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l.pedroso@tue.nl leonardopedroso.github.io Distributed decentralized control for very large-scale systems with application to LEO satellite mega-constellations



#### **Motivation**



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#### Distributed Decentralized Control

#### Introduction Motivation

Yet to transition from concept to **deployment** 



Inhibiting technical challenges on a very large-scale



**Decentralized** framework



Distributed synthesis



Paradigm revolution from a control standpoint



State-of-the-art overview





Goal: address the void to enable ground-breaking very large-scale applications

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Distributed Decentralized Control

#### Problem Framework

Control **objective** 



Regulator

Receding horizon (RHC)



Network of N systems

LTV

Approximate **nonlinear** systems

**Sparse** couplings

Decentralized framework



**Local** feedback

Very large-scale **feasibility** constraints

- On controller synthesis
  - On communication, computational, and memory
- **Feasible** real-time implementation

#### Approach overview



Local dynamics



Network dynamics

Directed dynamical coupling graph  $\mathcal{G}_d$ 



Directed **output** coupling graph  $\mathcal{G}_o$ 



$$\begin{cases} \mathbf{x}_i(k+1) = \sum_{j \in {}^d \mathcal{D}_i^-} \mathbf{A}_{i,j}(k) \mathbf{x}_j(k) + \sum_{j \in {}^d \mathcal{D}_i^-} \mathbf{B}_{i,j}(k) \mathbf{u}_j(k) \\ \mathbf{z}_i(k) = \sum_{j \in {}^o \mathcal{D}_i^-} \mathbf{H}_{i,j}(k) \mathbf{x}_j(k), \end{cases}$$

Grouping local dynamics

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{A}(k)\mathbf{x}(k) + \mathbf{B}(k)\mathbf{u}(k) \\ \mathbf{z}(k) = \mathbf{H}(k)\mathbf{x}(k), \end{cases}$$

#### Decentralized framework



#### Decentralized framework

Directed state feedback communication graph  $\mathcal{G}_c$ 

Each **system** is a **node** 

Each directed edge represents access to the state via communication



$$\mathbf{u}_i(k) = -\sum_{j \in {}^c \mathcal{D}_i^-} \mathbf{K}_{i,j}(k) \mathbf{x}_j(k)$$



Decentralized framework

$$\mathbf{u}_{i}(k) = -\sum_{j \in {}^{c}\mathcal{D}_{i}^{-}} \mathbf{K}_{i,j}(k) \mathbf{x}_{j}(k)$$
Grouping local control law

 $\mathbf{u}(k) = -\mathbf{K}(k)\mathbf{x}(k)$ 

But  $\mathbf{K}(k)$  must be sparse:  $\mathbf{K}(k) \in \text{Sparse}(\mathbf{E}_{\mathcal{G}_c})$ 

Sparse(**E**) := { [**K**]<sub>*ij*</sub> 
$$\in \mathbb{R}^{m \times n}$$
 : [**E**]<sub>*ij*</sub> = 0  $\implies$  [**K**]<sub>*ij*</sub> = 0; *i* = 1, ..., *m*, *j* = 1, ..., *n*}

Control objective



Control objective

$$J(k) = \mathbf{z}^{T}(k+H)\mathbf{Q}(k+H)\mathbf{z}(k+H) + \sum_{\tau=k}^{k+H-1} \left(\mathbf{z}^{T}(\tau)\mathbf{Q}(\tau)\mathbf{z}(\tau) + \mathbf{u}^{T}(\tau)\mathbf{R}(\tau)\mathbf{u}(\tau)\right),$$

Global finite-horizon cost:

- Finite linear-quadratic regulation problem
- **RHC** framework to approximate the **infinite-horizon** problem

#### Nonconvex optimization problem



Nonconvex optimization problem

At each discrete time instant k:

$$\begin{array}{ll}
\begin{array}{ll} \min_{\mathbf{K}(\tau)\in\mathbb{R}^{m\times n}} & J(k) \\
\tau\in\{k,\dots,k+H-1\} & \\
\end{array} \\ \text{subject to} & \mathbf{K}(\tau)\in\operatorname{Sparse}(\mathbf{E}_{\mathcal{G}_c}), \ \tau=k,\dots,k+H-1 \\
& \mathbf{u}(\tau)=-\mathbf{K}(\tau)\mathbf{x}(\tau), \ \tau=k,\dots,k+H-1 \\
& \mathbf{x}(\tau+1)=\mathbf{A}(\tau)\mathbf{x}(\tau)+\mathbf{B}(\tau)\mathbf{u}(\tau), \ \tau=k,\dots,k+H-1
\end{array}$$

#### Nonconvex!

#### Very large-scale feasibility constraints



Very large-scale feasibility constraints

Each system  $S_i$  is associated with a **computational unit**  $T_i$ 

**Synthesis** constraints on  $T_i$ :



Communication: instantaneous communication not allowed



**The communication**: complexity of  $\mathcal{O}(1)$  with N



Computational: complexity of  $\mathcal{O}(1)$  with N



**Memory**: complexity of  $\mathcal{O}(1)$  with N

**Convex relaxation** 



**Convex relaxation** 

#### Challenges:



Separation between **optimal** and **relaxed** solutions



Physically **meaningful** relaxation

#### Approach:



Obtain necessary conditions for a constrained minimum

**Optimal control** theory



Convex relaxation

Augment J(k) to write the Langrangian

$$J'(k) = \mathbf{x}^{T}(k+T)\mathbf{Q}(k+T)\mathbf{x}(k+T) + \sum_{\tau=k}^{k+T-1} \mathbf{x}^{T}(\tau) \left(\mathbf{Q}(\tau) + \mathbf{K}^{T}(\tau)\mathbf{R}(\tau)\mathbf{K}(\tau)\right) \mathbf{x}(\tau)$$
$$+ \sum_{\tau=k}^{k+T-1} \boldsymbol{\lambda}^{T}(\tau+1) \left[ \left(\mathbf{A}(\tau) - \mathbf{B}(\tau)\mathbf{K}(\tau)\right) \mathbf{x}(\tau) - \mathbf{x}(\tau+1) \right]$$

Define the **Hamiltonian** 

$$H(k) := \mathbf{x}^{T}(k) \left( \mathbf{Q}(k) + \mathbf{K}^{T}(k)\mathbf{R}(k)\mathbf{K}(k) \right) \mathbf{x}(k) + \boldsymbol{\lambda}^{T}(k+1) \left( \mathbf{A}(k) - \mathbf{B}(k)\mathbf{K}(k) \right) \mathbf{x}(k)$$

Convex relaxation

Rewrite the Langrangian

$$J'(k) = \mathbf{x}^T(k+T)\mathbf{Q}(k+T)\mathbf{x}(k+T) - \boldsymbol{\lambda}^T(k+T)\mathbf{x}(k+T) + H(k) + \sum_{\tau=k+1}^{k+T-1} \left(H(\tau) - \boldsymbol{\lambda}^T(\tau)\mathbf{x}(\tau)\right)$$

Stationarity:

$$\begin{cases} \frac{\partial J'(k)}{\partial \mathbf{\lambda}(\tau)} = 0, \quad \tau = k+1, \dots, k+T \\ \frac{\partial J'(k)}{\partial \mathbf{x}(\tau)} = 0, \quad \tau = k+1, \dots, k+T \\ \mathbf{l}_{i}^{T} \frac{\partial J'(k)}{\partial \mathbf{K}(\tau)} \mathbf{l}_{j} = 0, \quad [\mathbf{E}_{\mathcal{G}_{c}}]_{ij} \neq 0, \quad \tau = k, \dots, k+T-1 \\ \mathbf{l}_{i}^{T} \mathbf{K}(\tau) \mathbf{l}_{j} = 0, \quad [\mathbf{E}_{\mathcal{G}_{c}}]_{ij} = 0, \quad \tau = k, \dots, k+T-1 \end{cases} \qquad [\mathbf{l}_{i}]_{k} = \begin{cases} 1, \ k = i \\ 0, \ k \neq i \end{cases}$$

Result: neat identities involving the partial derivatives of the Hamiltonian

Convex relaxation

# Lemma From the stationarity conditions: $\lambda(k) = 2\mathbf{P}(k)\mathbf{x}(k)$ $\begin{cases} \mathbf{P}(k+T) = \mathbf{Q}(k+T) \\ \mathbf{P}(\tau) = \mathbf{Q}(\tau) + \mathbf{K}^{T}(\tau)\mathbf{R}(\tau)\mathbf{K}(\tau) + (\mathbf{A}(\tau) - \mathbf{B}(\tau)\mathbf{K}(\tau))^{T} \mathbf{P}(\tau+1) (\mathbf{A}(\tau) - \mathbf{B}(\tau)\mathbf{K}(\tau)) \end{cases}$ k+T-1 $\mathbf{x}(i)^{T} \mathbf{P}(i) \mathbf{x}(i) = \sum_{\tau=i}^{K+T} \mathbf{x}^{T}(\tau) \left( \mathbf{Q}(\tau) + \mathbf{K}^{T}(\tau) \mathbf{R}(\tau) \mathbf{K}(\tau) \right) \mathbf{x}(\tau) \\ + \mathbf{x}^{T}(k+T) \mathbf{Q}(k+T) \mathbf{x}(k+T), \quad i = k, \dots, k+T$

#### Proof by **induction**<sup>1</sup>

and

#### Similar to centralized

<sup>1</sup>Pedroso, L. and Batista, P., 2023. Discrete-time decentralized linear quadratic control for linear time-varying systems. International Journal of Robust and Nonlinear Control, 33(1), pp.67-101.

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Convex relaxation

Lemma Necessary condition for optimal gains:  $\begin{cases}
\mathbf{I}_{i}^{T} \left[ \left( \mathbf{S}(\tau) \mathbf{K}(\tau) - \mathbf{B}^{T}(\tau) \mathbf{P}(\tau+1) \mathbf{A}(\tau) \right) \mathbf{x}(\tau) \mathbf{x}^{T}(\tau) \right] \mathbf{I}_{j} = 0 &, [\mathbf{E}_{\mathcal{G}_{c}}]_{ij} \neq 0 \\
\mathbf{I}_{i}^{T} \mathbf{K}(\tau) \mathbf{I}_{j} = 0 &, [\mathbf{E}_{\mathcal{G}_{c}}]_{ij} \neq 0,
\end{cases}$ for  $\tau = k, \dots, k + T - 1$ ,  $\mathbf{S}(\tau) := \mathbf{B}^{T}(\tau) \mathbf{P}(\tau+1) \mathbf{B}(\tau) + \mathbf{R}(\tau)$ 

? Why is  $\mathbf{x}(\tau)\mathbf{x}^T(\tau)$  (of rank 1) here?

**Convex relaxation** 

Necessary condition for **optimal gains**  $(\tau = k, \dots, k + H - 1)$ 

$$\begin{cases} \left[ \left( \mathbf{S}(\tau) \mathbf{K}(\tau) - \mathbf{B}^T(\tau) \mathbf{P}(\tau+1) \mathbf{A}(\tau) \right) \mathbf{x}(\tau) \mathbf{x}^T(\tau) \right]_{ji} = 0 &, [\mathbf{E}_{\mathcal{G}_c}]_{ji} \neq 0 \\ [\mathbf{K}(\tau)]_{ji} = 0 &, [\mathbf{E}_{\mathcal{G}_c}]_{ji} = 0 \end{cases}$$

 $\mathbf{P}(\tau+1)$  and  $\mathbf{S}(\tau)$  given by a **backward** recursion

Saddle point satisfies these conditions

**?**  $\mathbf{x}(\tau)$  is **not fully known** by any individual system

**Relaxed** conditions:

$$\begin{cases} \left[ \mathbf{S}(\tau)\mathbf{K}(\tau) - \mathbf{B}^{T}(\tau)\mathbf{P}(\tau+1)\mathbf{A}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} \neq 0\\ \left[ \mathbf{K}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} = 0 \end{cases} \end{cases}$$

Convex relaxation

#### Lemma (One-step relaxed solution)

Let  $I_j$  denote a column vector whose entries are all set to zero except for the j-th one, which is set to 1, and  $\mathcal{L}_j := \operatorname{diag}(I_j)$ . Define  $\mathbf{m}_j \in \mathbb{R}^m$  as

$$\begin{cases} [\mathbf{m}_j]_i = 0, & [\mathbf{E}_{\mathcal{G}_c}]_{ij} = 0\\ [\mathbf{m}_j]_i = 1, & [\mathbf{E}_{\mathcal{G}_c}]_{ij} \neq 0 \end{cases}, \ i = 1, ..., m,$$

and let  $\mathcal{M}_j := \operatorname{diag}(\mathbf{m}_j)$ . Then, the gains of the one-step relaxation are given by

$$\mathbf{K}(\tau) = \sum_{j=1}^{n} (\mathbf{I} - \mathcal{M}_{j} + \mathcal{M}_{j} \mathbf{S}(\tau) \mathcal{M}_{j})^{-1} \mathcal{M}_{j} \mathbf{B}^{T}(\tau) \mathbf{P}(\tau + 1) \mathbf{A}(\tau) \mathcal{L}_{j},$$
  
$$\tau = k, \dots, k + H - 1.$$

**Convex relaxation** 

#### Overview:



- Does **not depend** on the initial condition  $\mathbf{x}(\tau)$ 
  - **is not fully known** by any individual system

**Closed-form** solution

Computational complexity<sup>1</sup> of  $O(n^3)$ 

- same as centralized
- **?** Can we find any **physical interpretation**?

<sup>1</sup>Pedroso, L. and Batista, P., 2021. Efficient algorithm for the computation of the solution to a sparse matrix equation in distributed control theory. Mathematics, 9(13), p.1497.

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**Convex relaxation** 

**?** Can we find any **physical interpretation**?



**One-step** relaxation is **equivalent** to

 $\begin{array}{ll} \underset{\mathbf{K}(\tau)\in\mathbb{R}^{m\times n}}{\text{minimize}} & \operatorname{tr}(\mathbf{P}(\tau))\\ \text{subject to} & \mathbf{K}(\tau)\in\operatorname{Sparse}(\mathbf{E}_{\mathcal{G}_c}) \end{array}$ 

for  $\tau = k, \dots, k + H - 1$ 

- Decoupled in time (greedy)
- lgn
  - Ignores cross-correlation between states

Proof <sup>1</sup>

<sup>1</sup>Pedroso, L. and Batista, P., 2023. Discrete-time decentralized linear quadratic control for linear time-varying systems. International Journal of Robust and Nonlinear Control, 33(1), pp.67-101.

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#### Linear quadratic tracker



<sup>1</sup>Pedroso, L. and Batista, P., 2023. Discrete-time decentralized linear quadratic control for linear time-varying systems. International Journal of Robust and Nonlinear Control, 33(1), pp.67-101.

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Distributed Decentralized Control



Challenges and approach

Challenges:



**One-step** synthesis is **not distributed** 



One-step synthesis does not follow the very large-scale feasibility constraints

#### Approach:



Particular case of **dynamically decoupled** systems



An approximation to decouple the one-step synthesis



Local computations scheduling

Gain synthesis decoupling

**Decoupled** dynamic coupling graph and  $\mathcal{G}_c = \mathcal{G}_o = \mathcal{G}$ 

**Relaxed original** one-step conditions:

$$\begin{cases} \left[ \mathbf{S}(\tau)\mathbf{K}(\tau) - \mathbf{B}^{T}(\tau)\mathbf{P}(\tau+1)\mathbf{A}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} \neq 0\\ \left[ \mathbf{K}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} = 0 \end{cases} \end{cases}$$

Block matrix decomposition

$$\begin{cases} \sum_{p \in \mathcal{D}_i^+} \mathbf{S}_{j,p}(\tau) \mathbf{K}_{p,i}(\tau) - \mathbf{B}_j^T(\tau) \mathbf{P}_{j,i}(\tau+1) \mathbf{A}_i(\tau) = \mathbf{0}, & j \in \mathcal{D}_i^+ \\ \mathbf{K}_{j,i}(\tau) = \mathbf{0}, & j \notin \mathcal{D}_i^+ \end{cases}$$

Gain synthesis decoupling

**Decoupled** dynamic coupling graph and  $\mathcal{G}_c = \mathcal{G}_o = \mathcal{G}$ 

Relaxed original one-step conditions:

$$\begin{cases} \left[ \mathbf{S}(\tau)\mathbf{K}(\tau) - \mathbf{B}^{T}(\tau)\mathbf{P}(\tau+1)\mathbf{A}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} \neq 0 \\ \left[ \mathbf{K}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} = 0 \end{cases} \\ \end{cases}$$

$$\begin{array}{l} \mathbf{Block \ matrix} \\ \text{decomposition} \end{array}$$

$$\mathbf{P}_{p,q}(\tau) = \sum_{r \in \mathcal{D}_{p}^{+} \cap \mathcal{D}_{q}^{+}} \mathbf{H}_{r,i}^{T}(\tau)\mathbf{Q}_{r}(\tau)\mathbf{H}_{r,j}(\tau) + \sum_{r \in \mathcal{D}_{p}^{+} \cap \mathcal{D}_{q}^{+}} \mathbf{K}_{r,i}^{T}(\tau)\mathbf{R}_{r}(\tau)\mathbf{K}_{r,j}(\tau) \\ + \sum_{r \in \mathcal{D}_{p}^{+} \cap \mathcal{D}_{q}^{+}} \mathbf{P}_{r,i}(\tau)\mathbf{N}_{r,i}(\tau) \mathbf{P}_{r,i}(\tau)\mathbf{R}_{r,$$

+  $\sum_{r \in \mathcal{D}_p^+} \sum_{s \in \mathcal{D}_q^+} \left( \mathbf{A}_p(\tau) \boldsymbol{\delta}_{pr} - \mathbf{B}_r(\tau) \mathbf{K}_{r,p}(\tau) \right)^T \mathbf{P}_{r,s}(\tau+1) \left( \mathbf{A}_q(\tau) \boldsymbol{\delta}_{qs} - \mathbf{B}_s(\tau) \mathbf{K}_{s,q}(\tau) \right)$ 

Gain synthesis decoupling

**Decoupled** dynamic coupling graph and  $\mathcal{G}_c = \mathcal{G}_o = \mathcal{G}$ 

Relaxed original one-step conditions:

$$\begin{cases} \left[ \mathbf{S}(\tau)\mathbf{K}(\tau) - \mathbf{B}^{T}(\tau)\mathbf{P}(\tau+1)\mathbf{A}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} \neq 0\\ \left[ \mathbf{K}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} = 0 \end{cases} \end{cases}$$

Block matrix decomposition

The local gains  $\mathbf{K}_{j,i}(\tau), \ j \in \mathcal{D}_i^+$  can be computed locally in  $\mathcal{T}_i$ But the propagation of  $\mathbf{P}_{j,i}(\tau+1)$  cannot!

$$\begin{aligned} \mathbf{P}_{p,q}(\tau) &= \sum_{r \in \mathcal{D}_p^+ \cap \mathcal{D}_q^+} \mathbf{H}_{r,i}^T(\tau) \mathbf{Q}_r(\tau) \mathbf{H}_{r,j}(\tau) + \sum_{r \in \mathcal{D}_p^+ \cap \mathcal{D}_q^+} \mathbf{K}_{r,i}^T(\tau) \mathbf{R}_r(\tau) \mathbf{K}_{r,j}(\tau) \\ &+ \sum_{r \in \mathcal{D}_p^+} \sum_{s \in \mathcal{D}_q^+} \left( \mathbf{A}_p(\tau) \boldsymbol{\delta}_{pr} - \mathbf{B}_r(\tau) \mathbf{K}_{r,p}(\tau) \right)^T \mathbf{P}_{r,s}(\tau+1) \left( \mathbf{A}_q(\tau) \boldsymbol{\delta}_{qs} - \mathbf{B}_s(\tau) \mathbf{K}_{s,q}(\tau) \right) \end{aligned}$$

Gain synthesis decoupling

**Decoupled** dynamic coupling graph and  $\mathcal{G}_c = \mathcal{G}_o = \mathcal{G}$ 

Relaxed original one-step conditions:

$$\begin{cases} \left[ \mathbf{S}(\tau)\mathbf{K}(\tau) - \mathbf{B}^{T}(\tau)\mathbf{P}(\tau+1)\mathbf{A}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} \neq 0\\ \left[ \mathbf{K}(\tau) \right]_{ji} = 0, & \left[ \mathbf{E}_{\mathcal{G}_{c}} \right]_{ji} = 0 \end{cases} \end{cases}$$



The local gains  $\mathbf{K}_{j,i}(\tau), \ j \in \mathcal{D}_i^+$  can be computed locally in  $\mathcal{T}_i$ But the propagation of  $\mathbf{P}_{j,i}(\tau+1)$  cannot!

Gain synthesis decoupling







Approximation:  $\psi_i o \mathbf{P}_{i,(r,s)}( au+1) pprox \mathbf{0}$ 





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 $\boldsymbol{q}$ 

May 2023

i

-

p

 $\boldsymbol{S}$ 

Gain synthesis decoupling



Scheduling

Obstacle:



Only the first gain in each finite-window used



The propagation of  $\mathbf{P}_{i,(p,q)}( au), \forall p,q \in \mathcal{D}_i^+$  is backward in time!



Computation of a whole finite-window every time instant



Infeasible due to transmission delays

Local RHC computations scheduling

$$t = kT_c$$
  $t = (k+1)T_c$   $t = (k+2)T_c$   $\cdots$ 

Scheduling

#### Obstacle:



Only the first gain in each finite-window used



The propagation of  $\mathbf{P}_{i,(p,q)}( au), \forall p,q \in \mathcal{D}_i^+$  is backward in time!



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Scheduling

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Computation of a whole finite-window every time instant



Infeasible due to transmission delays



$$t = kT_c$$
 $t = (k+d)T_c$ 
 $\mathbf{u}_i( au) = -\sum_{j\in\mathcal{D}_i^-} \mathbf{K}_{i,j}( au)\mathbf{x}_j( au), \ au = k, \dots, k+d-1$ 

Scheduling

#### Obstacle:



Only the first gain in each finite-window used



The propagation of  $\mathbf{P}_{i,(p,q)}( au), orall p,q\in\mathcal{D}_i^+$  is backward in time!



Computation of a whole finite-window every time instant



Infeasible due to transmission delays







Scheduling

#### Obstacle:



Only the first gain in each finite-window used



The propagation of  $\mathbf{P}_{i,(p,q)}( au), orall p,q\in\mathcal{D}_i^+$  is backward in time!



Computation of a whole finite-window every time instant



Infeasible due to transmission delays

#### Local RHC computations scheduling



Scheduling

Obstacle:



Only the first gain in each finite-window used



The propagation of  $\mathbf{P}_{i,(p,q)}( au), orall p,q\in\mathcal{D}_i^+$  is backward in time!



Computation of a whole finite-window every time instant



- Infeasible due to transmission delays
- Local RHC computations scheduling



Satisfies the very large-scale feasibility constraints!

Overview and extension

Overview:



Distributed decentralized real-time synthesis



Distributed RHC computations scheduling



Satisfies the very large-scale feasibility constraints!

#### Extension:



<sup>1</sup>Pedroso, L. and Batista, P., 2022. Distributed decentralized receding horizon control for very large-scale networks with application to LEO satellite mega-constellations. arXiv preprint arXiv:2209.14951.

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**Very large-scale** (Starlink: 11 900 satellites planned by 2027)







Greatest concern is economic viability



Centralized TT&C architecture



Expensive and challenging to maintain



**We** Inevitably evolving towards an **on-board distributed** solution



State-of-the-art decentralized solutions fail in this scale



Single shell of the Starlink mega-constellation

**Constellation model** 



y

Nominal constellation



Nonlinear orbital dynamics



**Linearization** about nominal orbit  $\bar{\mathbf{x}}_i(t) = \begin{bmatrix} \bar{a}_i(t) \ \bar{u}_i(t) \ \bar{e}_{xi}(t) \ \bar{e}_{yi}(t) \ \bar{i}_i(t) \ \bar{\Omega}_i(t) \end{bmatrix}^T$ 

$$\begin{aligned} \bar{a}_{i}(t) &= \bar{a} \\ \bar{u}_{i}(t) &= \bar{u}_{t_{0}} + ((i-1) \mod T/P) 2\pi P/T + \lfloor (i-1)P/T \rfloor 2\pi F/T + (\dot{M} + \dot{\omega})(t-t_{0}) \\ \bar{e}_{x,i}(t) &= 0 \\ \bar{e}_{y,i}(t) &= 0 \\ \bar{i}_{i}(t) &= \bar{i} \\ \bar{\Omega}_{i}(t) &= \bar{\Omega}_{t_{0}} + \lfloor (i-1)P/T \rfloor 2\pi/P + \dot{\Omega}(t-t_{0}) \end{aligned}$$

Nominal constellation



Nonlinear orbital dynamics



**Linearization** about nominal orbit  $\bar{\mathbf{x}}_i(t) = \begin{bmatrix} \bar{a}_i(t) \ \bar{u}_i(t) \ \bar{e}_{xi}(t) \ \bar{e}_{yi}(t) \ \bar{i}_i(t) \ \bar{\Omega}_i(t) \end{bmatrix}^T$ 

$$\begin{split} \bar{a}_i(t) &= \bar{a} \\ \bar{u}_i(t) &= \bar{u}_{t_0} + ((i-1) \mod T/P) 2\pi P/T + \lfloor (i-1)P/T \rfloor 2\pi F/T + (\dot{M} + \dot{\omega})(t-t_0) \\ \bar{e}_{x,i}(t) &= 0 \\ \bar{e}_{y,i}(t) &= 0 \\ \bar{i}_i(t) &= \bar{i} \\ \bar{\Omega}_i(t) &= \bar{\Omega}_{t_0} + \lfloor (i-1)P/T \rfloor 2\pi/P + \dot{\Omega}(t-t_0) \end{split}$$



Secular perturbations due to  $J_2$ 

Nominal constellation



Nonlinear orbital dynamics



**Linearization** about nominal orbit  $\bar{\mathbf{x}}_i(t) = \begin{bmatrix} \bar{a}_i(t) \ \bar{u}_i(t) \ \bar{e}_{xi}(t) \ \bar{e}_{yi}(t) \ \bar{i}_i(t) \ \bar{\Omega}_i(t) \end{bmatrix}^T$ 

$$\begin{split} \bar{a}_i(t) &= \bar{a} \\ \bar{u}_i(t) &= \bar{u}_{t_0} + ((i-1) \mod T/P) 2\pi P/T + \lfloor (i-1)P/T \rfloor 2\pi F/T + (\dot{M} + \dot{\omega})(t - t_0) \\ \bar{e}_{x,i}(t) &= 0 \\ \bar{e}_{y,i}(t) &= 0 \\ \bar{i}_i(t) &= \bar{i} \\ \bar{\Omega}_i(t) &= \bar{\Omega}_{t_0} + \lfloor (i-1)P/T \rfloor 2\pi/P + \dot{\Omega}(t - t_0) \end{split}$$

Secular perturbations due to  $J_2$ 

 $(t_0, \bar{u}_{t_0}, \bar{\Omega}_{t_0})$  is the **anchor** of the nominal constellation

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Linearization



**Relative** orbital elements (in relation to **nominal state**)

$$\delta \mathbf{x}_{i}(t) := \begin{bmatrix} a_{i}(t) \\ \delta u_{i}(t) \\ \delta e_{x,i}(t) \\ \delta e_{y,i}(t) \\ \delta i_{i}(t) \\ \delta \Omega_{i}(t) \end{bmatrix} = \begin{bmatrix} a_{i}(t)/\bar{a}_{i}(t) - 1 \\ u_{i}(t) - \bar{\Omega}_{i}(t) - \bar{\Omega}_{i}(t) \end{bmatrix} cos \bar{i}_{i}(t) \\ e_{x,i}(t) - \bar{e}_{x,i}(t) \\ e_{y,i}(t) - \bar{e}_{y,i}(t) \\ i_{i}(t) - \bar{i}_{i}(t) \\ (\Omega_{i}(t) - \bar{\Omega}_{i}(t)) \sin \bar{i}_{i}(t) \end{bmatrix}$$



D'Amico, S. (2010).

Autonomous formation flying in low earth orbit. PhD thesis, TU Delft.



$$\delta \mathbf{x}_i((k+1)T_c) = \mathbf{A}_i(k)\delta \mathbf{x}_i(kT_c) + \mathbf{B}_i(k)\mathbf{u}_i(kT_c)/m_i(kT_c)$$

Tracking output: Inertial







Inclination

**Solution** Inertial tracking output of satellite  $S_i$ 

$$\mathbf{z}_{i,in}(k) = \begin{bmatrix} a_i(k) - \bar{a}_i(k) \\ e_{x,i}(k) - \bar{e}_{x,i}(k) \\ e_{y,i}(k) - \bar{e}_{y,i}(k) \\ i_i(k) - \bar{i}_i(k) \end{bmatrix} = \begin{bmatrix} \bar{a}_i(k)\delta a_i(k) \\ \delta e_{x,i}(k) \\ \delta e_{y,i}(k) \\ \delta i_i(k) \end{bmatrix}$$

Tracking output: Relative



Relative tracking of

- Mean argument of latitude
- Longitude of ascending node
- Goal: maintain the constellation shape

Sparse couplings with satellites in close proximity

Within a range R up to a maximum of  $|\mathcal{D}^-|_{\max}$  satellites in each in-neighborhood

**We Relative tracking output** of satellite  $\mathcal{S}_i$  with respect to  $\mathcal{S}_j, \ j \in \mathcal{D}_i^-$ 

$$\mathbf{z}_{i,j}^{ref}(k) := \begin{bmatrix} u_i(k) - u_j(k) - (\bar{u}_i(k) - \bar{u}_j(k)) \\ \Omega_i(k) - \Omega_j(k) - (\bar{\Omega}_i(k) - \bar{\Omega}_j(k)) \end{bmatrix} = \begin{bmatrix} \delta u_i(k) - \delta u_j(k) - (\delta \Omega_i(k) - \delta \Omega_j(k)) / \tan \overline{i} \\ (\delta \Omega_i(k) - \delta \Omega_j(k)) / \sin \overline{i} \end{bmatrix}$$

Tracking output: Relative

**Relative tracking output** of satellite  $S_i$ 

$$\mathbf{z}_{i,j}^{ref}(k) := \begin{bmatrix} \mathbf{u}_i(k) - \mathbf{u}_j(k) - (\bar{\mathbf{u}}_i(k) - \bar{\mathbf{u}}_j(k)) \\ \Omega_i(k) - \Omega_j(k) - (\bar{\Omega}_i(k) - \bar{\Omega}_j(k)) \end{bmatrix} = \begin{bmatrix} \delta u_i(k) - \delta u_j(k) - (\delta \Omega_i(k) - \delta \Omega_j(k)) / \tan \overline{i} \\ (\delta \Omega_i(k) - \delta \Omega_j(k)) / \sin \overline{i} \end{bmatrix}$$



Satellites are **not driven** towards the **nominal** constellation!



Illustrative Constellation, Tuning and Simulation





#### Simulation

**High-fidelity** orbit propagation (TUDAT Toolbox)



**Perturbations:** EGM96 gravity potential, NRLMSISE-00 atmospheric drag, solar radiation pressure, third body



Simulation results



Global mean absolute error (MAE) of semi-major axis

Global mean absolute error (MAE) of mean argument of latitude and longitude of ascending node



#### Conclusion



Inhibiting technical challenges on a very large-scale networked control systems



Convex relaxation of the decentralized problem





Promising performance on the pressing shape-keeping task of LEO mega-constellations



No state-of-the-art solutions can address this problem in such scale

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