Security of distributed Model Predictive Control under False Data Injection

Rafael Accácio NOGUEIRA

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IETR

https://bit.ly/3g3S6X4

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Context

“Necessity is the mother of invention”

Context

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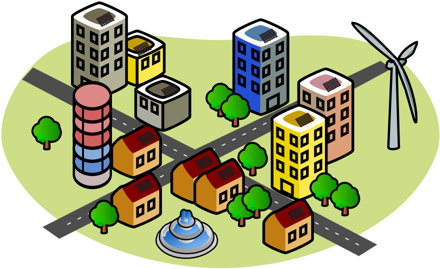
Context

"Necessity is the mother of invention"

- Electricity Distribution System

Context

" Necessity is the mother of invention "



- Electricity Distribution System
- Heat distribution
- Water distribution

Context

“Necessity is the mother of invention”

- Electricity Distribution System
- Heat distribution
- Water distribution
- Traffic management

Context

"Necessity is the mother of invention"

- Electricity Distribution System
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  (include your problem here)

Context

“Necessity is the mother of invention”

- Multiple systems interacting

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"Necessity is the mother of invention"

- Multiple systems interacting
- Coupled by constraints

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Context

❝ Necessity is the mother of invention ❞

- Multiple systems interacting
- Coupled by constraints
  - Technical/ Comfort

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"Necessity is the mother of invention"

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- Optimization objectives

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“Necessity is the mother of invention”

- Multiple systems interacting
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  - Minimize energy consumption

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Context

“Necessity is the mother of invention”

- Multiple systems interacting
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  - Technical/ Comfort
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  - Minimize energy consumption
  - Maximize user satisfaction

Context

"Necessity is the mother of invention"

- Multiple systems interacting
- Coupled by constraints
  - Technical/ Comfort
- Optimization objectives
  - Minimize energy consumption
  - Maximize user satisfaction
  - Follow a trajectory

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Context

“Necessity is the mother of invention”

- Multiple systems interacting
- Coupled by constraints
  - Technical/ Comfort
- Optimization objectives
  - Minimize energy consumption
  - Maximize user satisfaction
  - Follow a trajectory
- Solution → MPC

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Model-based Predictive Control

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Find best control sequence using predictions based on a model.

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Model-based Predictive Control

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Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

- We need an optimization problem

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

Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

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

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Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

- We need an optimization problem
  - Decision variable is the control sequence (Over horizon N)

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Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

- We need an optimization problem
  - Decision variable is the control sequence (Over horizon N)
  - Objective function to optimize

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

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Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

- We need an optimization problem
  - Decision variable is the control sequence (Over horizon N)
  - Objective function to optimize
  - System's Model (states and inputs)

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

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Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

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  - Decision variable is the control sequence (Over horizon N)
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  - System's Model (states and inputs)
  - Other constraints to respect

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

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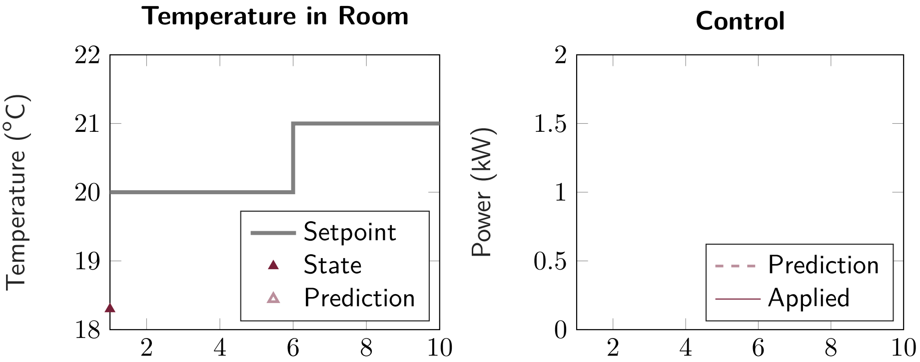
Model-based Predictive Control

Find optimal control sequence using predictions based on a model.

- We need an optimization problem
  - Decision variable is the control sequence (Over horizon N)
  - Objective function to optimize
  - System's Model (states and inputs)
  - Other constraints to respect (QoS, technical restrictions, ...)

$$
\begin{aligned}
\underset{\boldsymbol{u}[0:N-1|k]}{\text{minimize}} \quad & J(\boldsymbol{x}[0|k], \boldsymbol{u}[0:N-1|k]) \\
\text{subject to} \quad & \left.\begin{array}{r} \boldsymbol{x}[\xi|k] = f(\boldsymbol{x}[\xi-1|k], \boldsymbol{u}[\xi-1|k]) \\ g_i(\boldsymbol{x}[\xi-1|k], \boldsymbol{u}[\xi-1|k]) \leqslant 0 \\ h_j(\boldsymbol{x}[\xi-1|k], \boldsymbol{u}[\xi-1|k]) = 0 \end{array}\right\} \begin{array}{l} \forall \xi \in \{1, \ldots, N\} \\ \forall i \in \{1, \ldots, m\} \\ \forall j \in \{1, \ldots, p\} \end{array}
\end{aligned}
$$

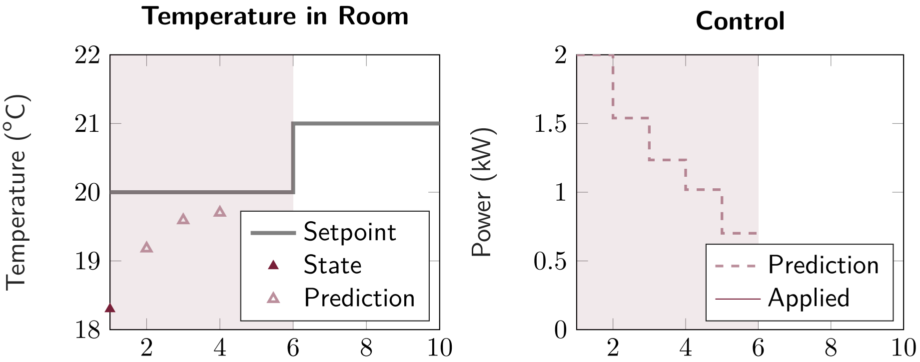
In a nutshell



Model Predictive Control

In a nutshell

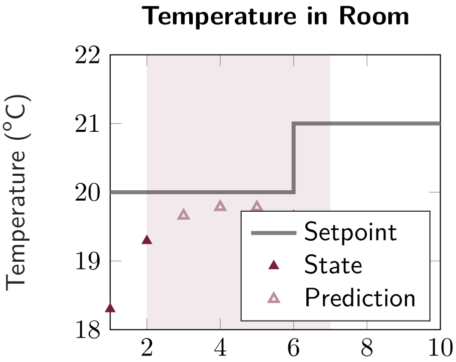
Find optimal control sequence

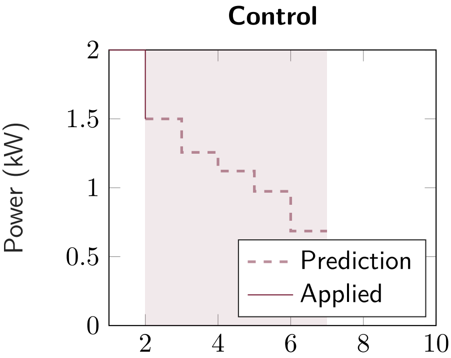


Model Predictive Control

In a nutshell

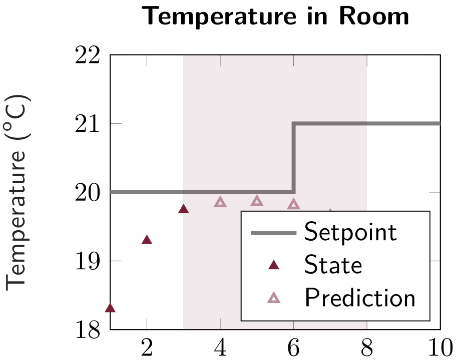
Find optimal control sequence, apply first element

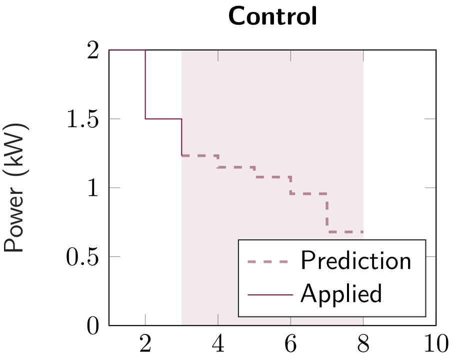




In a nutshell

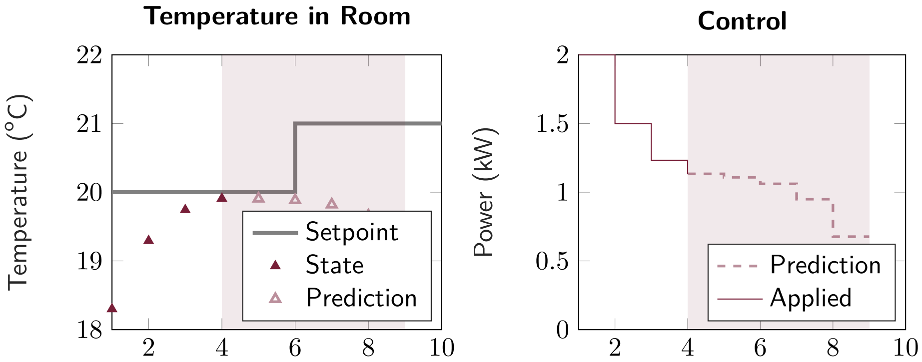
Find optimal control sequence, apply first element, rinse repeat





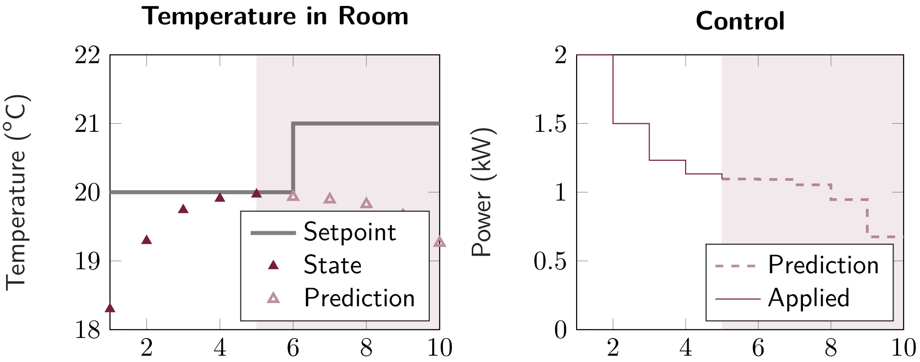
In a nutshell

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



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

Nothing is perfect

- Problems
  - Complexity of calculation

Model Predictive Control

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  - Topology (Geographical distribution)

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Model Predictive Control

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  - Complexity of calculation
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  - Privacy

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Model Predictive Control

Nothing is perfect

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- Solution: Divide and Conquer (distributed MPC)

Model Predictive Control

Nothing is perfect

- Problems
    - Complexity of calculation
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- Solution: Divide and Conquer (distributed MPC)
    - Break calculation

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Model Predictive Control

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- Problems
  - Complexity of calculation
  - Topology (Geographical distribution)
  - Flexibility (Add/remove parts)
  - Privacy
- Solution: Divide and Conquer (distributed MPC)
  - Break calculation
  - Make agents communicate

Distributed Model Predictive Control

It is about communication

- We break the MPC into multiple
- Make agents communicate.

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Distributed Model Predictive Control

It is about communication

- We break the MPC into multiple
- Make agents communicate. But how?

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Distributed Model Predictive Control

It is about communication

- We break the MPC into multiple
- Make agents communicate. But how?
  - Many flavors to choose from

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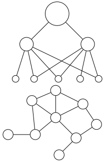
Distributed Model Predictive Control

It is about communication

- We break the MPC into multiple
- Make agents communicate. But how?
  - Many flavors to choose from
    - Hierarchical/Anarchical



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It is about communication

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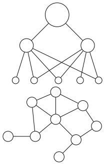

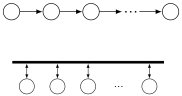

It is about communication

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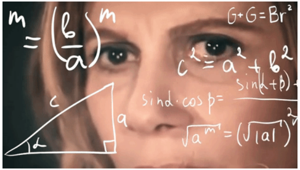

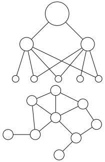

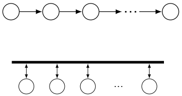

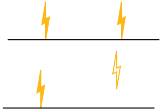

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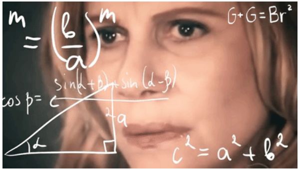

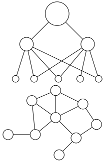

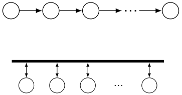

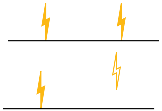

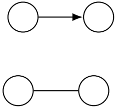

Distributed Model Predictive Control

It is about communication

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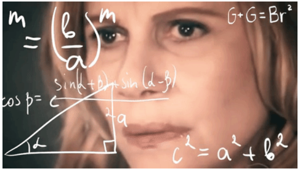

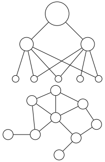

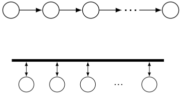

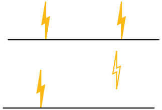

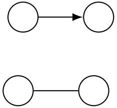

[1] Distributed Model Predictive Control made easy

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Distributed Model Predictive Control

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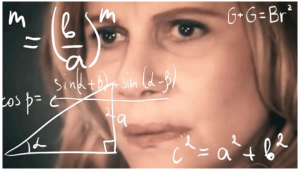

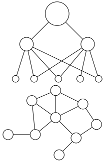

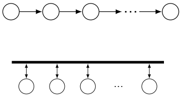

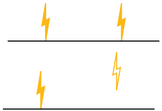

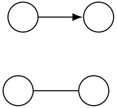

[1] Distributed Model Predictive Control made easy

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Distributed Model Predictive Control

Communication Frameworks

MPC

Communication Frameworks

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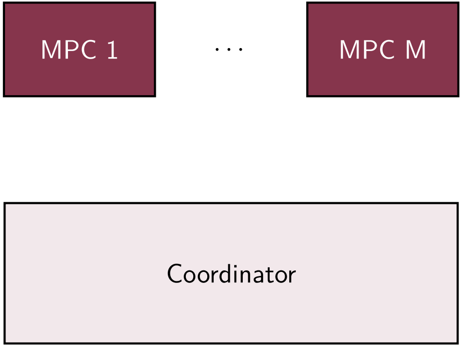
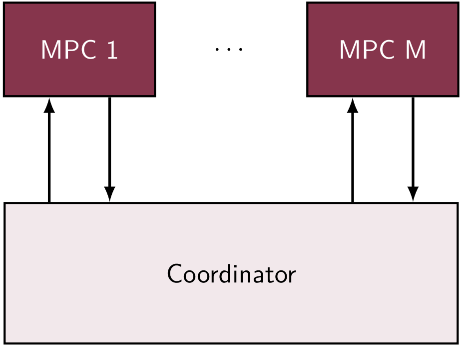
Communication Frameworks



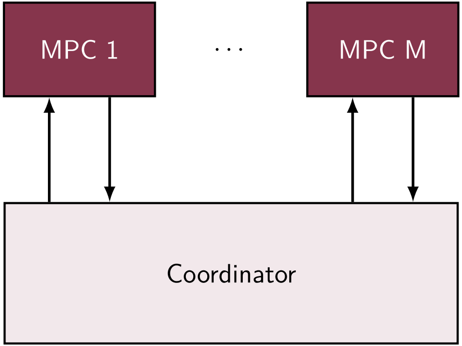
- Coordinator → Hierarchical

Communication Frameworks



- Coordinator → Hierarchical
- Bidirectional

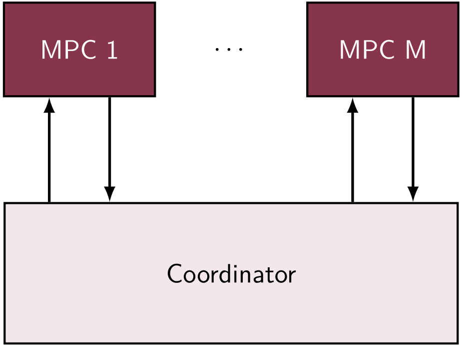
Communication Frameworks



- Coordinator → Hierarchical
- Bidirectional
- No delay → Synchronous

Distributed Model Predictive Control

Communication Frameworks



- Coordinator → Hierarchical
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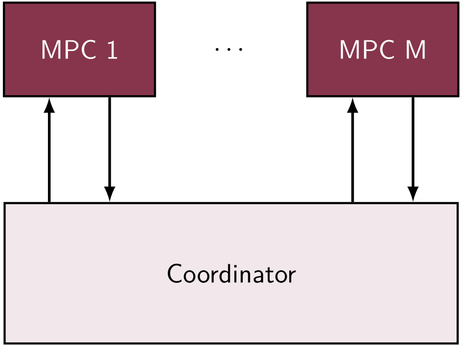
- Agents solve local problems

Communication Frameworks



- Coordinator → Hierarchical
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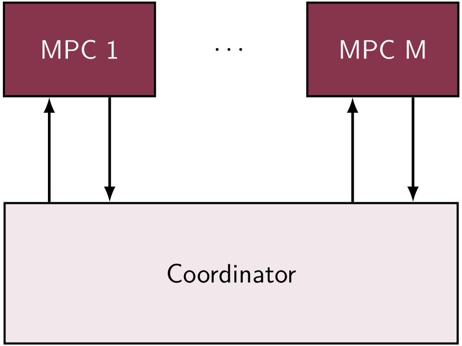
- Agents solve local problems
- Variables are updated

Distributed Model Predictive Control

Communication Frameworks



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} Until Convergence

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Distributed Model Predictive Control

Negotiation works if agents comply.

Distributed Model Predictive Control

Negotiation works if agents comply.
But what if some agents are ill-intentioned and attack the system?

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Distributed Model Predictive Control

Negotiation works if agents comply.
But what if some agents are ill-intentioned and attack the system?

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

Distributed Model Predictive Control

Negotiation works if agents comply.
But what if some agents are ill-intentioned and attack the system?

- How can an agent attack?
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Let's have a preview!

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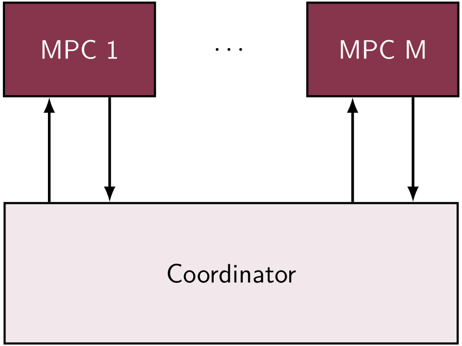
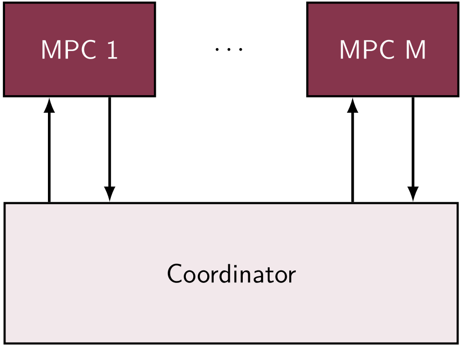
How can a non-cooperative agent attack?

Literature



How can a non-cooperative agent attack?

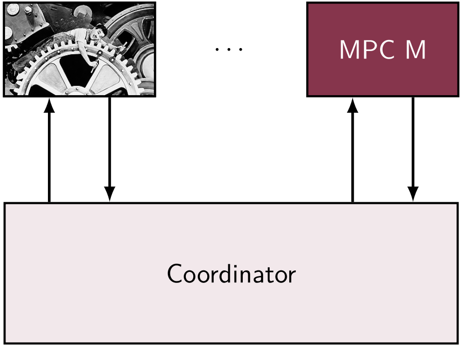
Literature



- [Vel+17a; CMI18] present attacks

How can a non-cooperative agent attack?

Literature



- [Vel+17a; CMI18] present attacks

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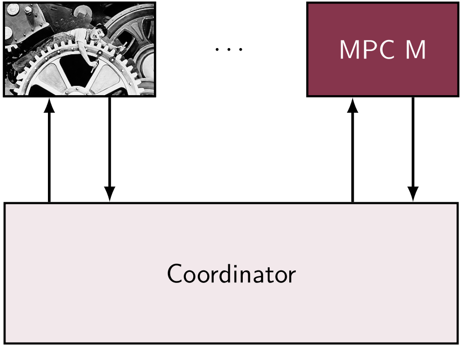

- [Vel+17a; CMI18] present attacks
  - Fake objective function
  - Fake constraints
  - Use different control

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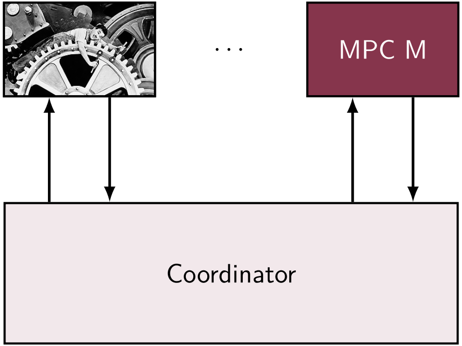

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  - Fake objective function
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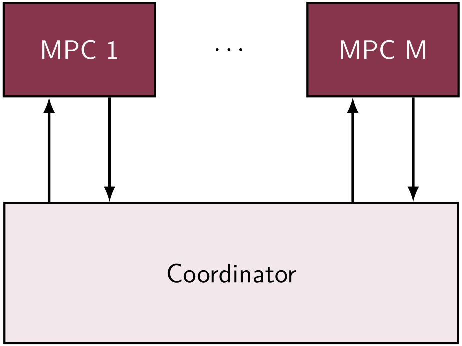
Deception Attacks

How can a non-cooperative agent attack?

Our approach



- We are in coordinator's shoes

How can a non-cooperative agent attack?

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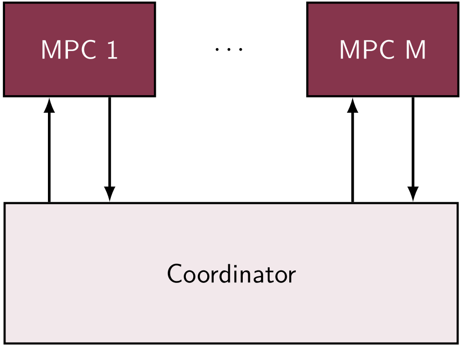

- We are in coordinator's shoes
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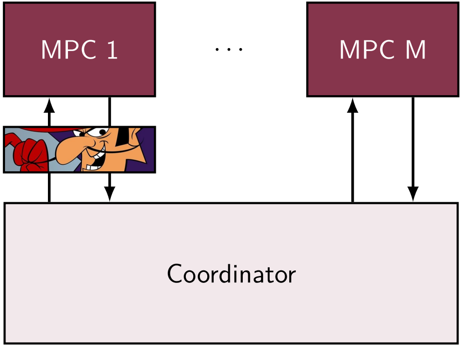

- We are in coordinator's shoes
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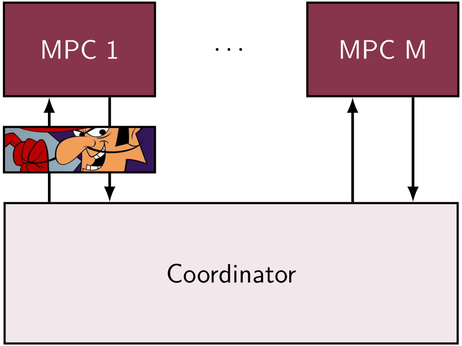

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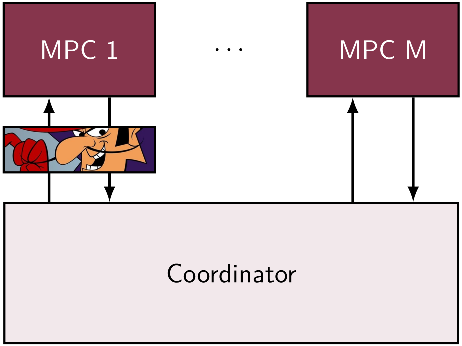

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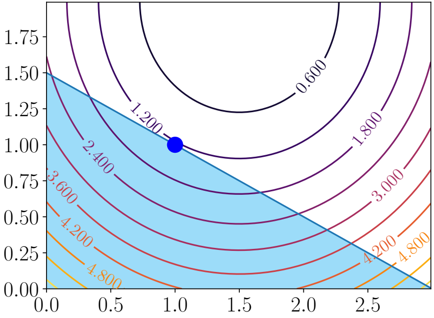
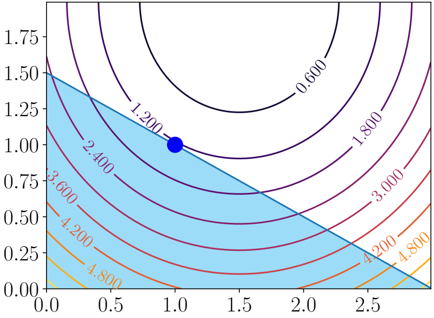


Original minimum.

Consequence of an attack

- Attack modifies optimization problem



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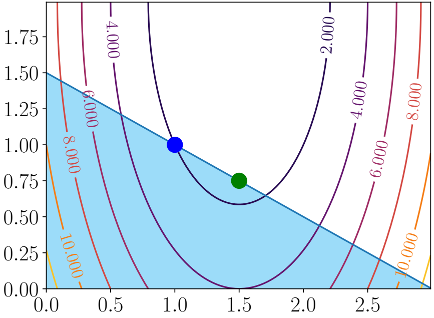
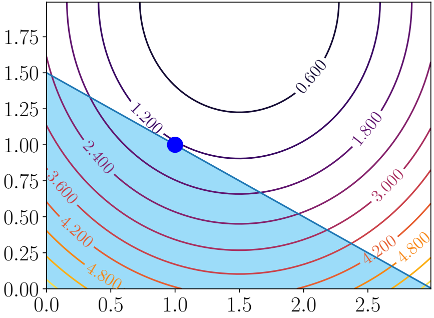


Minimum after attack.

- Attack modifies optimization problem
  - Optimum value is shifted



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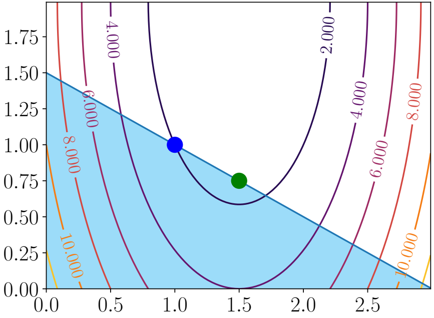

Minimum after attack.

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Mitigating the effects

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- We can recover by

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Mitigating the effects

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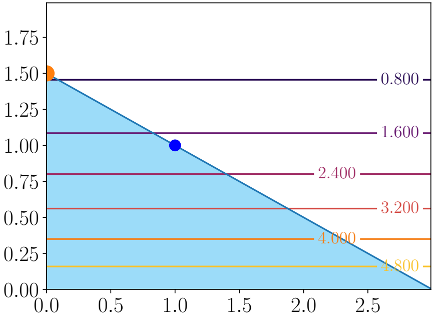

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Mitigating the effects

- We can recover by
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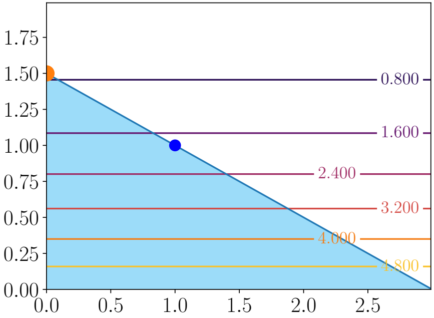
  - Recover original behavior (at least trying)



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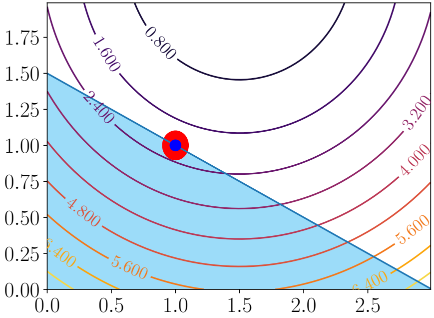

Recover original behavior.

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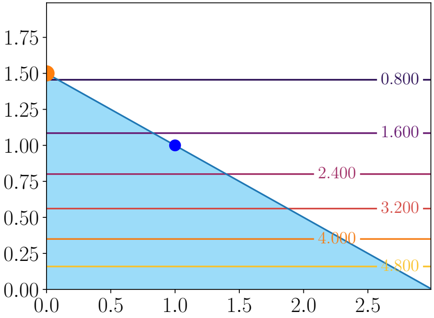

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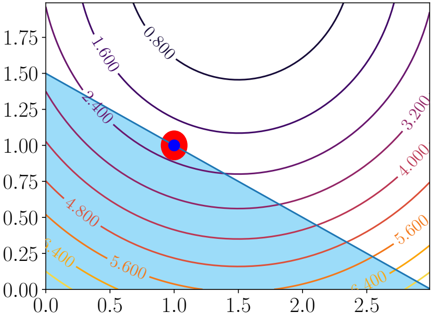

Recover original behavior.

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. Attack free
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State of art

Security dMPC

	Decomposition	Resilient/Robust
[Vel+17a] [Mae+21]	Dual	Robust (Scenario)
[Vel+17b] [Vel+18]	Dual	Robust (f-robust)
[CMI18]	Jacobi-Gauß	–
[Ana+18] [Ana+19] [Ana+20]	Dual	Resilient

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Our	Primal	Resilient	Active Analyt./Learn.	Data reconstruction

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State of art

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Outline

1. Vulnerabilities in distributed MPC based on Primal Decomposition

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2. Resilient Primal Decomposition-based dMPC for deprived systems

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3. Resilient Primal Decomposition-based dMPC using Artificial Scarcity

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4. Conclusion

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Simon Leglaive
AIMAC Team

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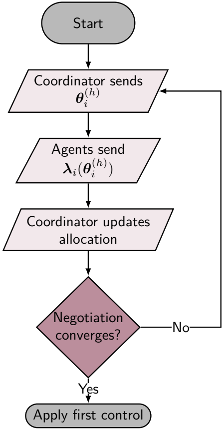
Outline

1. Vulnerabilities in distributed MPC based on Primal Decomposition
   - What is the Primal Decomposition?
   - How can an agent attack?
   - Consequences

Primal Decomposition

or Quantity Decomposition | or Resource Allocation



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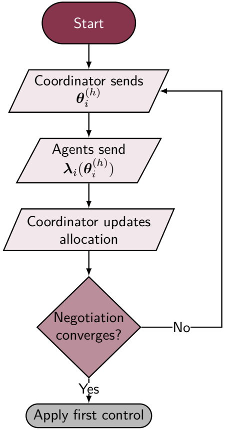

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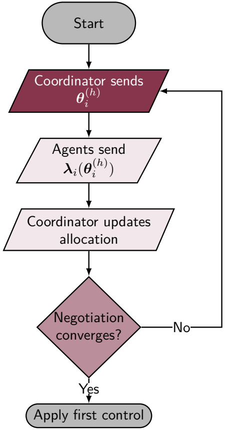

Allocation $\boldsymbol{\theta}_i$

Primal Decomposition

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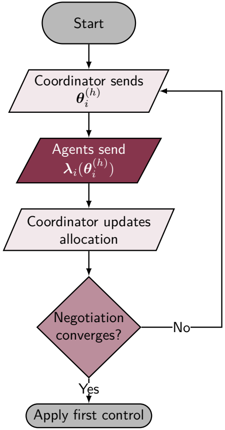

Allocation θ_i

Dissatisfaction λ_i

Primal Decomposition

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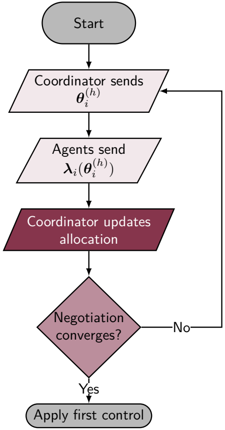

Allocation $\boldsymbol{\theta}_i$

Dissatisfaction $\boldsymbol{\lambda}_i$

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

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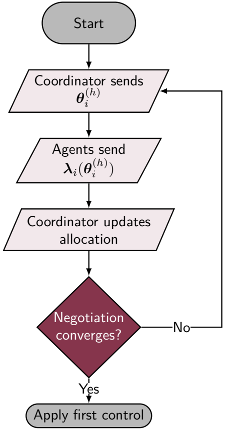

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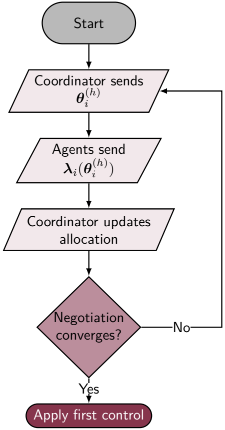

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Primal Decomposition

In detail

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

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Primal Decomposition

In detail

- Objective is sum of local ones

$$
\begin{aligned}
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Primal Decomposition

In detail

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- Constraints couple variables

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

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

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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

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Primal Decomposition

In detail

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

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Primal Decomposition

In detail

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3. Send dual variable $\boldsymbol{\lambda}_i$
4. Allocation is updated (respecting global constraint)

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

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

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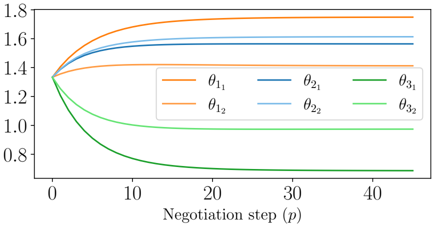
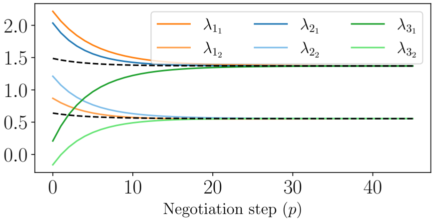
Example

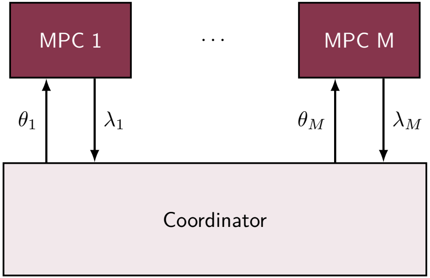
Until everybody is equally dissatisfied





How can a non-cooperative agent attack?

Our approach



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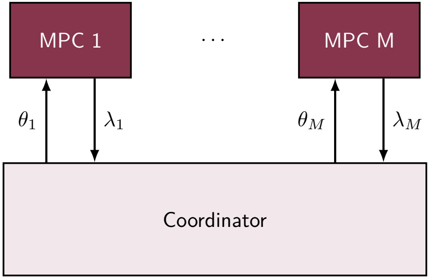

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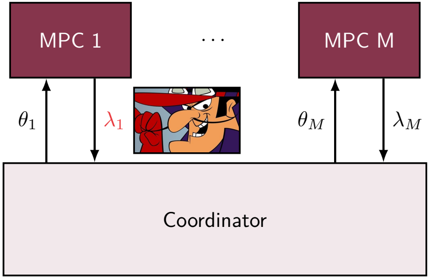

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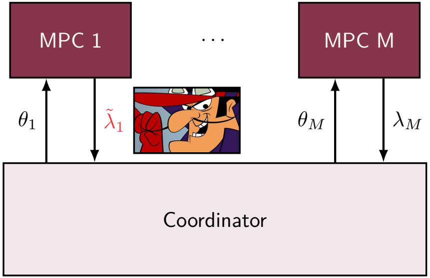

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$$\tilde{\boldsymbol{\lambda}}_i = \gamma_i(\boldsymbol{\lambda}_i)$$

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How does an agent lie?

Liar, Liar, Pants of fire

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Liar, Liar, Pants of fire

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Liar, Liar, Pants of fire

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Assumptions

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Liar, Liar, Pants of fire

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- *Same attack during negotiation*
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  - $\gamma(\lambda) = 0 \rightarrow \lambda = 0$
- $\tilde{\boldsymbol{\lambda}}_i = T_i[k]\boldsymbol{\lambda}_i$

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How does an agent lie?

Liar, Liar, Pants of fire

- $\lambda \geqslant 0$ means dissatisfaction
- $\lambda = 0$ means complete satisfaction

Assumptions

- *Same attack during negotiation*
- *Attacker satisfied only if it really is*
  - $\gamma(\lambda) = 0 \rightarrow \lambda = 0$
- $\tilde{\boldsymbol{\lambda}}_i = T_i[k]\boldsymbol{\lambda}_i$

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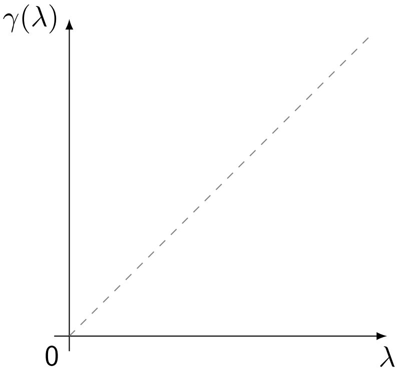

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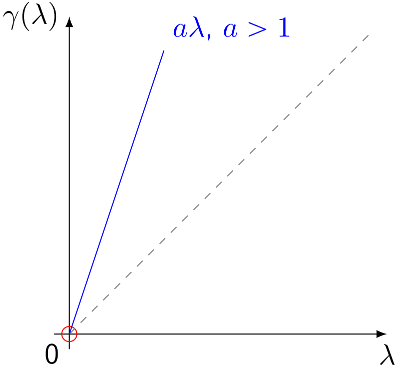

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Example

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4 distinct agents

- Agent 1 is non-cooperative
- It uses $\tilde{\boldsymbol{\lambda}}_1 = \gamma_1(\boldsymbol{\lambda}_1) = \tau_1 I \boldsymbol{\lambda}_1$

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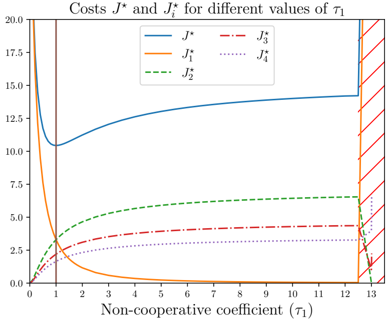

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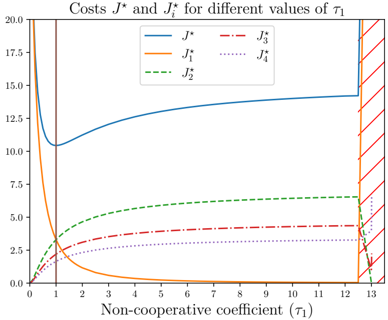

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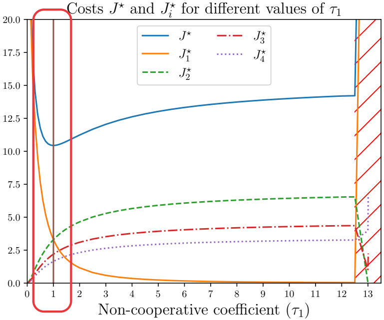

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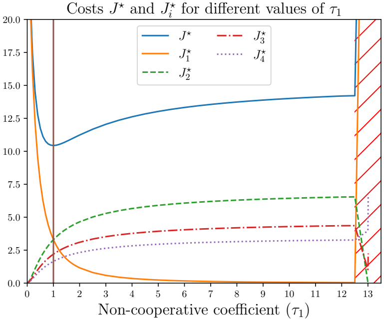

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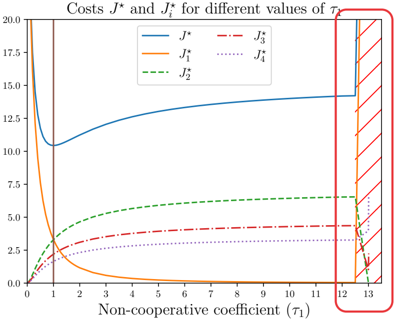

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  - All collapses if too greedy

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- But can we mitigate these effects?

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

Outline

2. Resilient Primal Decomposition-based dMPC for deprived systems
   - Analyzing deprived systems
   - Building an algorithm
   - Applying mechanism

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What are deprived systems?

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Systems whose optimal solution has all constraints active

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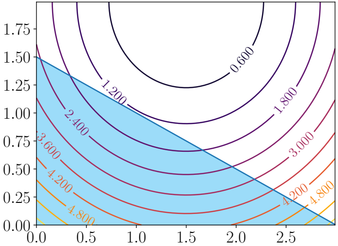

$$\begin{array}{ll} \underset{\boldsymbol{U}_i[k]}{\text{minimize}} & \frac{1}{2}\left\|\boldsymbol{U}_i[k]\right\|_{H_i}^2 + \boldsymbol{f}_i[k]^T\boldsymbol{U}_i[k] \\ \text{subject to} & \bar{\Gamma}_i\boldsymbol{U}_i[k] \preceq \boldsymbol{\theta}_i[k] : \boldsymbol{\lambda}_i[k] \end{array}$$

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Systems whose optimal solution has all constraints active

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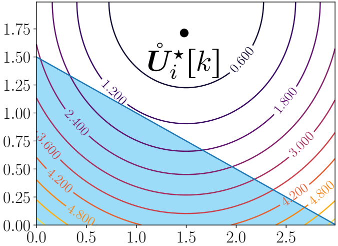

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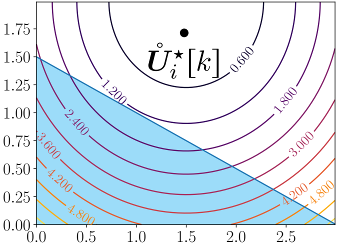

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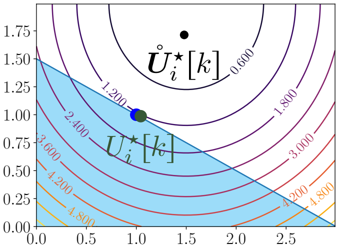

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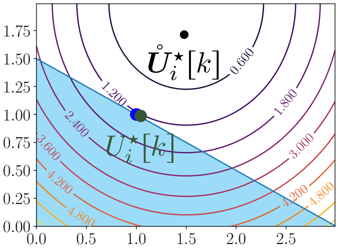
  - Same as with equality constraints[2]



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[2] If system can have all constraints active simultaneously ▸ see here

Deprived Systems

Analysis

Assumptions

Deprived Systems

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- *Quadratic local problems*

Deprived Systems

Analysis

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(local parameters unknown by coordinator) $\left\{ \right.$

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Under attack!

- Normal behavior

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Detection Mechanism

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- We estimate[3] $\hat{P}_i[k]$ and $\widehat{\tilde{\boldsymbol{s}}}_i[k]$ such as:

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[3] Using Recursive Least Squares for example

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- If $\left\|\widehat{\tilde{P}}_i[k] - \bar{P}_i\right\|_F > \epsilon_P \rightarrow$ Attack
- Ok, but how can we estimate $\widehat{\tilde{P}}_i[k]$?

[3] Using Recursive Least Squares for example

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Estimating $\widehat{\tilde{P}}_i[k]$

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[4] A random signal causes persistent excitation of any order (Adaptive Control)

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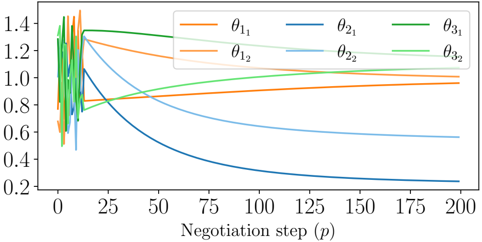

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Classification of mitigation techniques

- Active (Resilient)
  1. Detection/Isolation ✔
  2. Mitigation

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Reconstructing $\boldsymbol{\lambda}_i$

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- Reconstruct $\boldsymbol{\lambda}_i$

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- Choose adequate version for coordination

$$\overset{\text{mod}}{\boldsymbol{\lambda}}_i = \begin{cases} \overset{\text{rec}}{\boldsymbol{\lambda}}_i, & \text{if attack detected} \\ \tilde{\boldsymbol{\lambda}}_i, & \text{otherwise} \end{cases}$$

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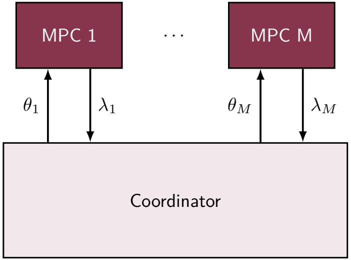
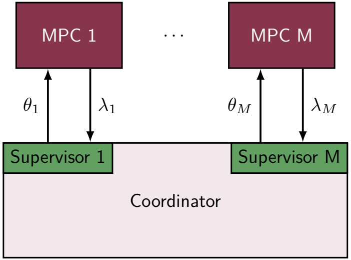
Complete Mechanism



Complete Mechanism



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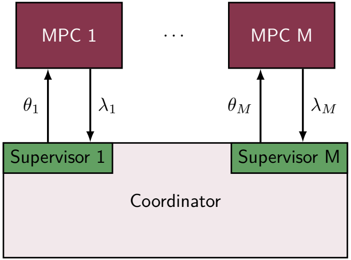
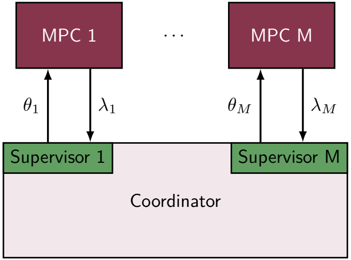
Complete Mechanism



- Supervise exchanges by inquiring the agents
- Estimate how they will behave

Complete Mechanism



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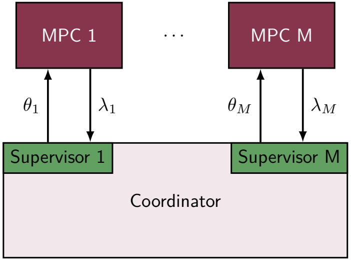
- Estimate how they will behave

Two Phases

Complete Mechanism



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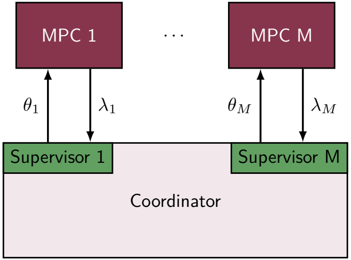

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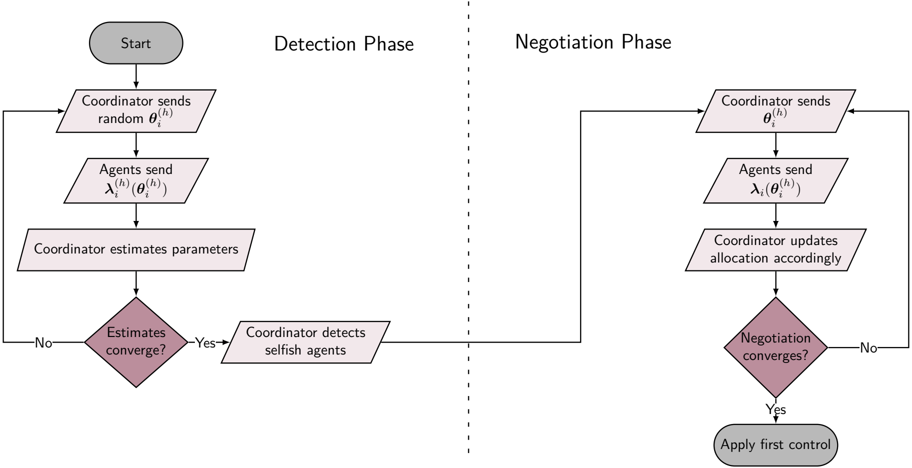
Two Phases

1. Detect which agents are non-cooperative
2. Reconstruct $\boldsymbol{\lambda}_i$ and use in negotiation

Complete algorithm

RPdMPC-DS



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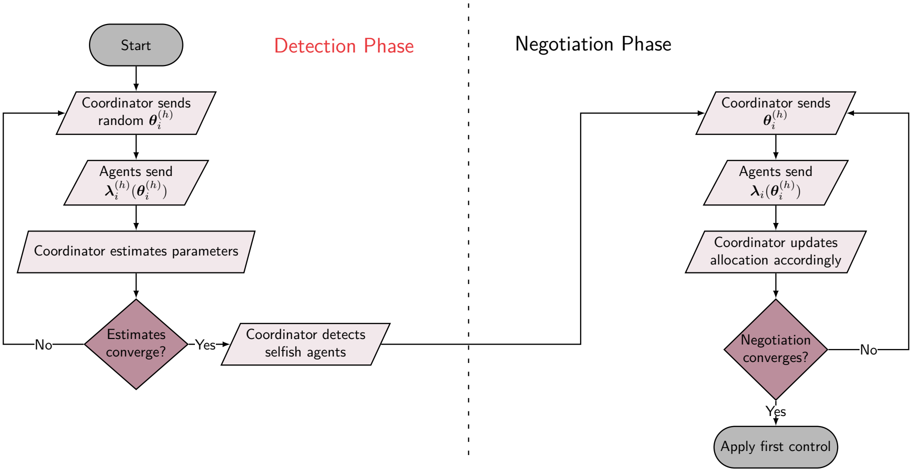

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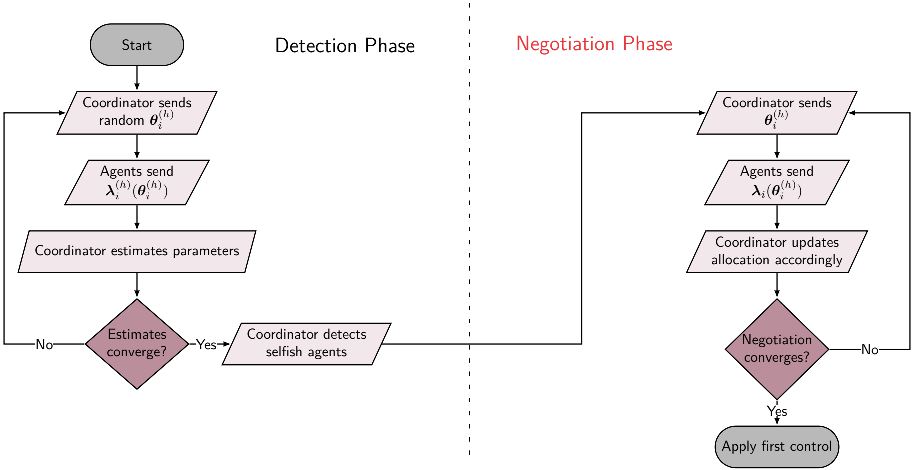

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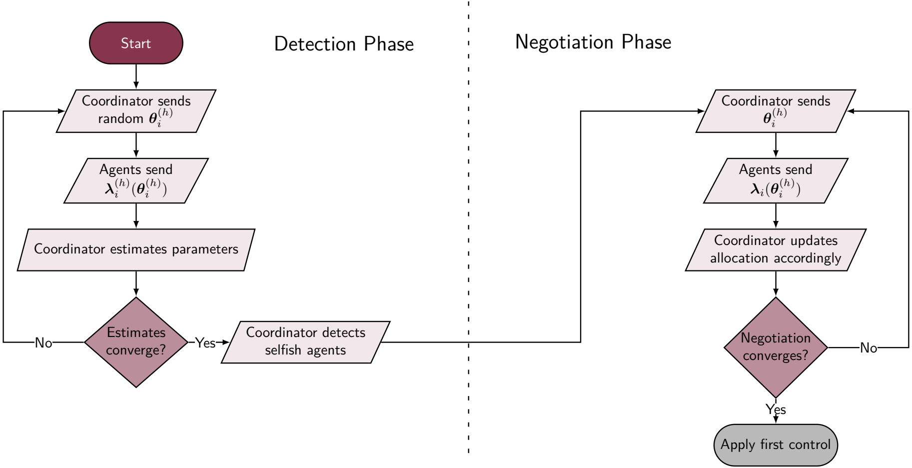

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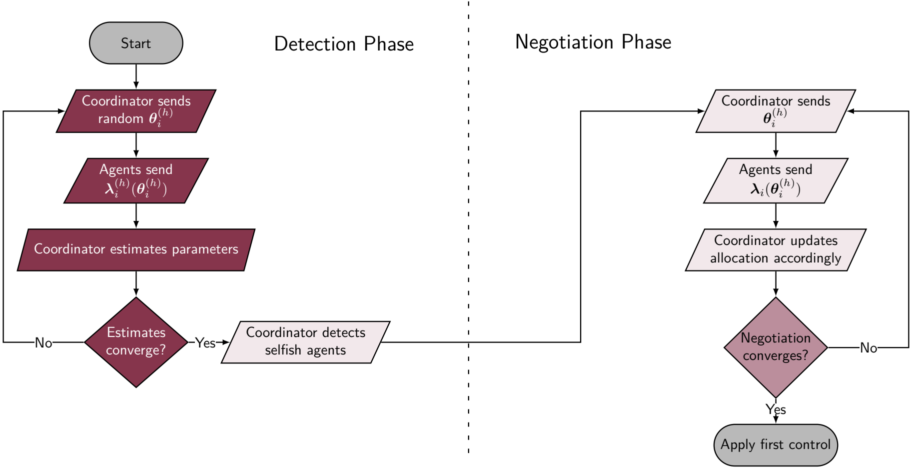

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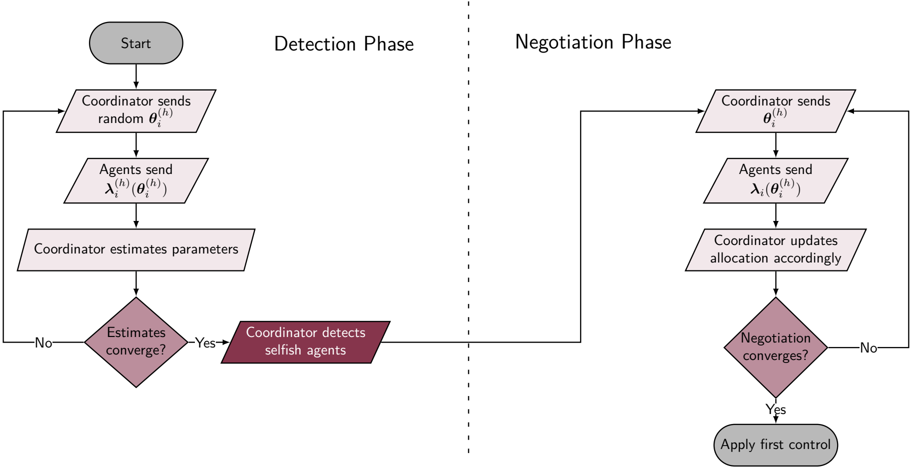

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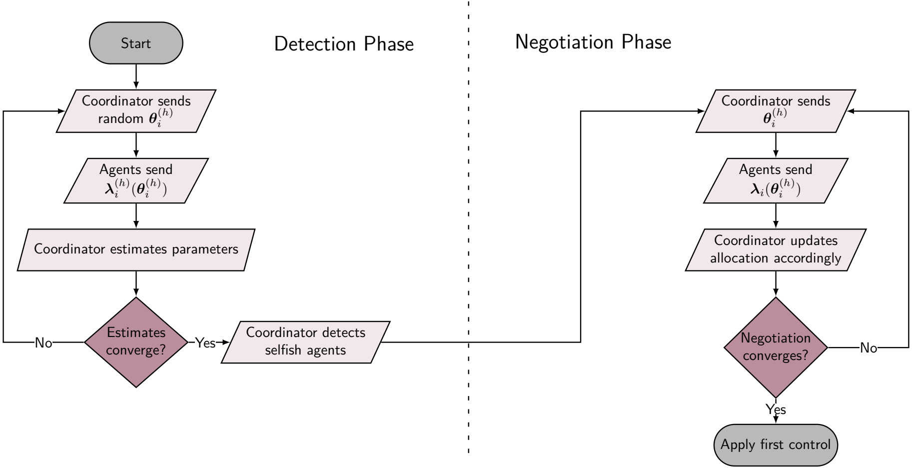

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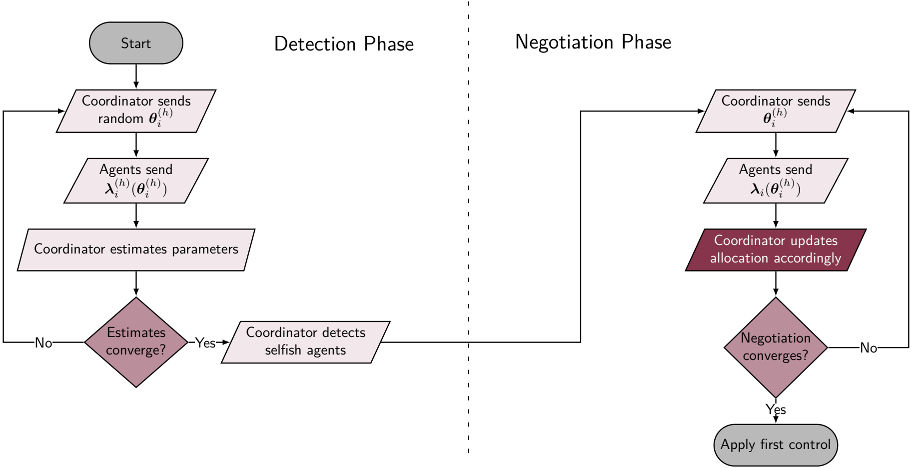
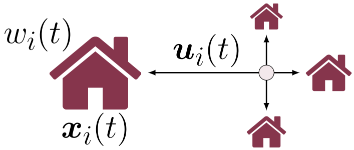
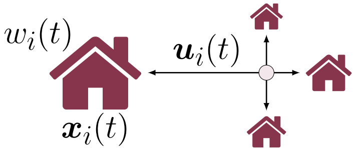


Example



District Heating Network (4 Houses)

Example



District Heating Network (4 Houses)

- Houses modeled using 3R-2C (monozone)

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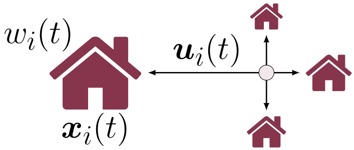

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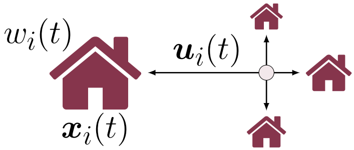

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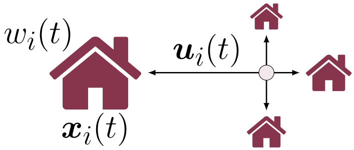

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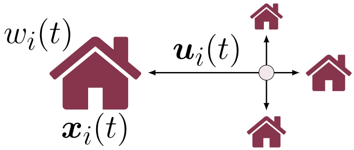

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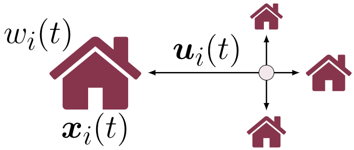

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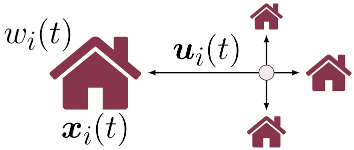

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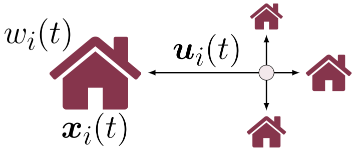

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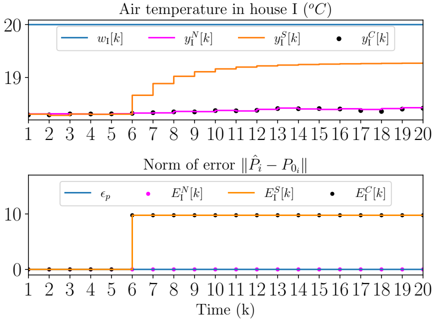
  - S Agent I cheats (RPdMPC-DS)

Results

Temporal



Temperature in house I.
Error $E_I(k)$.
N Nominal, S Selfish, C Corrected

Results

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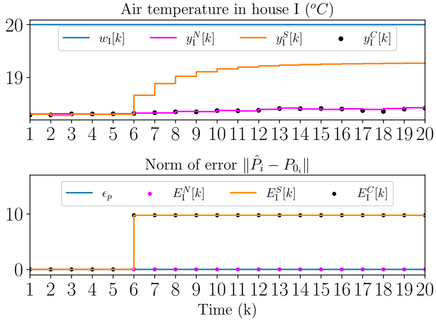

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Results

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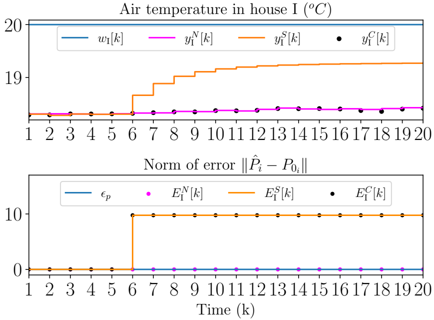

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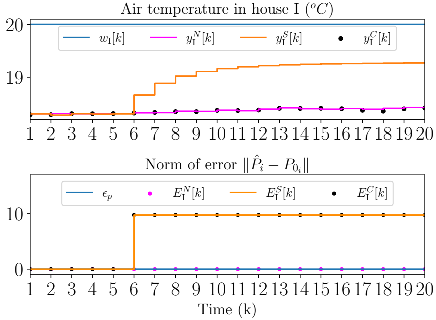

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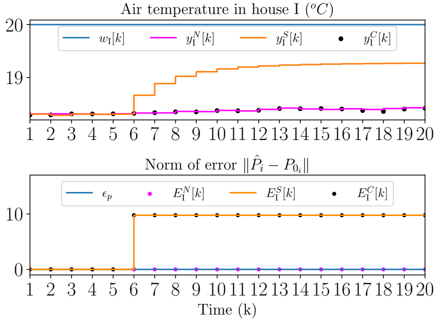

Temperature in house I.
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- Agent starts cheating in $k = 6$
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- C Restablish behavior close to N

Results

Costs

Objective functions J_i (Normalized error %)

Agent	Selfish	Corrected
I	-36.3	0.5
II	21.67	-0.55
III	17.39	-0.0
IV	17.63	-0.09
Global	3.53	0.02

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Outline

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Relaxing scarcity assumption

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$$\begin{aligned} \underset{\boldsymbol{U}_i[k]}{\text{minimize}} \quad & \frac{1}{2}\left\|\boldsymbol{U}_i[k]\right\|_{H_i}^2 + \boldsymbol{f}_i[k]^T\boldsymbol{U}_i[k] \\ \text{subject to} \quad & \bar{\Gamma}_i\boldsymbol{U}_i[k] \preceq \boldsymbol{\theta}_i[k] : \boldsymbol{\lambda}_i[k] \end{aligned}$$

Relaxing scarcity assumption

- Systems are not completely deprived
  - We can't change our constraints to equality ones anymore
  - Nor use the simpler update equation

$$\begin{array}{ll} \underset{\boldsymbol{U}_i[k]}{\text{minimize}} & \frac{1}{2}\left\|\boldsymbol{U}_i[k]\right\|_{H_i}^2 + \boldsymbol{f}_i[k]^T\boldsymbol{U}_i[k] \\ \text{subject to} & \bar{\Gamma}_i\boldsymbol{U}_i[k] \preceq \boldsymbol{\theta}_i[k] : \boldsymbol{\lambda}_i[k] \end{array}$$

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

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Analyzing System

Solution for $\lambda_i[k]$

Instead of having one single affine solution

$$\boldsymbol{\lambda}_i[k] = -P_i\boldsymbol{\theta}_i[k] - \boldsymbol{s}_i[k]$$

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Still the $P_i^{(z)}$ are time independent

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Analyzing System

Solution for $\lambda_i[k]$ (Continued)

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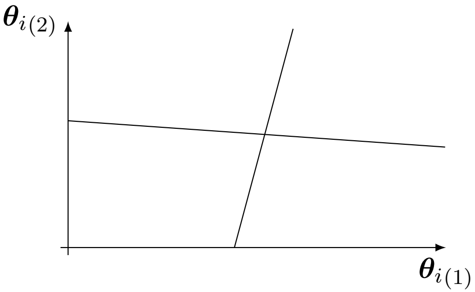

Separation surfaces depend on state and local parameters.

Analyzing System

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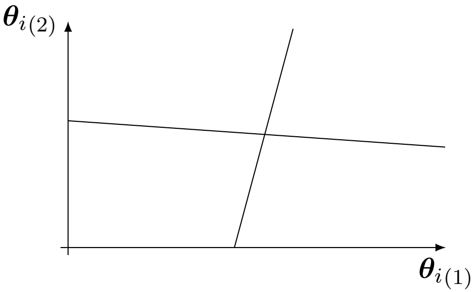

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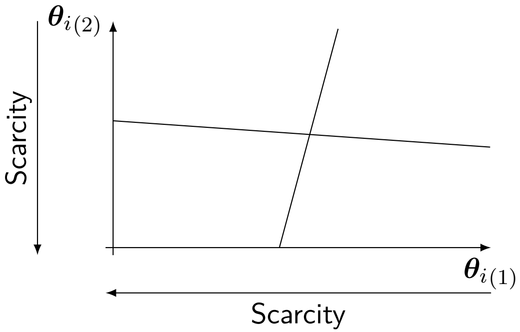

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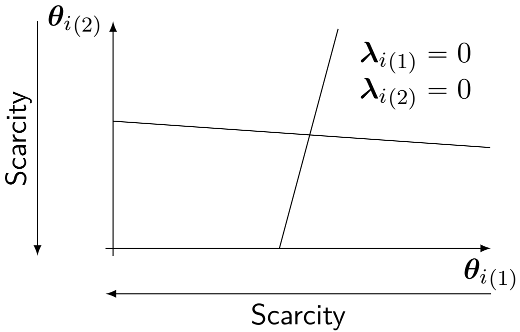

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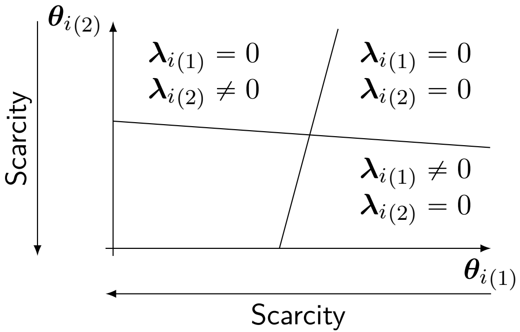

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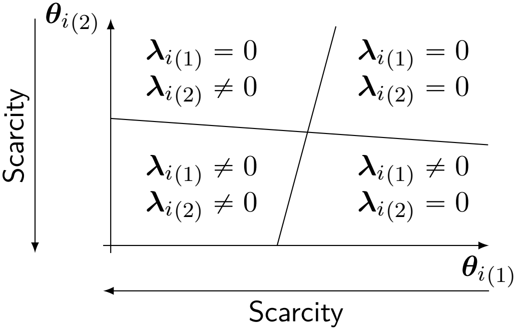

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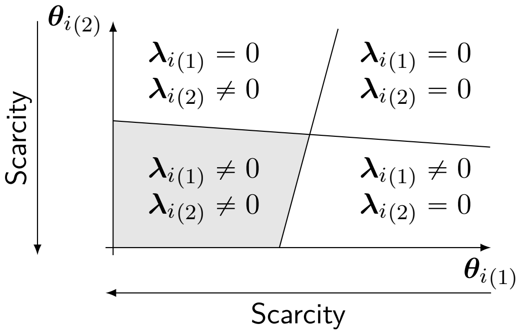

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Solution for $\lambda_i[k]$ (Continued) Still?

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Scarcity

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None constraints active	$-P_i^{(Z)}\boldsymbol{\theta}_i[k] - \boldsymbol{s}_i^{(Z)}[k]$	$\rightarrow$	$\mathbf{0}$

Analyzing System

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Assumptions

The region $\mathcal{R}^0_{\boldsymbol{\lambda}_i} \neq \emptyset$ and we known a point $\overset{\emptyset}{\boldsymbol{\theta}}_i \in \mathcal{R}^0_{\boldsymbol{\lambda}_i}$

Analyzing System

Under attack!

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$$\tilde{\boldsymbol{\lambda}}_i[k] = T_i[k]\boldsymbol{\lambda}_k$$

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Parameters are modified.

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Parameters are modified. But not the regions' limits

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Analyzing System

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Artificial Scarcity

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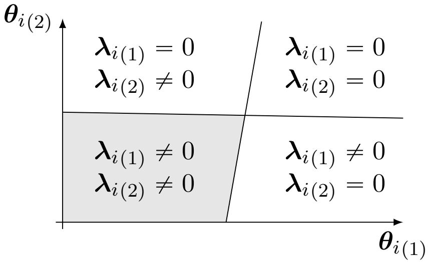

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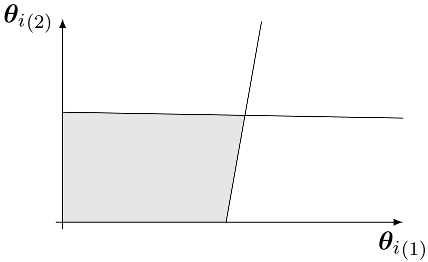

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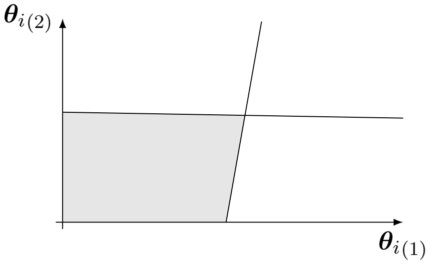

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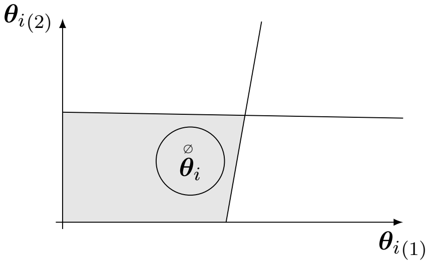

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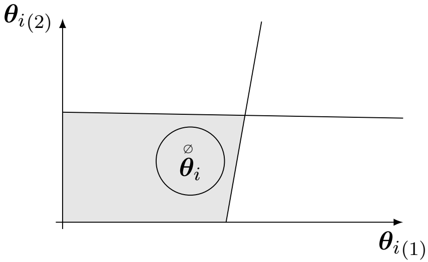

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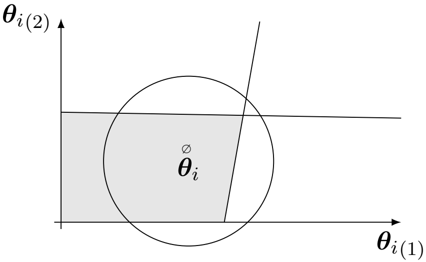

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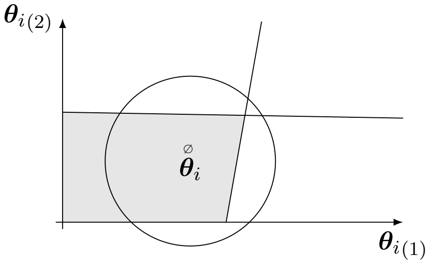

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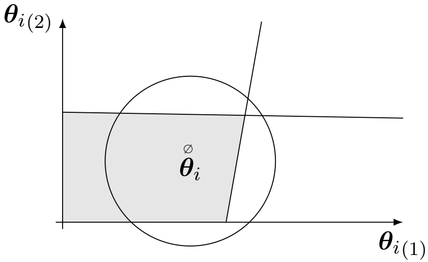

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- We recover the associated parameter, i.e., $\widehat{\widetilde{P}}_i^{(0)}[k]$

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Detection and Mitigation

Same same, but different

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Assumption

We estimate nominal $\bar{P}_i^{(0)}$ from attack free negotiation

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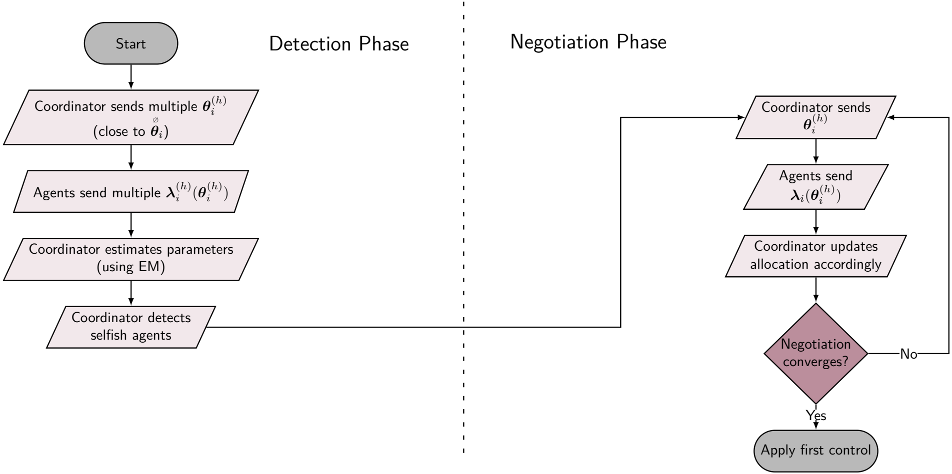
Complete algorithm

RPdMPC-AS



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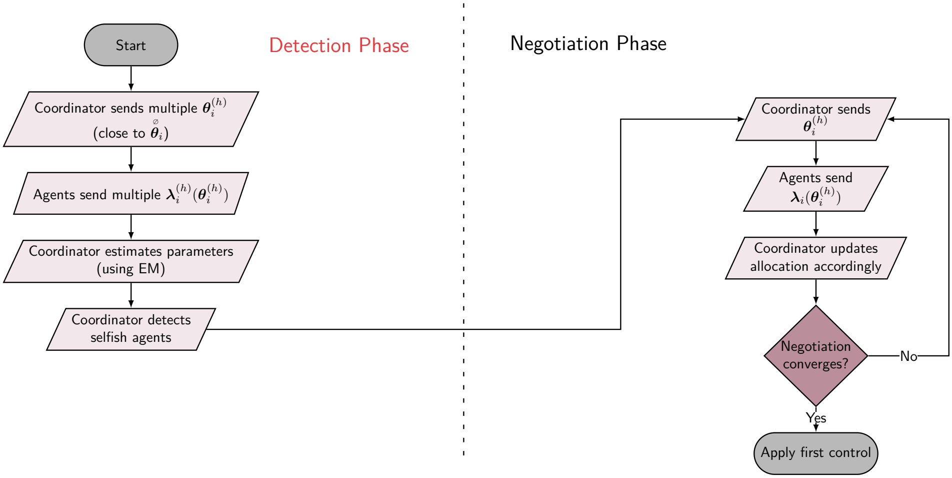

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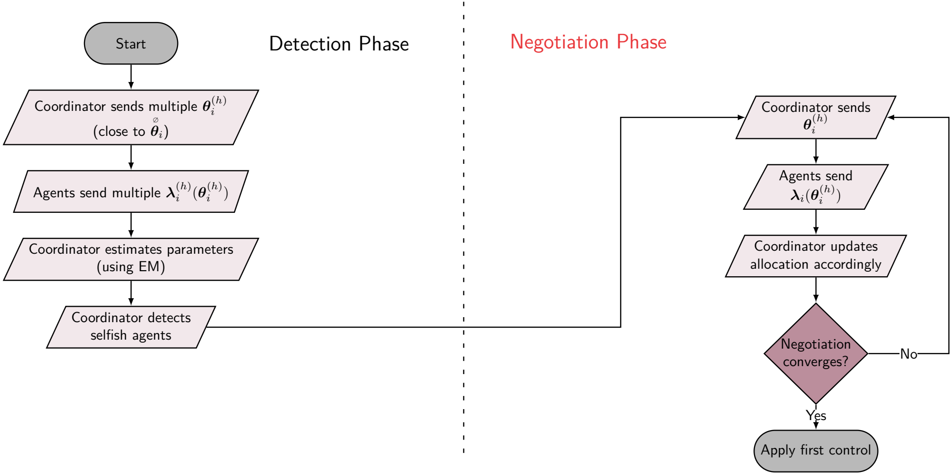

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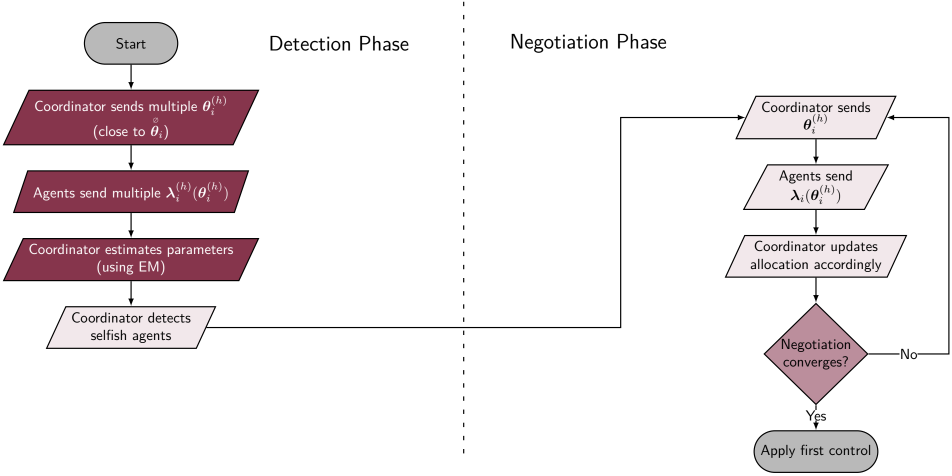

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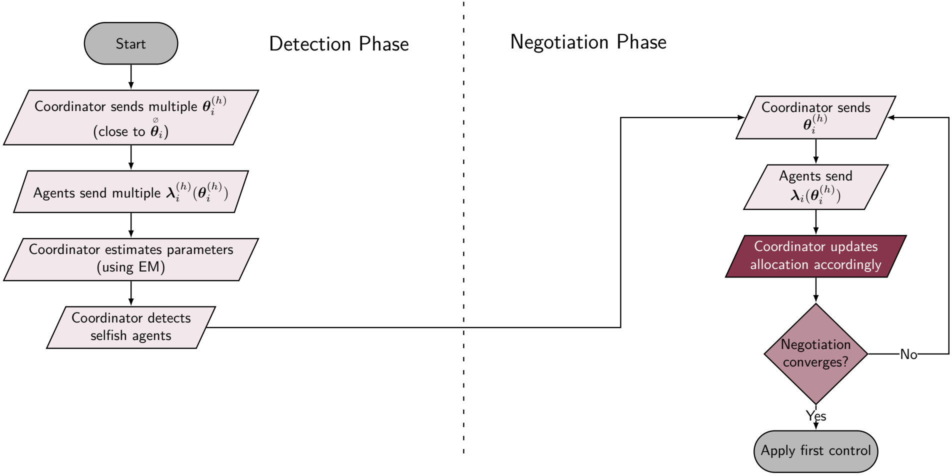
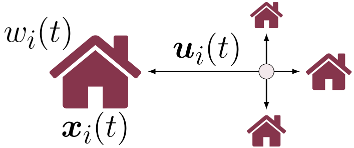


Example



District Heating Network (4 Houses)

- Houses modeled using 3R-2C
- Not enough power
- Period of 5h ($T_s = 0.25h \rightarrow k = \{1:20\}$)
- Prediction horizon ($N = 4$)
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  - C Agent I cheats (dMPC)
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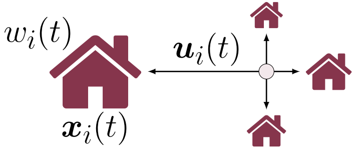

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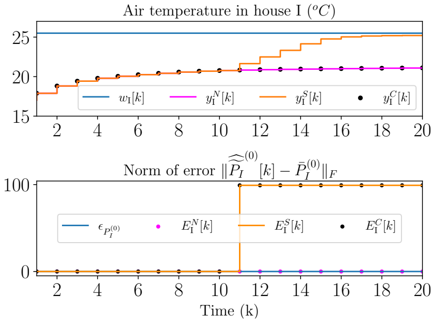
Results

Temporal



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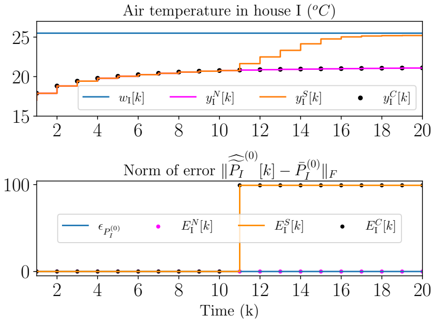

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Costs

Objective functions J_i (Normalized error %)

Agent	Selfish	Corrected
I	-36.49	$-4.12e-05$
II	35.81	$1.74e-05$
III	29.22	$2.14e-05$
IV	37.54	$1.73e-05$
Global	10.69	$-6e-07$

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Outline

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Conclusion

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  - Yes! By exploring the scarcity of the systems!

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Questions? Comments?

Repository
https://github.com/Accacio/thesis

Contact
rafael.accacio.nogueira@gmail.com

For Further Reading I

K.J. Åström and B. Wittenmark. Adaptive Control. Addison-Wesley series in electrical and computer engineering: Control engineering. Addison-Wesley, 1989. ISBN: 9780201097207. DOI: 10.1007/978-3-662-08546-2_24.

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

Wicak Ananduta et al. "Resilient Distributed Model Predictive Control for Energy Management of Interconnected Microgrids". In: Optimal Control Applications and Methods 41.1 (2020), pp. 146–169. DOI: 10.1002/oca.2534. URL: https://onlinelibrary.wiley.com/doi/pdf/10.1002/oca.2534.

For Further Reading II

José M. Maestre et al. “Scenario-Based Defense Mechanism Against Vulnerabilities in Lagrange-Based Dmpc”. In: Control Eng Pract 114 (2021), p. 104879. ISSN: 0967-0661. DOI: 10.1016/j.conengprac.2021.104879.

Rafael Accácio Nogueira et al. “Expectation-Maximization Based Defense Mechanism for Distributed Model Predictive Control”. In: IFAC-PapersOnLine 55.13 (2022). 9th IFAC Conference on Networked Systems NECSYS 2022, pp. 73–78. ISSN: 2405-8963. DOI: 10.1016/j.ifacol.2022.07.238.

Pablo Velarde et al. “Vulnerabilities in Lagrange-Based Distributed Model Predictive Control”. In: Optimal Control Applications and Methods 39.2 (Sept. 2018), pp. 601–621. DOI: 10.1002/oca.2368.

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For Further Reading III

Wicak Ananduta et al. “Resilient Distributed Energy Management for Systems of Interconnected Microgrids”. In: 2018 IEEE Conference on Decision and Control (CDC). 2018, pp. 3159–3164. DOI: 10.1109/CDC.2018.8619548.

Wicak Ananduta et al. “A Resilient Approach for Distributed MPC-Based Economic Dispatch in Interconnected Microgrids”. In: 2019 18th European Control Conference (ECC). 2019, pp. 691–696. DOI: 10.23919/ECC.2019.8796208.

P. Chanfreut, J. M. Maestre, and H. Ishii. “Vulnerabilities in Distributed Model Predictive Control based on Jacobi-Gauss Decomposition”. In: 2018 European Control Conference (ECC). June 2018, pp. 2587–2592. DOI: 10.23919/ECC.2018.8550239.

For Further Reading IV

Rafael Accácio Nogueira, Romain Bourdais, and Hervé Guéguen. "Detection and Mitigation of Corrupted Information in Distributed Model Predictive Control Based on Resource Allocation". In: 2021 5th Conference on Control and Fault-Tolerant Systems (SysTol). 2021, pp. 329–334. DOI: 10.1109/SysTol52990.2021.9595927.

Pablo Velarde et al. "Scenario-based defense mechanism for distributed model predictive control". In: 2017 IEEE 56th Annual Conference on Decision and Control (CDC). IEEE. Dec. 2017, pp. 6171–6176. DOI: 10.1109/CDC.2017.8264590.

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For Further Reading V

Pablo Velarde et al. “Vulnerabilities in Lagrange-Based DMPC in the Context of Cyber-Security”. In: 2017 IEEE International Conference on Autonomic Computing (ICAC). July 2017, pp. 215–220. DOI: 10.1109/ICAC.2017.53.

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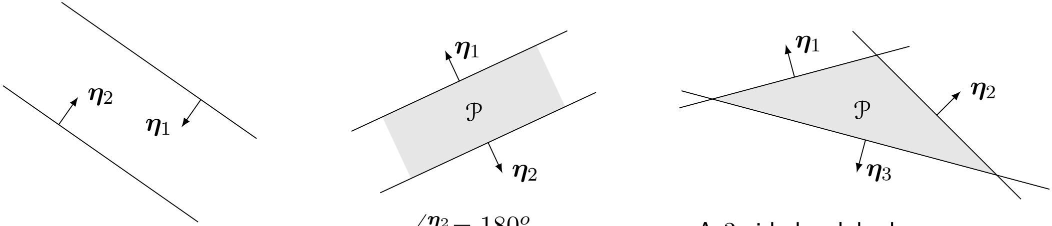
Conditions

back

One way to ensure this, is to make the original constraints to form a cone.



No intersection

$\langle^{\eta_2}_{\eta_1} = 180^o$

A 3-sided polyhedron.

θ dynamics

◂ back

$$\boldsymbol{\theta}^{(p+1)} = \mathcal{A}_\theta \boldsymbol{\theta}^{(p)} + \mathcal{B}_\theta[k]$$

where

$$\mathcal{A}_\theta = \begin{bmatrix} I - \frac{M-1}{M}\rho^{(p)}P_1 & \frac{1}{M}\rho^{(p)}P_2 & \dots & \frac{1}{M}\rho^{(p)}P_M \\ \frac{1}{M}\rho^{(p)}P_1 & I - \frac{M-1}{M}\rho^{(p)}P_2 & \dots & \frac{1}{M}\rho^{(p)}P_M \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{M}\rho^{(p)}P_1 & \frac{1}{M}\rho^{(p)}P_2 & \dots & I - \frac{M-1}{M}\rho^{(p)}P_M \end{bmatrix}$$

$$\mathcal{B}_\theta[k] = \begin{bmatrix} -\frac{M-1}{M}\rho^{(p)}\boldsymbol{s}_1[k] + \frac{1}{M}\rho^{(p)}\boldsymbol{s}_2[k] \dots - \frac{1}{M}\rho^{(p)}\boldsymbol{s}_M[k] \\ \frac{1}{M}\rho^{(p)}\boldsymbol{s}_1[k] - \frac{M-1}{M}\rho^{(p)}\boldsymbol{s}_2[k] \dots - \frac{1}{M}\rho^{(p)}\boldsymbol{s}_M[k] \\ \vdots \\ \frac{1}{M}\rho^{(p)}\boldsymbol{s}_1[k] + \frac{1}{M}\rho^{(p)}\boldsymbol{s}_2[k] \dots - \frac{M-1}{M}\rho^{(p)}\boldsymbol{s}_M[k] \end{bmatrix}$$

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Parameters estimated depending on Prediction Horizon N

\# constraints depend on \# global constraints c and prediction horizon N

- Number of Regions $= 2^{Nc}$
- Parameters in each region $=$ Matrix $P_i^{(z)} = (Nc)^2 +$ vector $\boldsymbol{s}_i^{(z)}[k] = Nc$
  - Total $((Nc)^2 + Nc)2^{Nc}$

Some examples

- 1 constraint
  - $N = 3 \rightarrow$ 96 elements
  - $N = 4 \rightarrow$ 320 elements

Remark

We can reduce number of elements estimated from $P_i^{(z)}$ if we assume $P_i^{(z)} \in \mathbb{S}$
New total $\rightarrow ((Nc)^2 + 3Nc)2^{Nc-1}$