



# Dynamic Max-Consensus with Local Self-Tuning

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# Outline

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# Scenarios



Peer-to-Peer Networks



Wireless Sensor Networks



Multi-Robot Systems

## Problem set-up

Undirected network  $\rightarrow \mathcal{G} = (\mathcal{V}, \mathcal{E})$

Set of agents  $\rightarrow \mathcal{V} = \{1, \dots, n\}$

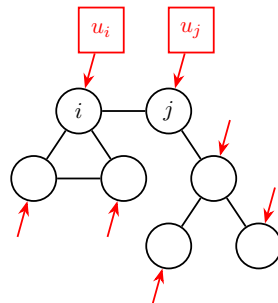
Set of interactions  $\rightarrow \mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$

State of agent  $i \rightarrow x_i \in \mathbb{R}$

Reference signal of agent  $i \rightarrow u_i \in \mathbb{R}$

Neighbors of agent  $i \rightarrow \mathcal{N}_i = \{j \mid (i, j) \in \mathcal{E}\}$

Framework  $\rightarrow$  Discrete-time  $k \in \mathbb{N}$



$$x_i(k) = f_i(u_i(k), x_i(k-1), x_j(k-1) : j \in \mathcal{N}_i), \quad i \in \mathcal{V} \quad (1)$$

### Objective

The agents must cooperate to track the time-varying **maximum value** of the reference signals,

$$\bar{u}(k) = \max\{u_1(k), \dots, u_n(k)\}.$$

## Definition: Dynamic consensus problem

Design the local interaction rules  $f_i$  such that the agents' state  $x_i$  converges to a scalar function  $g: \mathbb{R}^n \rightarrow \mathbb{R}$  of the reference signals  $u_1, \dots, u_n$ , i.e., there exists  $\varepsilon \geq 0$  such that

$$\|x_i(k) - g(u_1(k), \dots, u_n(k))\| \leq \varepsilon, \quad k \geq k^*, \quad i \in \mathcal{V},$$

The **average** (*sum of values of a data set divided by number of values*):

- Spanos, Olfati-Saber, and Murray, "Dynamic consensus on mobile networks", in *IFAC World Congr.* (2005)
- Freeman, Yang, and Lynch, "Stability and convergence properties of dynamic average consensus estimators", in *IEEE 45th Conf. on Dec. and Control* (2006)
- Zhu and Martinez, "Discrete-time dynamic average consensus", in *Automatica* (2010)
- Chen, Cao and Ren, "Distributed average tracking of multiple time-varying reference signals with bounded derivatives", in *IEEE Trans. Autom. Control* (2012).
- Kia, Cortés, and Martinez "Dynamic average consensus under limited control authority and privacy requirements", in *Int. Journal of Robust and Nonlin. Control* (2015)
- Scoy, Freeman, and Lynch, "A fast robust nonlinear dynamic average consensus estimator in discrete time", in *5th IFAC NecSys* (2015)
- Franceschelli, and Gasparri, "Multi-stage discrete time and randomized dynamic average consensus", in *Automatica* (2019)
- George and Freeman, "Robust dynamic average consensus algorithms", in *IEEE Trans. Autom. Control* (2019)
- Montijano E. and J.I., Sagues, and Martinez, "Robust discrete time dynamic average consensus", in *IEEE Trans. Autom. Control* (2019)
- Kia, Scoy, Cortés, Freeman, Lynch and Martinez, "Tutorial on dynamic average consensus: The problem, its applications, and the algorithms", in *IEEE Control Systems Magazine* (2019).

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$$\|x_i(k) - g(u_1(k), \dots, u_n(k))\| \leq \varepsilon, \quad k \geq k^*, \quad i \in \mathcal{V},$$

The **median** (*middle value separating the greater and lesser halves of a data set*):

- Sanai Dashti, Seatzu, and Franceschelli, "Dynamic consensus on the median value in open multi-agent systems", in *IEEE 58th Conf. on Dec. and Control* (2019).
- Vasiljevic, Petrovic, Arbanas, and Bogdan, "Dynamic median consensus for marine multi-robot systems using acoustic communication", in *IEEE Robot. and Autom. Lett.* (2020).
- Yu, Chen and Kar, "Dynamic median consensus over random networks", in *IEEE 60th Conf. on Dec. and Control* (2021).

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$$\|x_i(k) - g(u_1(k), \dots, u_n(k))\| \leq \varepsilon, \quad k \geq k^*, \quad i \in \mathcal{V},$$

The **maximum** (*highest value of a data set*).

- Deplano, Franceschelli, Giua, "Discrete-time Dynamic consensus on the max value", in *15th European Workshop on Advanced Control and Diagnosis*, Springer (2021)
- Deplano, Franceschelli, and Giua, "Dynamic min and max consensus and size estimation of anonymous multi-agent networks", in *IEEE Trans. Autom. Control* (2021, in press).
- Sen, Sahoo, and Slingh, "Global max-tracking of multiple time-varying signals using a distributed protocol", in *IEEE Control and Sys. Lett.* (2022)



# Main contributions

## Contribution 1

A novel protocol to solve the dynamic max-consensus problem with the following features:

- **Robustness** to re-initialization;
- **Scalability** in large networks;
- **Self-tuning logic** for arbitrary small steady state error;
- **Boundedness** of the tracking error.

## Contribution 2

A novel algorithm to track graph's parameters tracking problems in open time-varying networks:

- **Cardinality**, the number of agents in a network;
- **Radius/diameter**, the length of the minimum/maximum distance between the agents.

Possible applications of the proposed protocol range across different fields:

- **Real-time monitoring** in decentralized systems;  
Simpson-Porco and Bullo, "Distributed monitoring of voltage collapse sensitivity indices", in *IEEE Trans. Smart Grid* (2016)
- **Network's parameter estimation** in anonymous networks;  
Garin, Varagnolo, and Johansson, "Distributed estimation of diameter, radius and eccentricities in anonymous networks", in *3rd IFAC NecSys* (2012)  
Varagnolo, Pillonetto, and Schenato, "Distributed cardinality estimation in anonymous networks", in *IEEE Trans. Autom. Control* (2013)
- **Online optimization** in distributed systems;  
Jiang and Charalambous, "Distributed ADMM using finite-time exact ratio consensus in digraphs", in *European Control Conf.* (2021)  
Bastianello and Carli, "ADMM for Dynamic Average Consensus Over Imperfect Networks", in *9th IFAC NecSys* (2022)
- **Distributed synchronization** in wireless sensor networks;  
Z. Dengchang *et al.*, "Time synchronization in wireless sensor networks using max and average consensus protocol" (2013)
- **Leader election** in multi-agent systems;  
T. Borsche and S. A. Attia, "On leader election in multi-agent control systems" (2010)
- and many others...

# Outline

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## STDMC Protocol: SELF-TUNING DYNAMIC MAX-CONSENSUS

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**(Input):** Tuning parameters  $\alpha^{\text{MAX}} \geq \alpha^{\text{MIN}} > 0$ .

**(Initialization):**  $x_i(0) \in \mathbb{R}$  for  $i \in \mathcal{V}$ ;  
 $\alpha_i(0) \in \{\alpha^{\text{MIN}}, \alpha^{\text{MAX}}\}$  for  $i \in \mathcal{V}$

**(Execution):** for  $k = 1, 2, 3, \dots$  each node  $i$  does

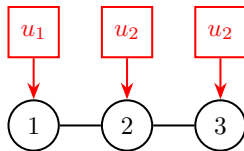
- 1) Gather  $x_j(k-1)$  and  $\alpha_j(k-1)$  from each neighbor  $j \in \mathcal{N}_i$
- 2) Update the current state according to

$$x_i(k) = \max_{j \in \mathcal{N}_i \cup \{i\}} \{x_j(k-1) - \alpha_j(k-1), u_i(k)\}$$

- 3) Update the current parameter according to

$$\alpha_i(k) = \begin{cases} \alpha^{\text{MAX}} & \text{if } x_i(k) < x_i(k-1) \\ \alpha^{\text{MIN}} & \text{otherwise} \end{cases}$$

## A simple example



Initial conditions

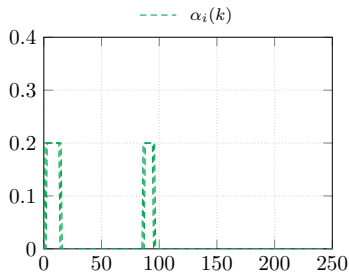
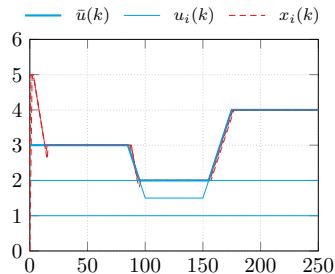
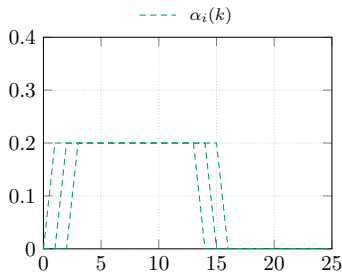
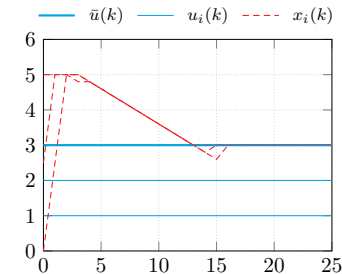
$$u_1(0) = 1, \quad x_1(0) = 0, \quad \alpha_1(0) = 0$$

$$u_2(0) = 2, \quad x_2(0) = 2, \quad \alpha_2(0) = 0$$

$$u_3(0) = 3, \quad x_3(0) = 5, \quad \alpha_3(0) = 0$$

Parameters

$$\alpha^{\text{MAX}} = 0.2, \quad \alpha^{\text{MIN}} = 10^{-8}$$



### Assumption 1

The variation of the reference signals  $u_i(k)$  are bounded a constant  $\Pi \geq 0$ , i.e., for  $k \geq 0$  it holds

$$\Delta u_i(k) = |u_i(k) - u_i(k-1)| \leq \Pi$$

*Any continuous-time signal with bounded derivative can be over-sampled to reduce its absolute variation.*

## Theorem 1: Tracking error of STDMC Protocol

Consider time-varying reference signals  $u_i(k) \in \mathbb{R}$  under Assumption 1 and let  $\delta_{\mathcal{G}}$  be the diameter of graph  $\mathcal{G}$ . If  $\mathcal{G}$  is connected and if

$$\alpha^{\text{MAX}} > \Pi, \quad (2)$$

then  $\exists T_c \geq 0$  such that the tracking error  $e_i(k)$  of each agent is bounded by  $\varepsilon_{tr}$ , i.e., for  $k \geq T_c$  it holds

$$e_i(k) = |x_i(k) - \bar{u}(k)| \leq \varepsilon_{tr} = (\alpha^{\text{MAX}} + \Pi)\delta_{\mathcal{G}}, \quad i \in \mathcal{V} \quad (3)$$

and moreover

$$T_c \leq \max \left\{ \frac{\bar{x}(0) - \bar{u}(0)}{\alpha^{\text{MAX}} - \Pi}, \delta_{\mathcal{G}} \right\}. \quad (4)$$

## Theorem 2: Steady-state error of STDMC Protocol

If the reference signals remain constant for  $k \geq k_0$ , then the steady state error  $e_i(k)$  of each agent is bounded by  $\varepsilon_{ss}$ , i.e., for  $k \geq k_0 + 2\delta_{\mathcal{G}}$  by  $\varepsilon_{ss}$ ,

$$e_i(k) = |x_i(k) - \bar{u}(k)| \leq \varepsilon_{ss} = \alpha^{\text{MIN}} \delta_{\mathcal{G}}, \quad i \in \mathcal{V}. \quad (5)$$

### Theorem 3: Tracking error when the bound $\Pi$ is unknown

If the agents update their local parameter  $\alpha_i^{\text{MAX}}$  according to

$$\alpha_i^{\text{MAX}}(k) = \max_{j \in \mathcal{N}_i \cup \{i\}} \{\alpha_j^{\text{MAX}}(k-1), \theta \cdot \Delta u_i(k)\}, \quad \theta > 1, \quad (6)$$

then  $\exists T_c \geq 0$  such that the tracking error  $e_i(k)$  is bounded for  $k \geq T_c$  by the following

$$e_i(k) = |x_i(k) - \bar{u}(k)| \leq (\theta + 1)\Pi\delta_{\mathcal{G}} = \varepsilon_{tr}, \quad i \in \mathcal{V}. \quad (7)$$



# Outline

## Piece-wise linear inputs - Line graph of 6 nodes

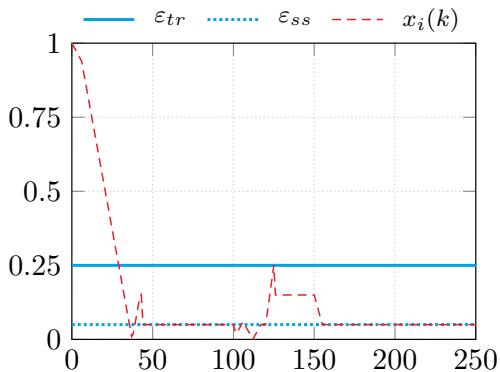
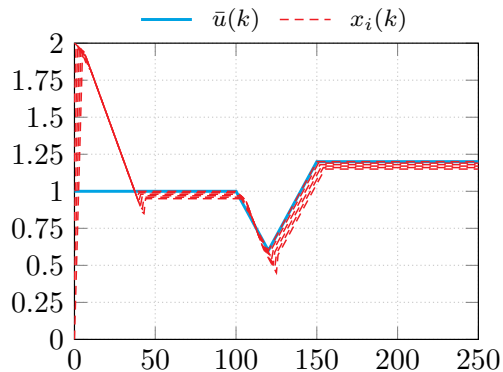
$$\alpha^{\text{MAX}} = 0.03$$

$$\alpha^{\text{MIN}} = 0.01$$

$$\Pi = 0.02$$

$$\varepsilon_{tr} = 0.25$$

$$\varepsilon_{ss} = 0.05$$



## Piece-wise linear inputs - Line graph of 6 nodes

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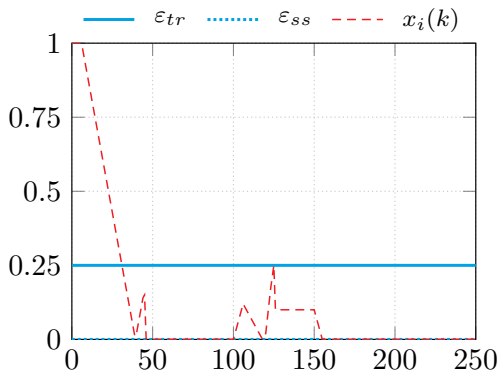
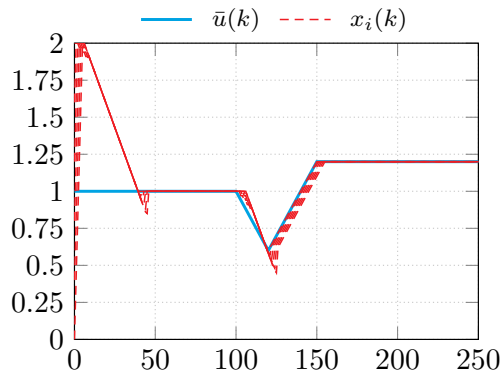
$$\alpha^{\text{MIN}} = 1 \cdot 10^{-8}$$

$$\Pi = 0.02$$

$$\varepsilon_{tr} = 0.25$$

$$\varepsilon_{ss} = 5 \cdot 10^{-8}$$

Arbitrary small steady state error!



## Piece-wise linear inputs - Line graph of 6 nodes

$$\alpha^{\text{MAX}} = 0.06$$

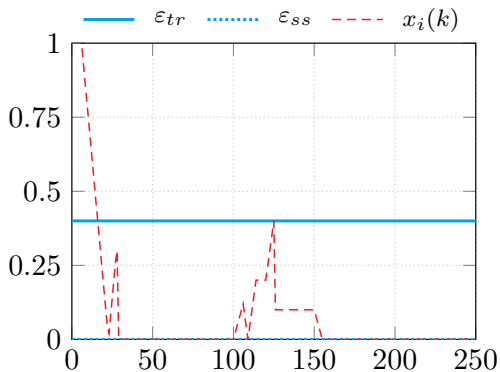
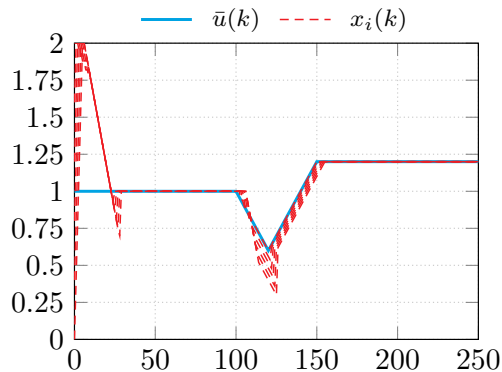
$$\alpha^{\text{MIN}} = 1 \cdot 10^{-8}$$

$$\Pi = 0.02$$

$$\varepsilon_{tr} = 0.40$$

$$\varepsilon_{ss} = 5 \cdot 10^{-8}$$

Faster convergence rate! But higher tracking error...



## Unknown bound $\Pi$ - Line graph of 6 nodes

$$\alpha_i^{\text{MAX}}(0) = 0.01$$

$$\alpha^{\text{MIN}} = 1 \cdot 10^{-8}$$

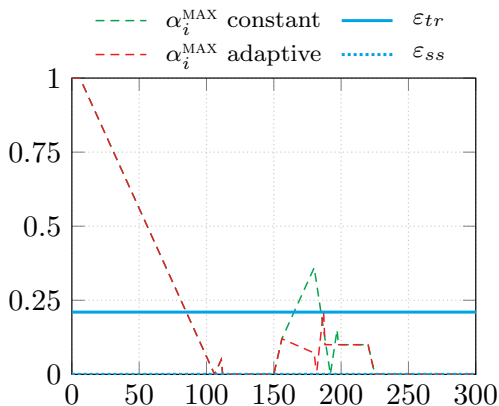
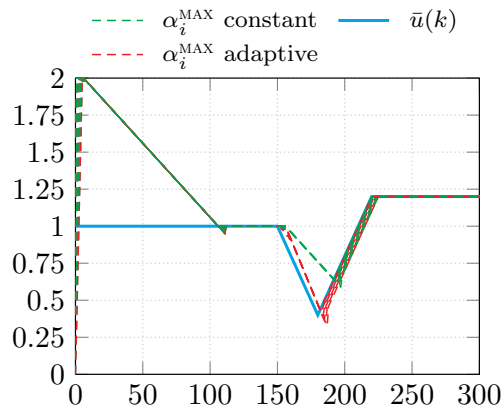
$$\Pi = 0.02$$

$$\theta = 1.1$$

$$\varepsilon_{tr} = 0.22$$

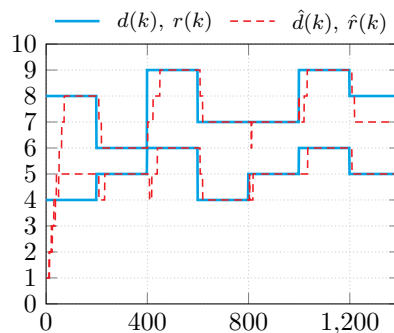
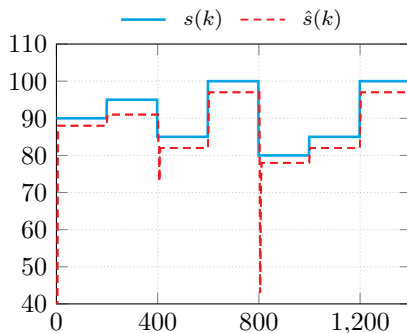
$$\varepsilon_{ss} = 5 \cdot 10^{-8}$$

The assumption  $\alpha_i^{\text{MAX}}(0) > \Pi$  is not satisfied!



## Application to graph's parameters estimation - Random graph of $n \in [80, 100]$ nodes

$\alpha^{\text{MAX}} = 0.1$ ,  $\alpha^{\text{MIN}} = 10^{-12}$ , cardinality  $s(k)$ , diameter  $d(k)$ , radius  $r(k)$



- Deplano, Franceschelli, and Giua, "Dynamic min and max consensus and size estimation of anonymous multi-agent networks", in *IEEE Trans. Autom. Control* (2021, in press).
- Deplano, Franceschelli, and Giua, "Distributed tracking of graph parameters in anonymous networks with time-varying topology", in *IEEE 60th Conf. on Dec. and Control* (2021).
- Varagnolo, Pillonetto, and Schenato, "Distributed cardinality estimation in anonymous networks", in *IEEE Trans. Autom. Control* (2013).

# Outline

## Conclusions and future directions

### Contributions:

- The STDMC protocol solving the dynamic max-consensus (or max-tracking) problem;
- Theoretical characterization of tracking and steady-state errors, as well as convergence time;
- Employment to track time-varying graphs' parameters in open networks.

### Potential extensions:

- Reference signals with unbounded variations;
- Noise in the measurements;
- Delays in the communications.

### Future application perspectives:

- Core-periphery structure detection;
- Distributed online optimization algorithms;
- ...





# Dynamic Max-Consensus with Local Self-Tuning

Thank you for your attention!

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**Webpage:** <https://sites.google.com/view/deplanodiego/>

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