictive Control

Optimization Decomposition

MPC

Distributed Model Predictive Control

Optimization Decomposition

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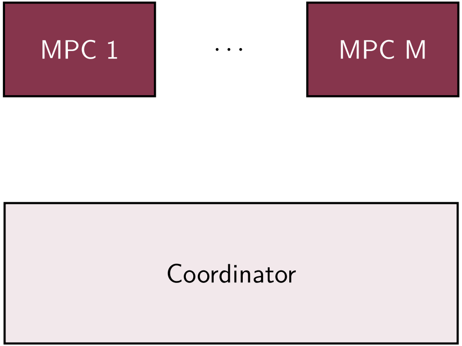
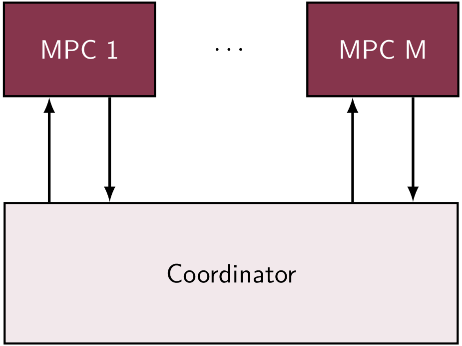


- Coordinator → Hierarchical

Distributed Model Predictive Control

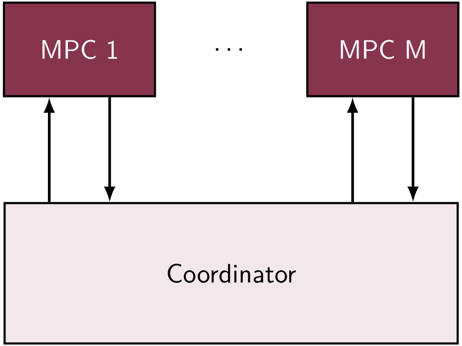
Optimization Decomposition



- Coordinator → Hierarchical
- Bidirectional

Distributed Model Predictive Control

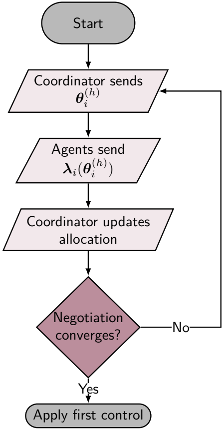
Optimization Decomposition



- Coordinator $\rightarrow$ Hierarchical
- Bidirectional
- No delay $\rightarrow$ Synchronous

Primal Decomposition

or Quantity Decomposition | or Resource Allocation



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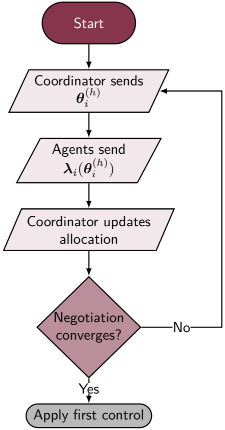

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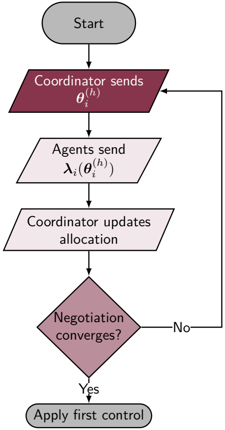

Allocation $\boldsymbol{\theta}_i$

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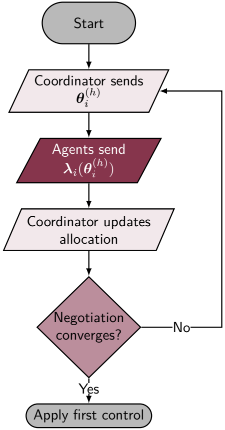
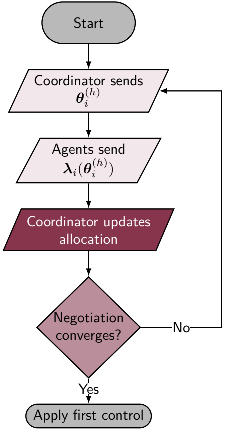


Allocation $\boldsymbol{\theta}_i$

Dissatisfaction $\boldsymbol{\lambda}_i$

Primal Decomposition

or Quantity Decomposition | or Resource Allocation



Allocation $\boldsymbol{\theta}_i$

Dissatisfaction $\boldsymbol{\lambda}_i$

Update $\boldsymbol{\theta}_i^+ = f_i(\boldsymbol{\theta}_i, \boldsymbol{\lambda}_i)$

Primal Decomposition

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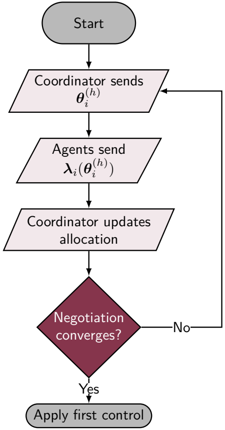

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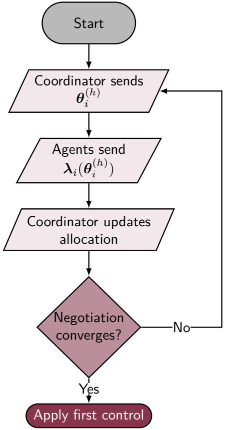

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Update $\boldsymbol{\theta}_i^+ = f_i(\boldsymbol{\theta}_i, \boldsymbol{\lambda}_i)$

Primal Decomposition

In detail

$$\begin{aligned} \underset{\boldsymbol{u}_1,\ldots,\boldsymbol{u}_M}{\text{minimize}} \quad & \sum_{i \in \mathcal{M}} J_i(\boldsymbol{x}_i, \boldsymbol{u}_i) \\ \text{s.t.} \quad & \sum_{i \in \mathcal{M}} \boldsymbol{h}_i(\boldsymbol{x}_i, \boldsymbol{u}_i) \preceq \boldsymbol{u}_{\mathsf{total}} \end{aligned}$$

Primal Decomposition

In detail

- Objective is sum of local ones

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Primal Decomposition

In detail

- Objective is sum of local ones
- Constraints couple variables

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$$\downarrow \text{ For each } i \in \mathcal{M}$$

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Primal Decomposition

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In detail

- Objective is sum of local ones
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1. Allocate $\boldsymbol{\theta}_i$ for each agent
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3. Send dual variable $\boldsymbol{\lambda}_i$

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Primal Decomposition

In detail

- Objective is sum of local ones
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1. Allocate $\boldsymbol{\theta}_i$ for each agent
2. They solve local problems and
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4. Allocation is updated

$$\begin{aligned} \underset{\boldsymbol{u}_i}{\text{minimize}} \quad & J_i(\boldsymbol{x}_i, \boldsymbol{u}_i) \\ \text{s. t.} \quad & \boldsymbol{h}_i(\boldsymbol{x}_i, \boldsymbol{u}_i) \preceq \boldsymbol{\theta}_i : \boldsymbol{\lambda}_i \end{aligned}$$

$$\boldsymbol{\theta}[k]^{(p+1)} = \boldsymbol{\theta}[k]^{(p)} + \rho^{(p)} \boldsymbol{\lambda}[k]^{(p)}$$

Primal Decomposition

In detail

- Objective is sum of local ones
- Constraints couple variables

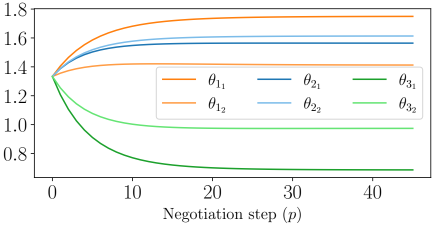
1. Allocate $\boldsymbol{\theta}_i$ for each agent
2. They solve local problems and
3. Send dual variable $\boldsymbol{\lambda}_i$
4. Allocation is updated (respect global constraint)

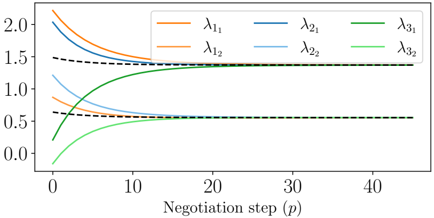
$$\begin{array}{ll} \underset{\boldsymbol{u}_i}{\text{minimize}} & J_i(\boldsymbol{x}_i, \boldsymbol{u}_i) \\ \text{s. t.} & \boldsymbol{h}_i(\boldsymbol{x}_i, \boldsymbol{u}_i) \preceq \boldsymbol{\theta}_i : \boldsymbol{\lambda}_i \end{array}$$

$$\boldsymbol{\theta}[k]^{(p+1)} = \mathrm{Proj}^{\mathcal{S}}(\boldsymbol{\theta}[k]^{(p)} + \rho^{(p)} \boldsymbol{\lambda}[k]^{(p)})$$

Example

Until everybody is evenly[5] dissatisfied





[5] For inequality constraints dynamics are more complex

Distributed Model Predictive Control

Negotiation works if agents comply.

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But what if some agents are ill-intentioned and attack the system?

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Recent in dMPC literature[6] (First article from 2017[7])

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- How can an agent attack?
- What are the consequences of an attack?
- Can we mitigate the effects? How?

---

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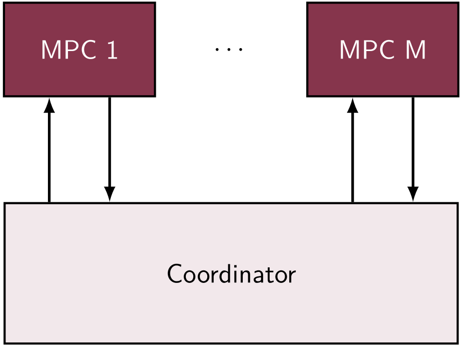
Outline

2 Attacks on the dMPC

How can a non-cooperative agent attack?

Literature



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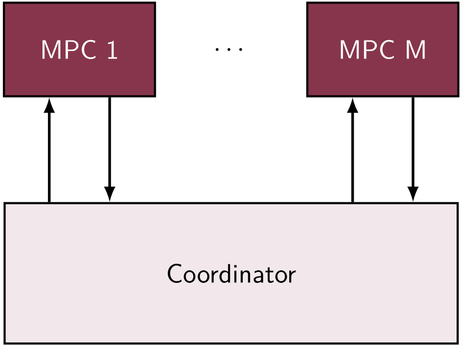

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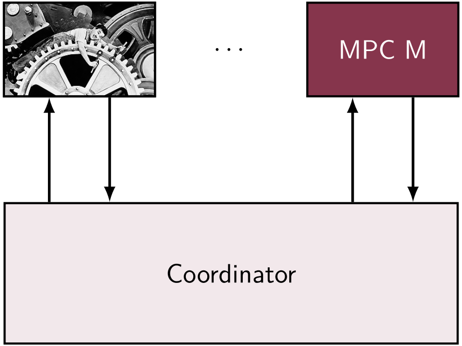

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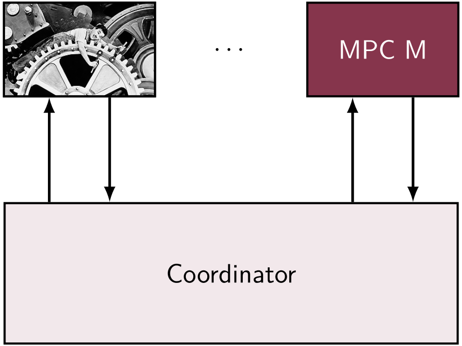

- Common attacks[8]
  - Fake objective function
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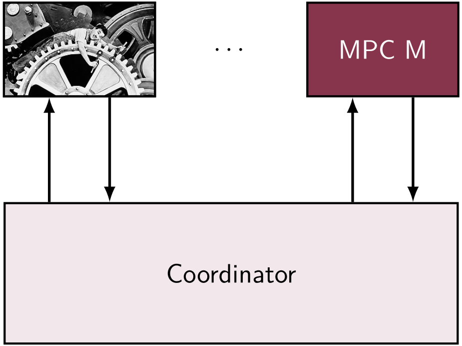

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} Deception Attacks

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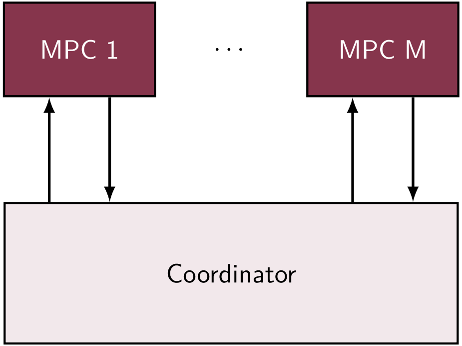
Our approach



- Primal decomposition

How can a non-cooperative agent attack?

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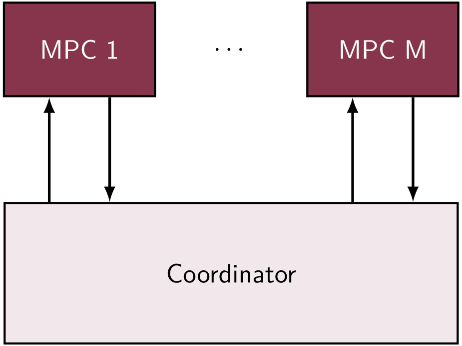

- Primal decomposition
  - Maximum resources fixed

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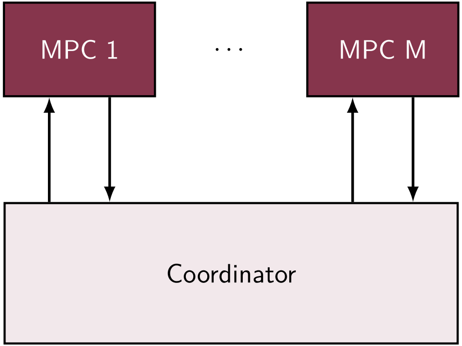

- Primal decomposition
    - Maximum resources fixed
- We are in coordinator's shoes

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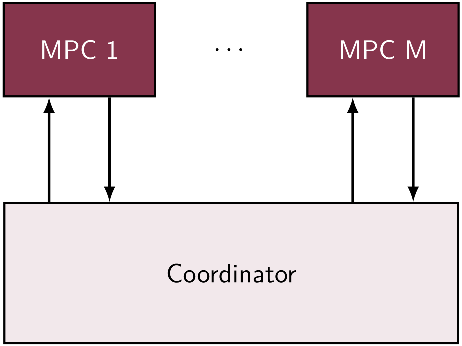

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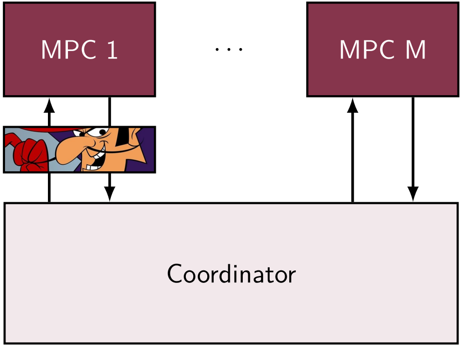

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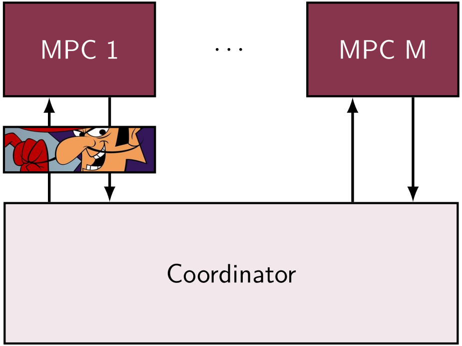

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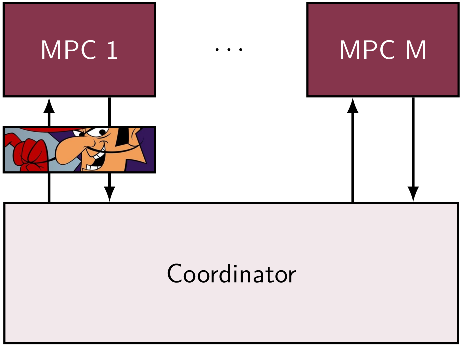

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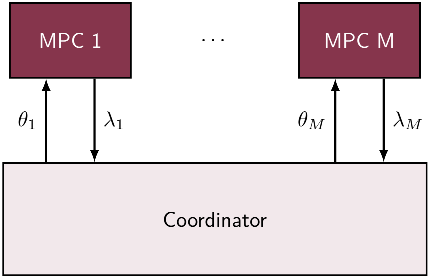

- $\boldsymbol{\lambda}_i$ is the only interface

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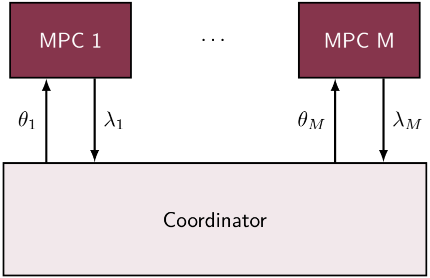

- $\boldsymbol{\lambda}_i$ is the only interface
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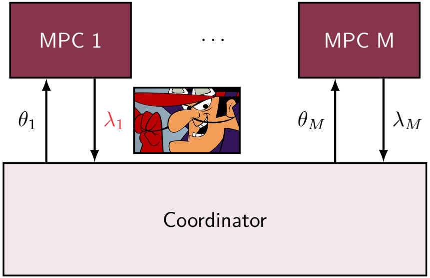

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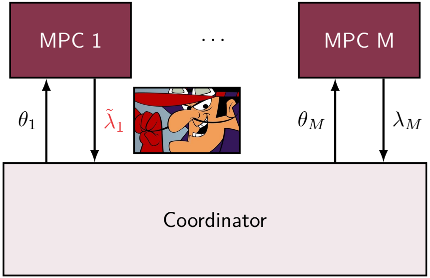

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$$\tilde{\boldsymbol{\lambda}}_i = \gamma_i(\boldsymbol{\lambda}_i)$$

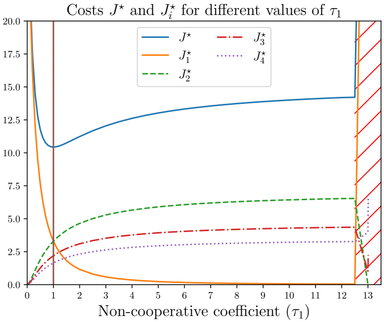
Example

Example

4 distinct agents

- Agent 1 is non-cooperative
- It uses $\tilde{\boldsymbol{\lambda}}_1 = \gamma_1(\boldsymbol{\lambda}_1) = \tau_1 I \boldsymbol{\lambda}_1$
- Simulate for different τ_1 get J_i

Example



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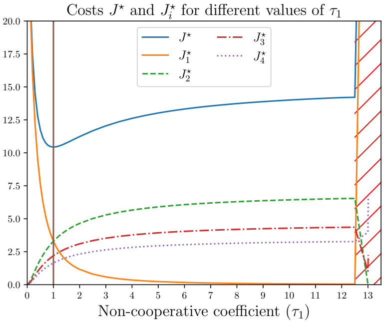

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- We can observe 3 things

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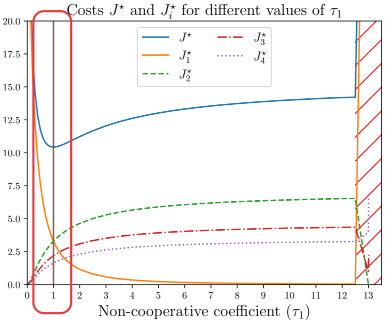

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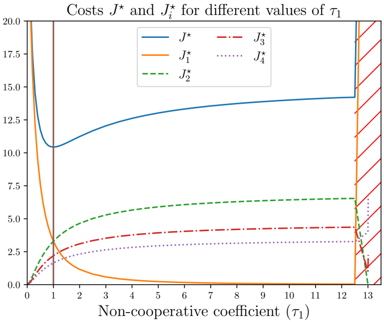

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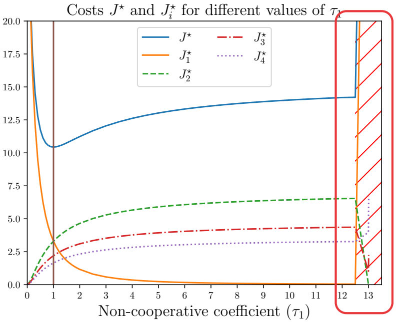

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- We can observe 3 things
  - Global minimum when $\tau_1 = 1$
  - Agent 1 benefits if τ_1 increases (inverse otherwise)
  - All collapses if too greedy

- But can we mitigate these effects?

- But can we mitigate these effects?
- Yes! (At least in some cases)

Outline

3. Securing the dMPC

Classification of mitigation techniques

Passive (Robust)

Active (Resilient)

Classification of mitigation techniques

Passive (Robust)

- 1 mode

Active (Resilient)

- 2 modes

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- 1 mode

Active (Resilient)

- 2 modes
  1. Attack free
  2. When attack is detected

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     - Mitigation

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State of art

Security dMPC

	Decomposition	Resilient/Robust
[9]	Dual	Robust (Scenario)
[10]	Dual	Robust (f-robust)
[11]	Jacobi-Gauß	–
[12]	Dual	Resilient

[9] José M. Maestre et al., "Scenario-Based Defense Mechanism Against Vulnerabilities in Lagrange-Based Dmpc".

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[11] Chanfreut, J. M. Maestre, and H. Ishii, "Vulnerabilities in Distributed Model Predictive Control based on Jacobi-Gauss Decomposition".

[12] Ananduta et al., "Resilient Distributed Model Predictive Control for Energy Management of Interconnected Microgrids".

State of art

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[11] Chanfreut, J. M. Maestre, and H. Ishii, "Vulnerabilities in Distributed Model Predictive Control based on Jacobi-Gauss Decomposition".

[12] Ananduta et al., "Resilient Distributed Model Predictive Control for Energy Management of Interconnected Microgrids".

State of art

Security dMPC

	Decomposition	Resilient/Robust
[9]	Dual	Robust (Scenario)
[10]	Dual	Robust (f-robust)
[11]	Jacobi-Gauß	–
[12]	Dual	Resilient
Our	Primal	Resilient

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State of art

Security dMPC

	Decomposition	Resilient/Robust	Detection	Mitigation
[9]	Dual	Robust (Scenario)	NA	NA
[10]	Dual	Robust (f-robust)	NA	NA
[11]	Jacobi-Gauß	–	–	–
[12]	Dual	Resilient	Analyt./Learn.	Disconnect (Robustness)
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Liar, Liar, Pants of fire

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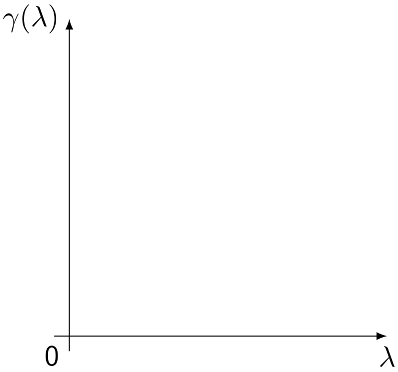

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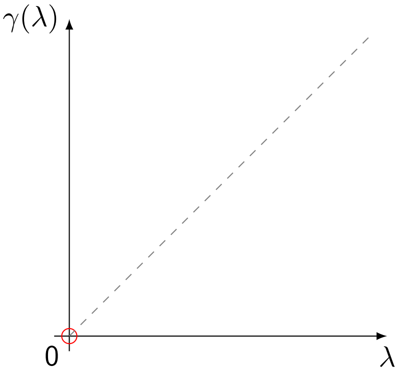

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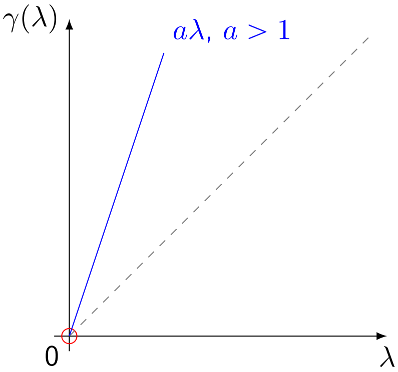

For Further Reading I

Maestre, José M, Rudy R Negenborn, et al. Distributed Model Predictive Control made easy. Vol. 69. Springer, 2014. ISBN: 978-94-007-7005-8.

Nogueira, Rafael Accácio. "Security of DMPC under False Data Injection". 2022CSUP0006. PhD thesis. CentraleSupélec, 2022. URL: http://www.theses.fr/2022CSUP0006.