Security of distributed Model Predictive Control under False Data injection

or How I Learned to Stop and Worry about Everything

Rafael Accácio NOGUEIRA

December 12, 2022

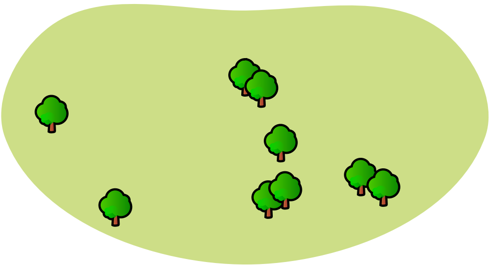
https://bit.ly/3g3S6X4

45 minutes !!!!

Good afternoon, thank you all for being here.I'm Rafael Accácio and I'm going to present my work on the security of distributed model predictive control under false data injection.

Context

Requirements evolve with time



These cyberphysical systems are the majority of the systems in our everyday lives.We can give example the traffic management,water distribution,electricity distribution, heat and cold and many more.But how to control those kinds of systems. Each has its own Dynamics and constraints, such comfort (Quality of service) or technical. Solution, mpc since we use models and it is easy to integrate the constraints.

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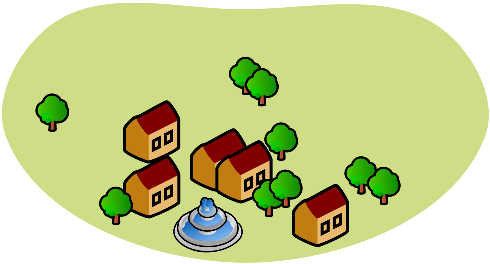

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CentraleSupélec

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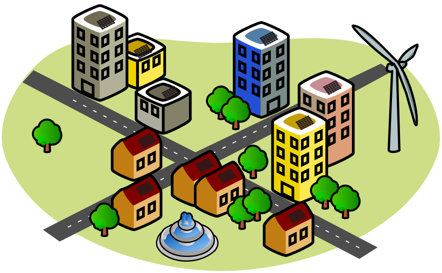

- Electricity Distribution System
- Heat distribution
- Water distribution
- Traffic management

  (include your problem here)

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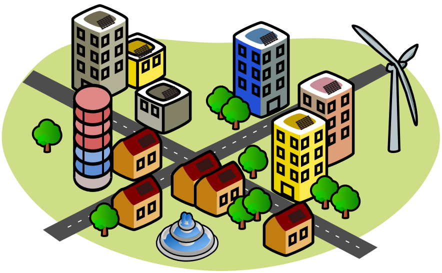

- Electricity Distribution System
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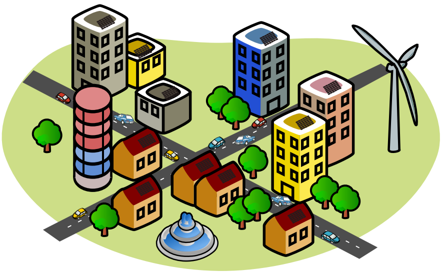

- Multiple systems interacting
- Coupled by constraints
- Optimization objectives
  - Minimize energy consumption
  - Maximize user satisfaction
  - Follow a trajectory
  - ...
- Solution → MPC

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Model-based Predictive Control

Find best control sequence using predictions based on a model.

- Objective function to optimize
- System's Model (states and inputs)
- Other constraints to respect (QoS, technical restrictions, ...)

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For those who are not familiar with mpc. Mpc is the model based predictive controller.

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The objective is to find the best control sequence using predictions based on a model.

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When we say best,

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we mean optimal.

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\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]) &\leq 0 \\
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\end{aligned}\right\}
\begin{aligned}
&\forall \xi \in \{1, \ldots, N\} \\
&\forall i \in \{1, \ldots, m\} \\
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So we need to solve an optimization problem.

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And we have the control sequence of u as the decision variable.

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which is calculated for a horizon N

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So, we need an objective function. For example follow a trajectory while minimizing the energy.

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A model of the system

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with its states

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and inputs

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But we can also integrate some constraints, such QoS or technical restrictions

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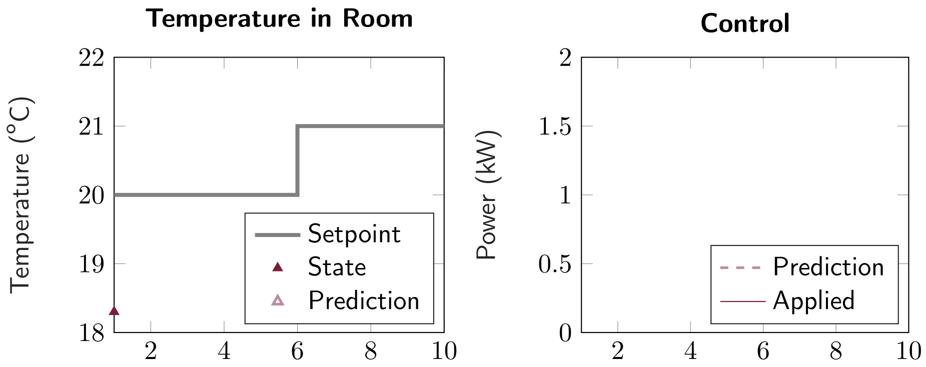
Model Predictive Control

In a nutshell

Find optimal control sequence



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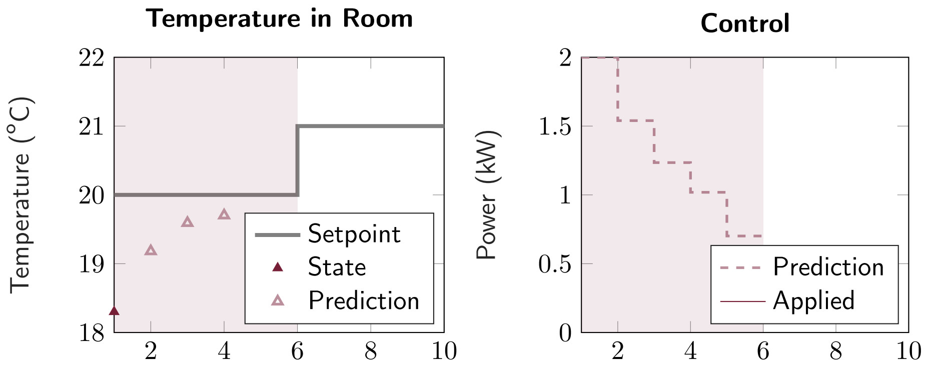
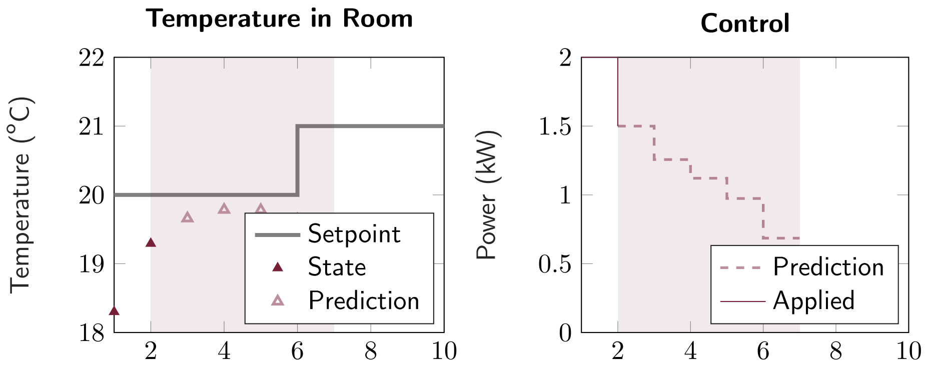
So, for example, if we may have a setpoint to follow

Find optimal control sequence



We find an optimal control sequence

Find optimal control sequence, apply first element

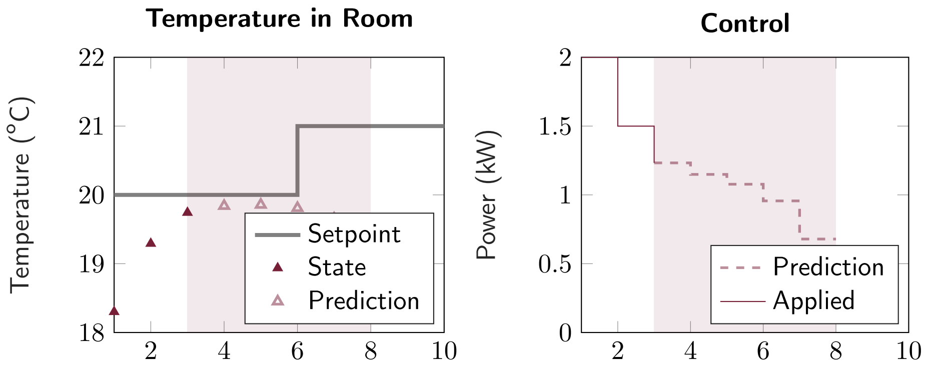


We apply only the first element

Model Predictive Control

In a nutshell

Find optimal control sequence, apply first element, rinse repeat



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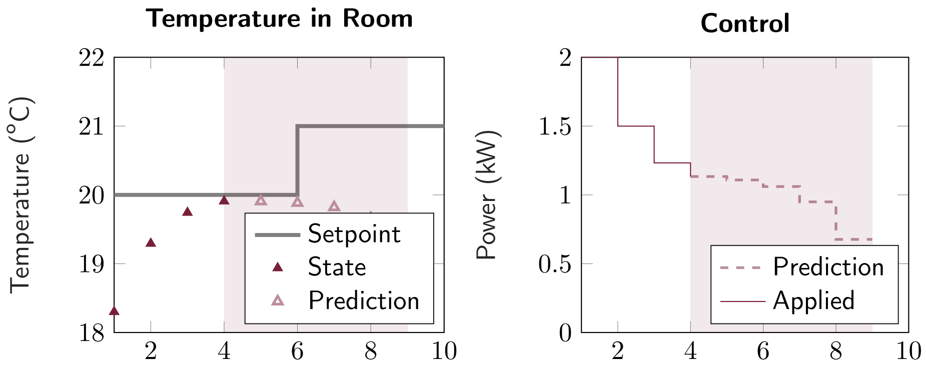
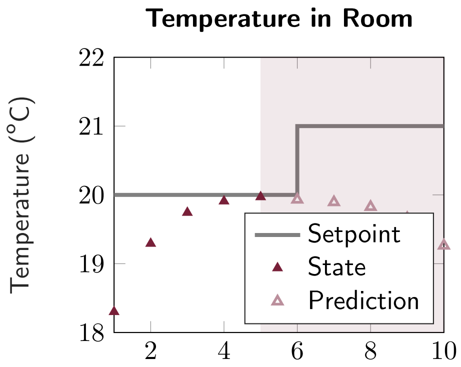
and then we repeat

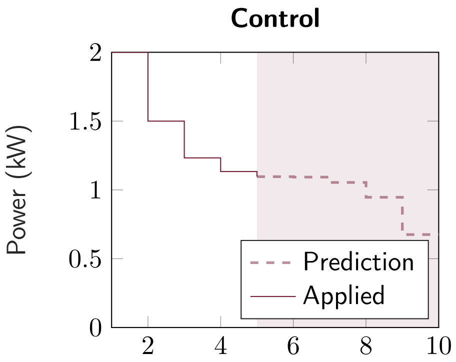
Find optimal control sequence, apply first element, rinse repeat → Receding Horizon



following what we call the receding horizon strategy. However this problem is not always straightforward to solve, for some cases it can be easier.

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





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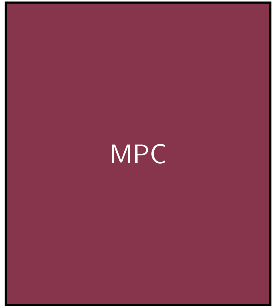
- Problem: Complexity depends on N, m, p and sizes of $\boldsymbol{x}$ and $\boldsymbol{u}$
- Solution: Divide and Conquer[1]



1

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However, the solution will depend on the horizon, the number of constraints, and sizes of input and states, increasing the complexity of the calculation

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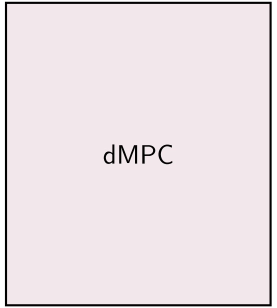

[1] *Distributed Model Predictive Control made easy*

A strategy to alleviate is to distribute the calculation whenever possible. And there are many ways to divide it as the book shows.

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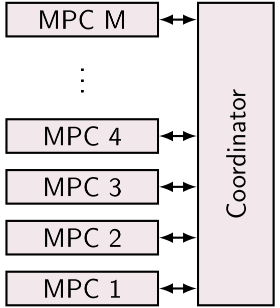

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Here we opt for a hierarchical strategy where we use multiple MPCs and an agent to coordinate and manage the coupling aspects of the problem.

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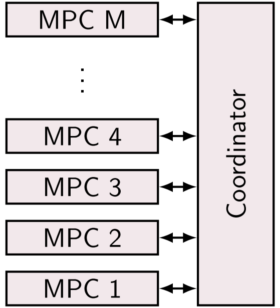

[1] *Distributed Model Predictive Control made easy*

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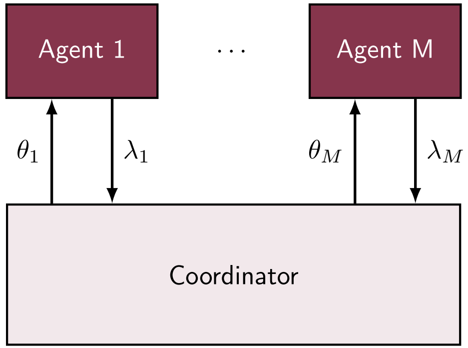
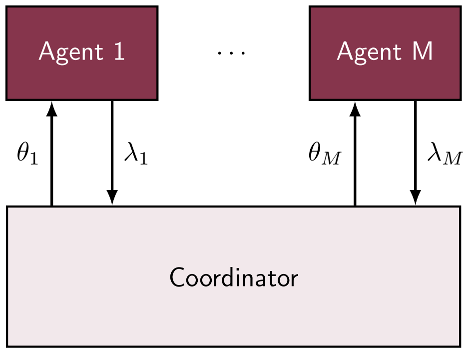


- Agents solve local problems
- Variables are updated

$\Big\}$ Until Convergence



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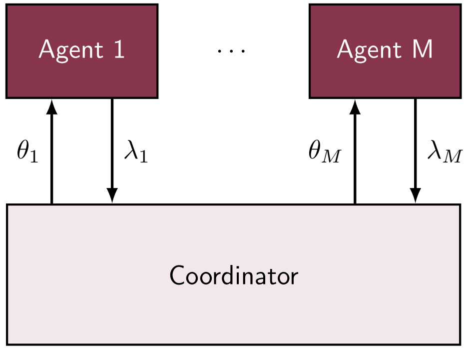

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Distributed Model Predictive Control

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

- What are the consequences of an attack?
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Distributed Model Predictive Control

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State of art

	Decomposition	Present vulnerabilities?	Resilient/Robust	Detection	Mitigation
[Vel+17a] [Mae+21]	Dual	Yes	Robust (Scenario)	NA	NA
[Vel+17b] [Vel+18]	Dual	Yes	Robust (f-robust)	NA	NA
[CMI18]	Jacobi-Gauß	Yes	–	–	–
[Ana+18] [Ana+19] [Ana+20]	Dual	Yes	Resilient	Analyt./Learn.	Disconnect (Robustness)
Our	Primal	Yes	Resilient	Active Analyt./Learn.	Data reconstruction

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Outline

1. Vulnerabilities in distributed MPC based on Primal Decomposition
2. Resilient Primal Decomposition-based dMPC for deprived systems
3. Resilient Primal Decomposition-based dMPC using Artificial Scarcity

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To respond this this presentation is divided into 3 parts.First we present the decomposition and its vulnerabilites,

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Distributed Model Predictive Control

Primal Decomposition | Quantity Decomposition | Resource Allocation

Decompose original problem using primal problem

An example of decomposition method is the Quantity decomposition where a semi-decomposable problem with a global coupling constraints can be decomposed into

Distributed Model Predictive Control

Decompose original problem using primal problem

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

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An example of decomposition method is the Quantity decomposition where a semi-decomposable problem with a global coupling constraints can be decomposed into multiple sub-problems, which can be solved in parallel, and a master problem which corresponds to the initial problem. Those coupling constraints are replaced by local constraints with an allocation theta i.

Distributed Model Predictive Control

Primal Decomposition | Quantity Decomposition | Resource Allocation

Decompose original problem using primal problem

$$
\begin{aligned}
\underset{\boldsymbol{u}[0:N-1|k]}{\text{minimize}} \quad & \sum_{i\in\mathcal{M}}\sum_{\xi\in\mathcal{N}}\left[\|\boldsymbol{v}_i[\xi|k]\|^2_{Q_i}+\|\boldsymbol{u}_i[\xi-1|k]\|^2_{R_i}\right] \\
\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])\leq 0 \\ h_j(\boldsymbol{x}[\xi-1|k],\boldsymbol{u}[\xi-1|k])=0\end{array}\right\}\begin{array}{l}\forall\xi\in\{1,\dots,N\} \\ \forall i\in\{1,\dots,m\} \\ \forall j\in\{1,\dots,p\}\end{array}
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Distributed Model Predictive Control

Decompose original problem using primal problem E.g. $v_i = w_i - x_i$

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Primal Decomposition | Quantity Decomposition | Resource Allocation

Decompose original problem using primal problem

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$$\begin{aligned} \underset{\boldsymbol{U}_1[k],\dots,\boldsymbol{U}_M[k]}{\text{minimize}} \quad & \sum_{i\in\mathcal{M}} \left[\frac{1}{2}\left\|\boldsymbol{U}_i[k]\right\|^2_{H_i} + \boldsymbol{f}_i[k]^T\boldsymbol{U}_i[k]\right] \\ \text{subject to} \quad & \sum_{i\in\mathcal{M}} \left[\bar{\Gamma}_i\boldsymbol{U}_i[k]\right] \preceq \boldsymbol{U}_{\max} \end{aligned}$$

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\text{subject to} \quad & \bar{\Gamma}_1\boldsymbol{U}_1[k] \preceq \boldsymbol{\theta}_1[k] : \boldsymbol{\lambda}_1[k] \\
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$$\boldsymbol{\theta}[k]^{(p+1)} = \mathrm{Proj}^{\mathcal{S}}(\boldsymbol{\theta}[k]^{(p)} + \rho^{(p)}\boldsymbol{\lambda}[k]^{(p)})$$

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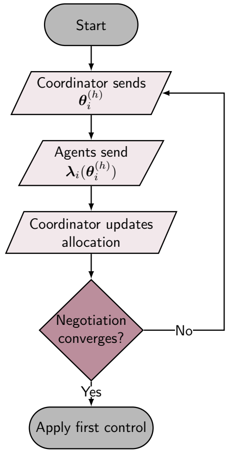
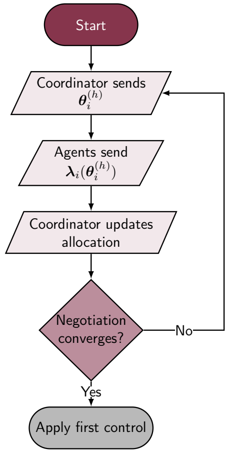
Quantity Decomposition | Resource Allocation



In a flowchart for a quantity decomposition based DMPC,

Quantity Decomposition | Resource Allocation



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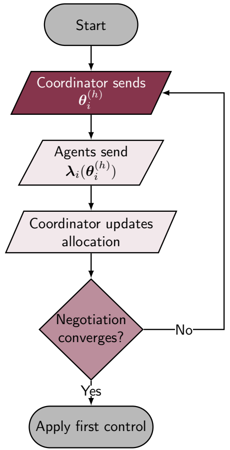

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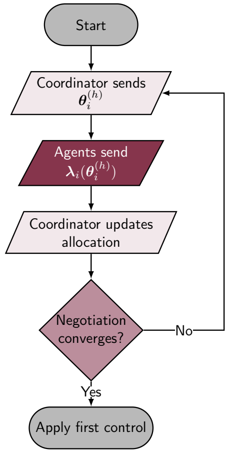
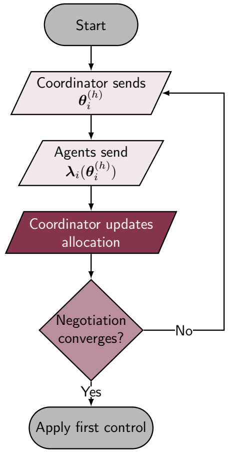
Quantity Decomposition | Resource Allocation



In a flowchart for a quantity decomposition based DMPC,the coordinator sends the allocation theta, the agents send the dual variable lambda,

Quantity Decomposition | Resource Allocation



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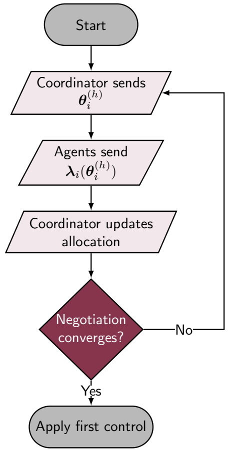
Quantity Decomposition | Resource Allocation



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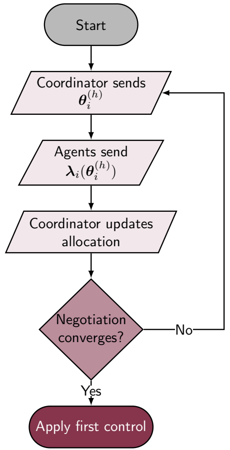
In a flowchart for a quantity decomposition based DMPC,the coordinator sends the allocation theta, the agents send the dual variable lambda, the coordinator updates the allocation. If negotiation converges,

Quantity Decomposition | Resource Allocation



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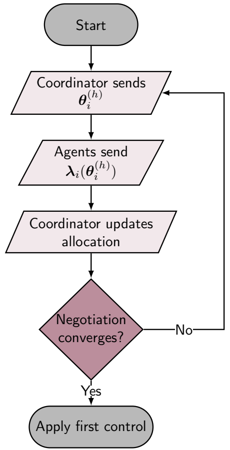

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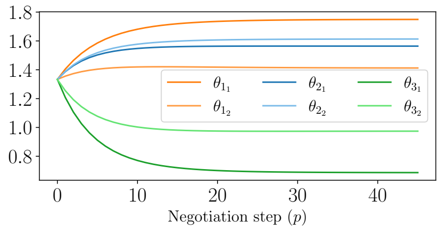

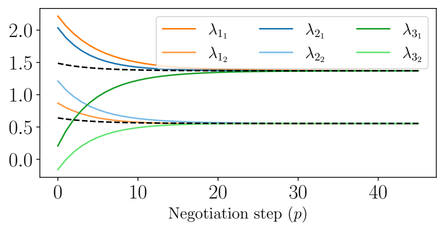

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How can a non-cooperative agent attack?

Literature

- [Vel+17a; CMI18] present some kinds of attacks
  - Objective function
    - Selfish Attack
    - Fake weights
    - Fake reference
  - Fake constraints
  - Liar agent (use different control)

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How can a non-cooperative agent attack?

Our approach

- $\boldsymbol{\lambda}_i$ is the only interface with coordination
- $\boldsymbol{\lambda}_i$ depends on the parameters of the system
- Malicious agent sends a different $\boldsymbol{\lambda}_i$

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How can an agent attack the system? Its only interface with the coordination is lambda

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How can an agent attack the system? Its only interface with the coordination is lambdaso we suppose it attacks by sending a different $lambda_i$, modified by a function $gamma_i$ of $lambda_i$

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Let's suppose $\gamma_i(\boldsymbol{\lambda}_i) = T_i$

How can an agent attack the system? Its only interface with the coordination is lambdaso we suppose it attacks by sending a different $lambda_i$, modified by a function $gamma_i$ of $lambda_i$

Example

4 distinct agents

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

We give an example of 4 agents negotiating

Example

4 distinct agents

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- It uses $\tilde{\boldsymbol{\lambda}}_1 = \gamma_1(\boldsymbol{\lambda}_1) = \tau_1 I \boldsymbol{\lambda}_1$

We give an example of 4 agents negotiating Agent 1 is non-cooperative

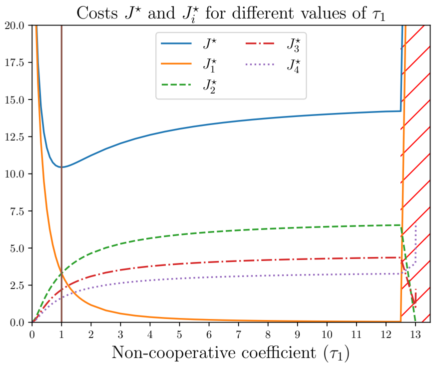
Example

4 distinct agents

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

We give an example of 4 agents negotiating Agent 1 is non-cooperative
It uses a linear cheating function gamma tau times identity times the original lambda i
In the figure we can see the cost functions for each agent, we see that agent 1 cost decreases if we increase tau, but the overall cost is increased, The minimum value of the global cost is when

Example



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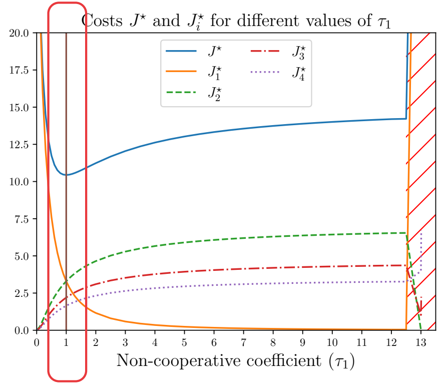

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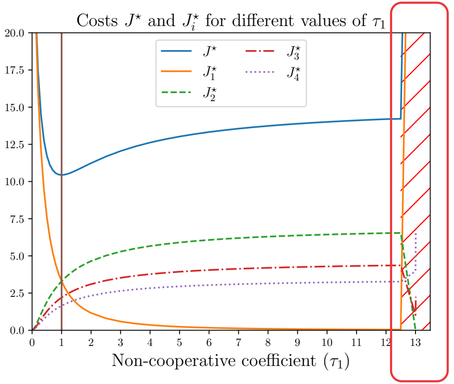

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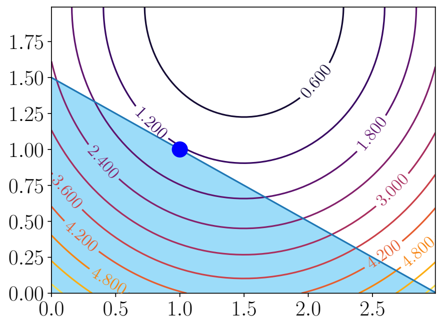

Original minimum.

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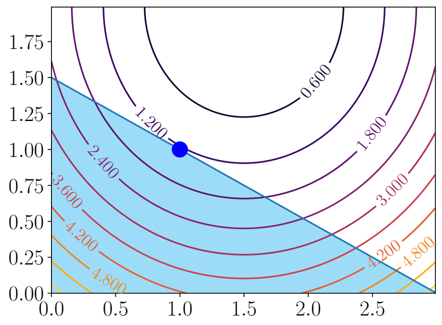

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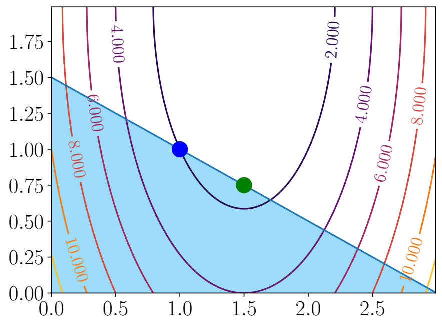

Minimum after attack.

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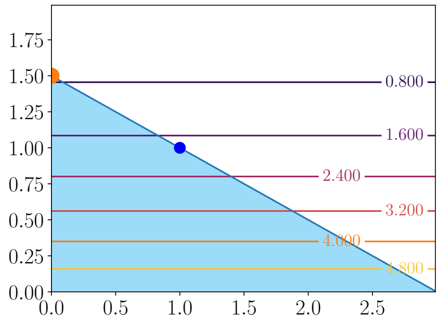

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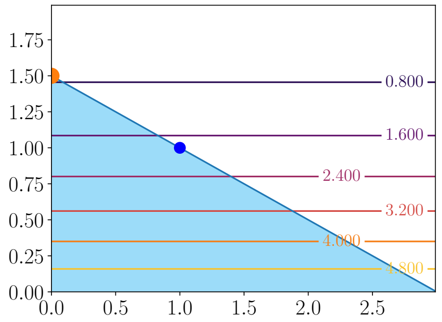

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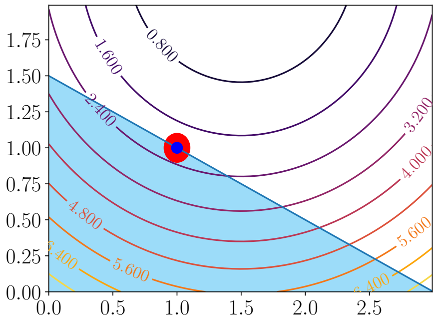

Recover original behavior.

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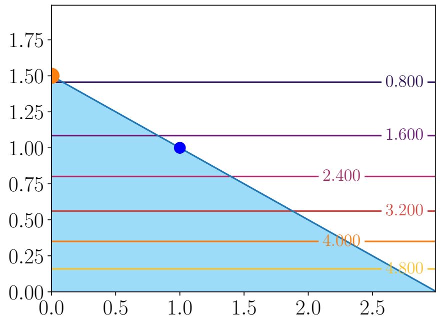

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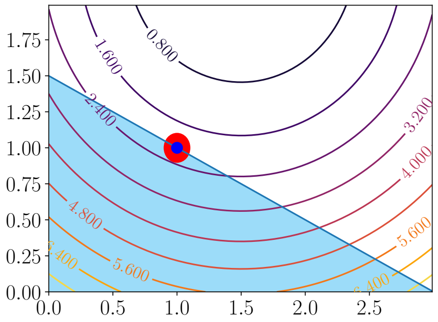

Recover original behavior.

Outline

2. Resilient Primal Decomposition-based dMPC for deprived systems

Strategy

- Recover original behavior
  - Invert effects of function $\gamma_i(\boldsymbol{\lambda}_i)$
- Is $\gamma_i(\boldsymbol{\lambda}_i)$ invertible?
  - Not necessarily, but let's reason

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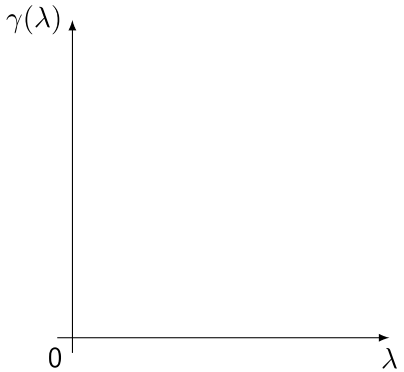
Unidimensional Case



- $\lambda \geq 0$ means dissatisfaction
- $\lambda = 0$ means complete satisfaction
  - $\gamma(\lambda) = 0 \Leftrightarrow \lambda = 0$

Assumptions

- Attacker is greedy $\gamma(\lambda) > \lambda$
- But not smart

  $\lambda_b > \lambda_a \rightarrow \gamma(\lambda_b) > \gamma(\lambda_a)$

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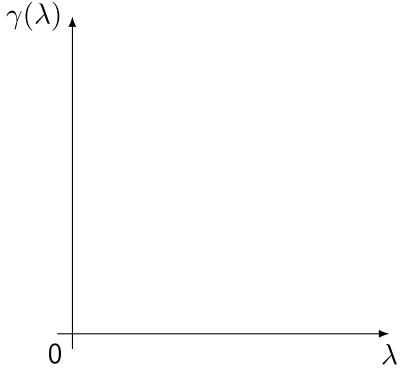

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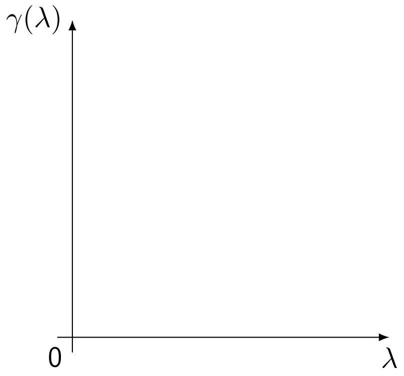

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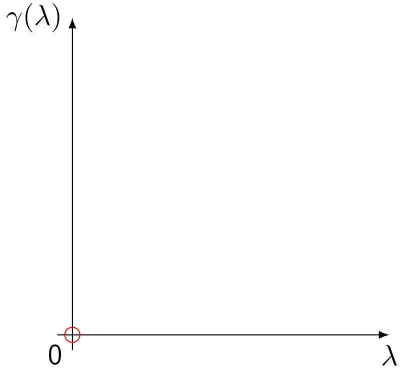

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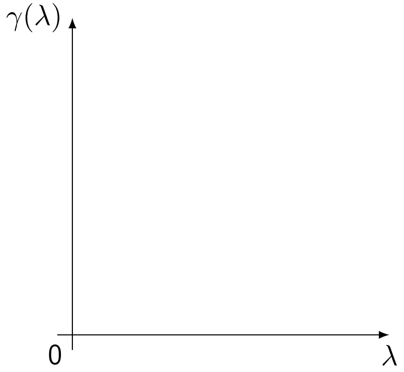

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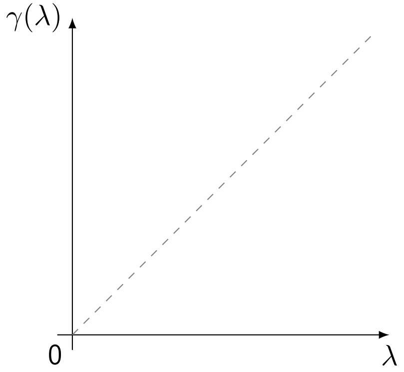

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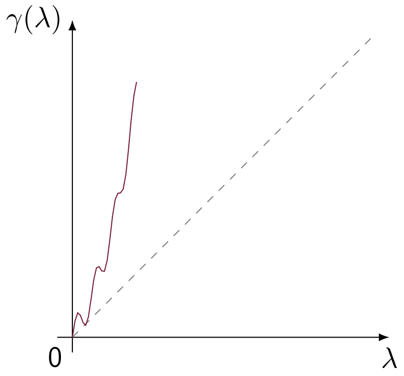

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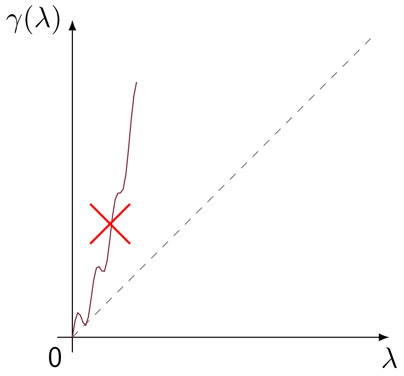

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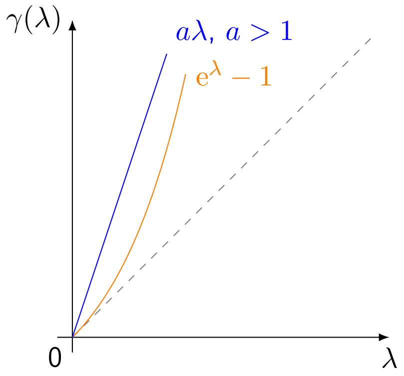

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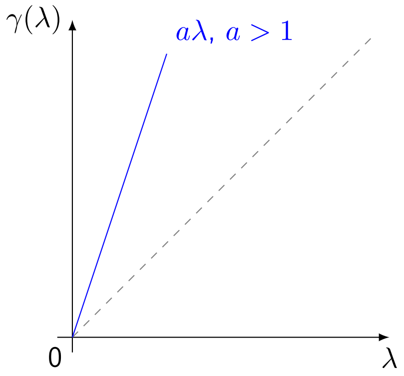

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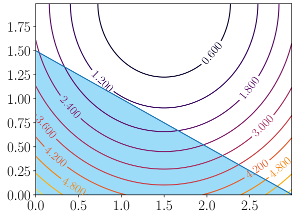

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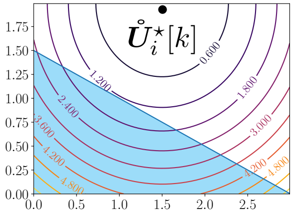

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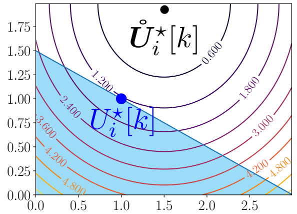

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- No Scarcity $\rightarrow$ All satisfied $\rightarrow \lambda_i = 0 \rightarrow$ No coordination needed
- Scarcity $\rightarrow$ Competition $\rightarrow$ Consensus/Compromise (or cheating)

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Deprived Systems

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- We can transform inequality constraints into equality ones[2]
- Solution is analytical and trivial.
  - If we solve for λ_i

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

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

where $P_i = (\bar{\Gamma}_i H_i^{-1}\bar{\Gamma}_i^T)^{-1}$ and $\boldsymbol{s}_i[k] = P_i\bar{\Gamma}_i H_i^{-1}\boldsymbol{f}_i[k]$.

[2]Under some conditions, see here

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Deprived Systems

Analysis

- We can transform inequality constraints into equality ones[2]
- Solution is analytical and trivial.
  - If we solve for λ_i

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

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

where $P_i = (\bar{\Gamma}_i H_i^{-1}\bar{\Gamma}_i^T)^{-1}$ and $\boldsymbol{s}_i[k] = P_i\bar{\Gamma}_i H_i^{-1}\boldsymbol{f}_i[k]$.

[2]Under some conditions, see here

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Outline

3. Resilient Primal Decomposition-based dMPC using Artificial Scarcity

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Thank you!

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

Contact
rafael.accacio.nogueira@gmail.com

If you want to see the simulations of this paper we have a github repository, and if you want to send me an email about this paper or this presentation you can flash the QR code in the right. Thank you!

For Further Reading I

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.

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.

As a recommended reading I give a book about distributed MPC and an article with another secure dmpc algorithm based in another decomposition method. That's all

For Further Reading II

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.

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.

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For Further Reading III

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.

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.

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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