

A Robustness Analysis to Structured Channel Tampering over Secure-by-design Consensus Networks

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Overview and preliminaries

Cyber-attacks and Multi-Agent Systems (MASs)

Cyber-attacks: malicious and deliberate attempts to breach the information system of an individual or organization.

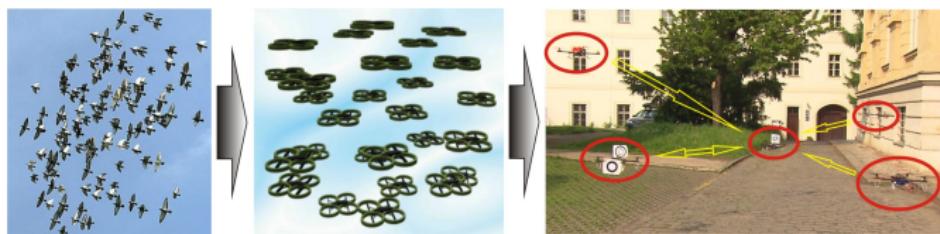
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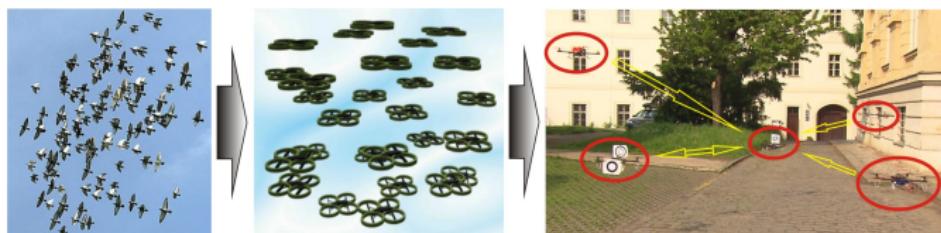


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Distinctive features:

- distributed architecture
- autonomy
- scalability
- robustness to failure

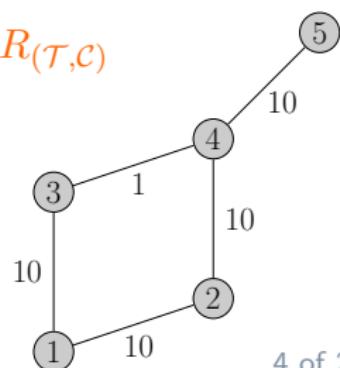


Graph-based network model

The secure smart networks under analysis are defined as n -agent systems modeled through graph theoretical tools.

Notation

- weighted undirected graph: $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$, $|\mathcal{V}| = n$, $|\mathcal{E}| = m$
- vertex set: $\mathcal{V} = \{1, \dots, n\}$
- edge set: $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$
- i -th neighborhood: $\mathcal{N}_i = \{j \in \mathcal{V} \setminus \{i\} \mid (i, j) \in \mathcal{E}\}$
- a spanning tree: $\mathcal{T} \subseteq \mathcal{G}$
- the cut-set matrix of \mathcal{G} w.r.t. \mathcal{T} and $\mathcal{C} = \mathcal{G} \setminus \mathcal{T}$: $R_{(\mathcal{T}, \mathcal{C})}$
- weight on edge (i, j) : $w_{ij} \in \mathbb{R}$ if $(i, j) \in \mathcal{E}$
- weight matrix: W s.t. $[W]_{kk} = w_{ii}$, $k = (i, j)$
- incidence matrix: $E \in \mathbb{R}^{n \times m}$
- weighted Laplacian matrix: $L(\mathcal{G}) = EWE^\top$



Weighted consensus protocol

- n homogeneous agents with dynamic state $x_i = x_i(t) \in \mathbb{R}^D$, $i = 1, \dots, n$
- ensemble state: $\mathbf{x} = \text{vec}_{i=1}^n(x_i) \in X \subset \mathbb{R}^N$, with $N = nD$

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Definition (Weighted Consensus)

An n -agent network achieves consensus if $\lim_{t \rightarrow +\infty} \mathbf{x}(t) \in \mathcal{A}$, where $\mathcal{A} = (\text{span}(\mathbf{1}_n) \otimes \omega)$, $\omega \in \mathbb{R}^D$, is called *agreement set*.

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Proposition

For a MAS described by an undirected and connected graph \mathcal{G} the network state \mathbf{x} driven by dynamics

$$\dot{\mathbf{x}} = -\mathbf{L}(\mathcal{G})\mathbf{x}, \quad \text{with } \mathbf{L}(\mathcal{G}) = L(\mathcal{G}) \otimes I_D,$$

fulfills weighted consensus.

Weighted consensus protocol: classic example

Rendez-vous, $n = 5$, $D = 2$.

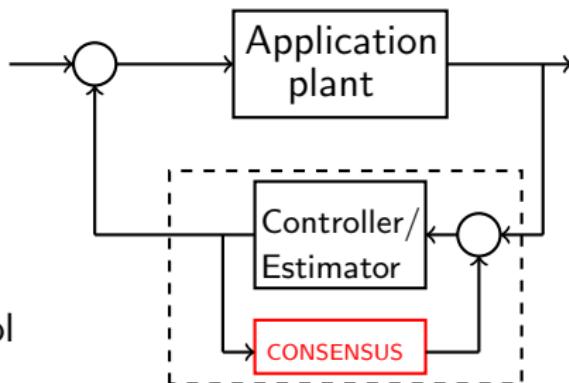
The Secure-by-Design Consensus Protocol

Edge weight encryption: motivations

Edge weight values affect convergence performances of consensus.

Practical motivations suggesting their encryption:

- **preserving privacy**, in general;
- **ensuring performances of existing applications**, e.g. decentralized estimation, opinion dynamics;
- **achieving synchronization** for a group of agents subject to Byzantine attacks through learning-based control techniques.

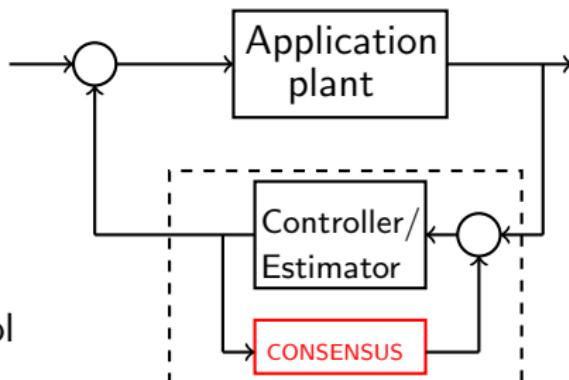


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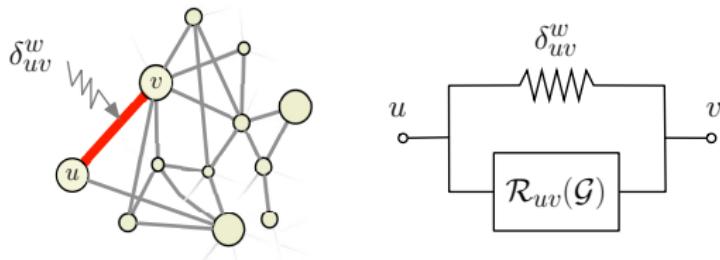
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We want to embed edge weight encryption into consensus networks and study the related robustness

“Robustness” within consensus networks

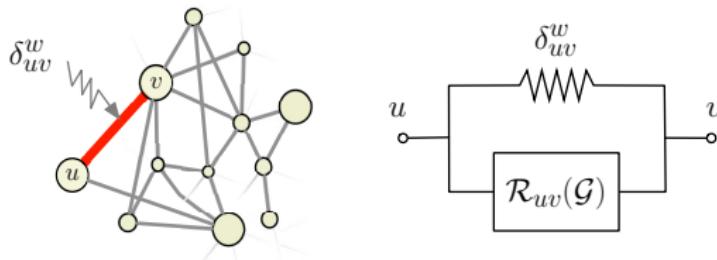
Meaning: **robust stability to small-magnitude perturbations** altering the agent dynamics



Effective resistance (EF): $\mathcal{R}_{uv}(\mathcal{G}) = [L^\dagger(\mathcal{G})]_{uu} - 2[L^\dagger(\mathcal{G})]_{uv} + [L^\dagger(\mathcal{G})]_{vv}$

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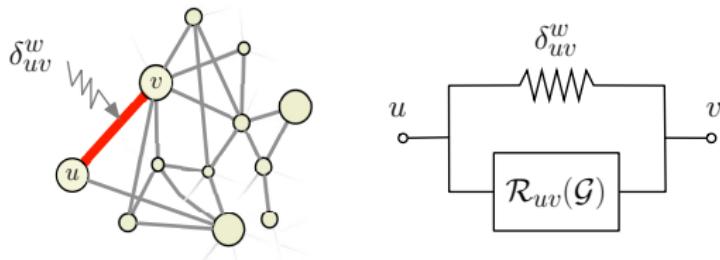


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Generalized EF w.r.t. the subset $\mathcal{E}_\Delta \subseteq \mathcal{E}$ of uncertain edges:

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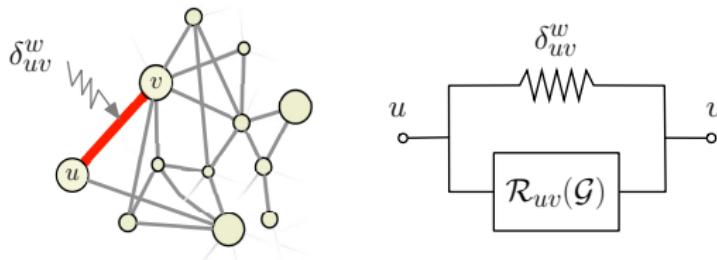
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Uncertain consensus protocol: $\dot{\mathbf{x}} = -L(\mathcal{G}_{\Delta^W})\mathbf{x}$, where Δ^W is a (structured diagonal) disturbance and $L(\mathcal{G}_{\Delta^W}) = E(W + \Delta^W)E^\top$

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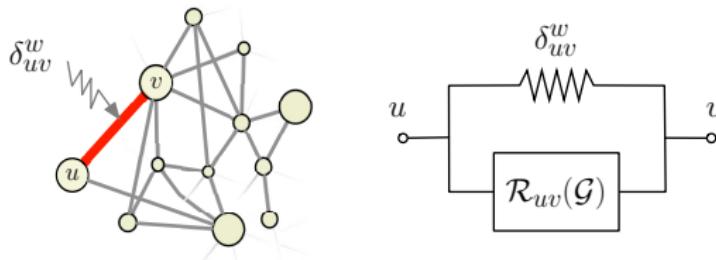
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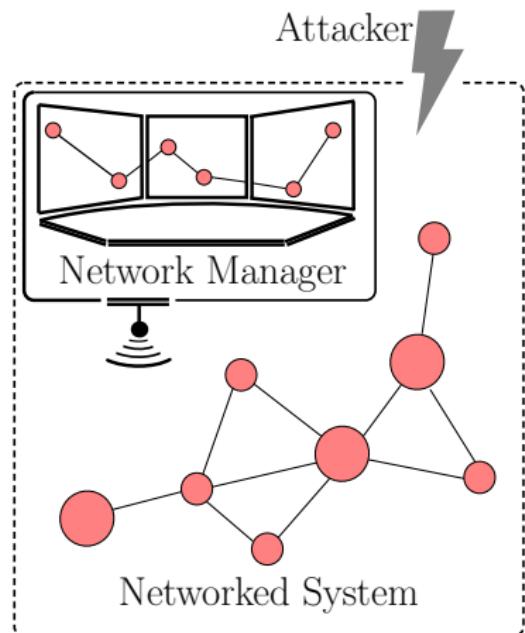
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known small-gain theorem result

Introduction of the network manager

One method to increase security among networks is adopting the so-called **network manager**.



The network manager

- is **not** a global controller
- is used **to secure** distributed algorithms running on MASs
- defines tasks: within consensus, the task corresponds to **(encrypted) edge weight selection**
- its goal is to guarantee **robust** consensus convergence

Objective coding and information localization

Objective coding: a task is described by an encoded parameter $\theta \in \mathbb{R}^{n^2}$ called *codeword*. Decoding functions p_i are used by agents to interpret θ .

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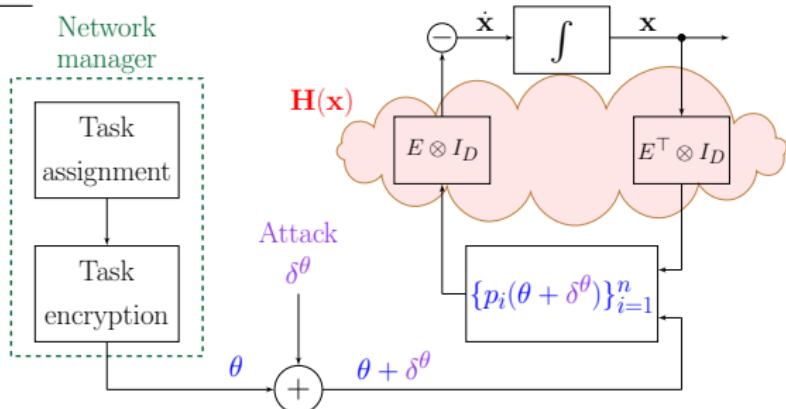
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- θ_{ii} takes arbitrary value
- $p_{ij}(\theta) = p_{ij}(\theta_{ij})$

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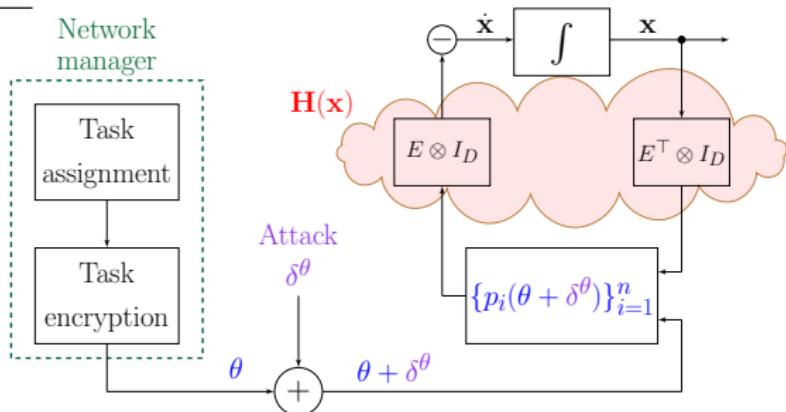


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Information localization: $h_{ij}(\mathbf{x}) := \text{col}_j[h_i(\mathbf{x})] = \begin{cases} x_i - x_j, & (i, j) \in \mathcal{E} \\ \mathbf{0}_D, & \text{otherwise} \end{cases}$
 $\mathbf{H}(\mathbf{x}) = \text{diag}_{i=1}^n(h_i(\mathbf{x}))$

Secure-by-design consensus dynamics

Assume that decoding functions p_i , $i = 1, \dots, n$, obey this rule:

$$[p_i(\theta)]_j = p_{ij}(\theta) = \begin{cases} w_{ij}, & (i, j) \in \mathcal{E} \\ 0, & \text{otherwise} \end{cases}$$

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$$\dot{x}_i = - \sum_{j \in \mathcal{N}_i} p_{ij}(\theta) h_{ij}(\mathbf{x}), \quad i = 1, \dots, n$$

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or, equivalently, setting $\mathbf{p} = \text{vec}(p_i)$ and recalling that $\mathbf{H}(\mathbf{x}) = \text{diag}(h_i(\mathbf{x}))$

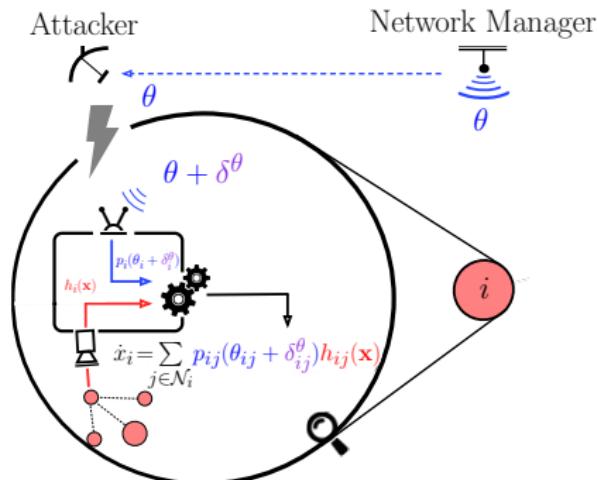
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Model for the channel tampering

Attack is a codeword deviation: $\delta^\theta \in \Delta^\theta = \{\delta^\theta : \|\delta^\theta\|_\infty \leq \bar{\delta}^\theta\}$

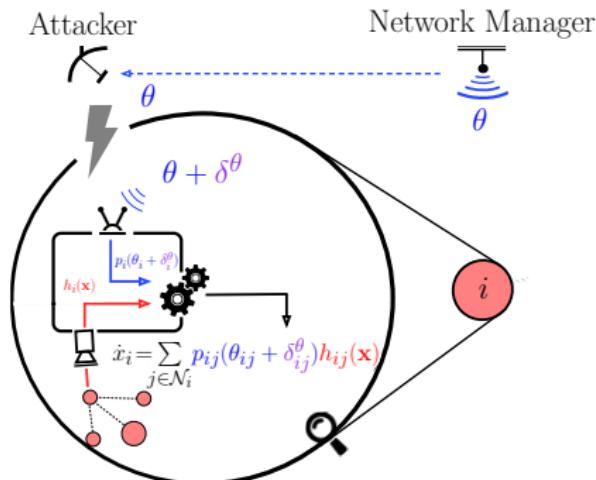
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Then the **perturbed consensus protocol** (PCP) can be described by

$$\dot{x}_i = - \sum_{j \in \mathcal{N}_i} p_{ij}(\theta_{ij} + \delta_{ij}^\theta)h_{ij}(\mathbf{x}), \quad i = 1, \dots, n$$

where $\delta_{ij}^\theta = [\delta_i^\theta]_j$ and δ_i^θ satisfies $\delta^\theta = \text{vec}(\delta_i^\theta)$.

Channel tampering: multi-edge attack problem

Problem

Design p_{ij} such that the PCP reaches agreement

- independently from the value of θ
- while the MAS is subject to an attack δ^θ striking all the edges in \mathcal{E}_Δ , that is $\delta_{ij}^\theta = 0$ for all $(i, j) \in \mathcal{E} \setminus \mathcal{E}_\Delta$

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Moreover, provide resilience guarantees for a given perturbation set Δ^θ in terms of the maximum allowed magnitude (say ρ_Δ^θ) for the norm of δ^θ .

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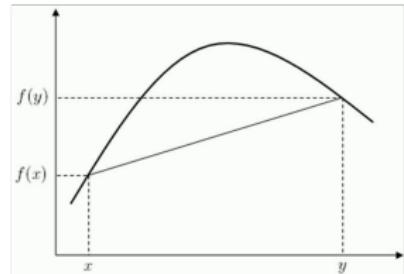
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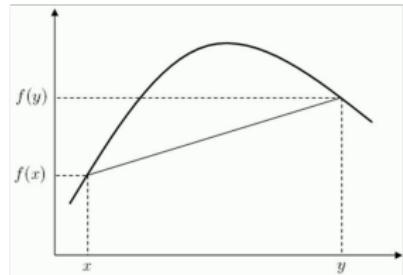
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(ii) $p_{ij}(\theta)$ is **concave** for all admissible θ



(iii) p_{ij} is **Lipschitz continuous and differentiable** w.r.t. θ , implying

$$\exists K_{ij} \geq 0: |p'_{ij}(\theta_{ij})| \leq K_{ij}, \forall (i, j) \in \mathcal{E}$$

Robustness to channel tampering (cont'd)

With the previous assumptions holding and setting $K_\Delta := \max_{(u,v) \in \mathcal{E}_\Delta} \{K_{uv}\}$:

Theorem (Agreement of the PCP under single edge perturbation)

For an injection attack δ^θ on edge all the edges in \mathcal{E}_Δ the PCP achieves agreement if

$$\|\delta^\theta\|_\infty < \rho_\Delta^\theta = (K_\Delta \mathcal{R}_{\mathcal{E}_\Delta}(\mathcal{G}))^{-1},$$

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The three assumptions (i)-(iii) are sufficient and necessary to figure out the worst case scenario in which the absolute slope of each p_{uv} , $(u, v) \in \mathcal{E}_\Delta$, is maximum, i.e. the absolute slope reaches K_Δ for any given θ .

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Up to minor changes this result is also valid for **discrete-time** consensus.

Further analysis and numerical results

A trade-off: information hiding vs robust stability

Observation: if $\mathcal{E}_\Delta = \{(u, v)\}$, the Lipschitz constant K_{uv} plays a crucial role in either improving information hiding or robust stability!

Considering $p_{uv}(\theta_{uv}) = b_{uv}\theta_{uv}$, the perturbation on θ_{uv} is directly “amplified” by $K_{uv} = |b_{uv}|$. Let’s focus on this case.

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- if K_{uv} increases then the value of $\rho_{uv}^\theta = (K_{uv}\mathcal{R}_{uv}(\mathcal{G}))^{-1}$ decreases

$K_{uv} \uparrow$ then robust stability of PCP \downarrow

The resilience gap

Let us define the quantities:

$$\mathcal{R}_{\mathcal{E}_\Delta}^*(\mathcal{G}) = \max_{(u,v) \in \mathcal{E}_\Delta} \{\mathcal{R}_{(u,v)}(\mathcal{G})\};$$

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It is known that:

$$\mathcal{R}_{\mathcal{E}_\Delta}^*(\mathcal{G}) \leq \mathcal{R}_{\mathcal{E}_\Delta}(\mathcal{G}) \leq \mathcal{R}_{\mathcal{E}_\Delta}^{tot}(\mathcal{G})$$

[D. Zelazo and M. Bürger, *On the Robustness of Uncertain Consensus Networks*, TCNS, 2017]

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The following ratio is named *resilience gap*

$$g(\mathcal{G}, \mathcal{E}_\Delta) = 1 - \frac{\mathcal{R}_{\mathcal{E}_\Delta}^*(\mathcal{G})}{\mathcal{R}_{\mathcal{E}_\Delta}(\mathcal{G})} \in [0, 1).$$

This quantity measures the **emerging amount of conservatism** related to the fact that multiple edges are under attack.

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Let us define the quantities:

$$\mathcal{R}_{\mathcal{E}_\Delta}^*(\mathcal{G}) = \max_{(u,v) \in \mathcal{E}_\Delta} \{\mathcal{R}_{(u,v)}(\mathcal{G})\};$$

$$\mathcal{R}_{\mathcal{E}_\Delta}^{tot}(\mathcal{G}) = \text{tr} \left[P^\top R_{(\mathcal{T},\mathcal{C})}^\top (R_{(\mathcal{T},\mathcal{C})} W R_{(\mathcal{T},\mathcal{C})}^\top)^{-1} R_{(\mathcal{T},\mathcal{C})} P \right].$$

It is known that:

$$\mathcal{R}_{\mathcal{E}_\Delta}^*(\mathcal{G}) \leq \mathcal{R}_{\mathcal{E}_\Delta}(\mathcal{G}) \leq \mathcal{R}_{\mathcal{E}_\Delta}^{tot}(\mathcal{G})$$

[D. Zelazo and M. Bürger, *On the Robustness of Uncertain Consensus Networks*, TCNS, 2017]

The following ratio is named *resilience gap*

$$g(\mathcal{G}, \mathcal{E}_\Delta) = 1 - \frac{\mathcal{R}_{\mathcal{E}_\Delta}^*(\mathcal{G})}{\mathcal{R}_{\mathcal{E}_\Delta}(\mathcal{G})} \in [0, 1).$$

This quantity measures the **emerging amount of conservatism** related to the fact that multiple edges are under attack.

Observation

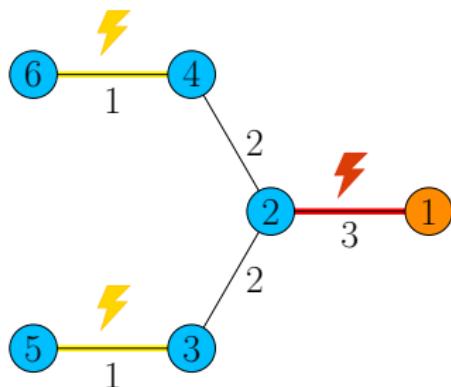
If i) $|\mathcal{E}_\Delta| = 1$, or
 ii) $2 \leq |\mathcal{E}_\Delta| \leq n - 1 = |\mathcal{E}|$ then $g(\mathcal{G}, \mathcal{E}_\Delta) = 0$

Numerical simulations

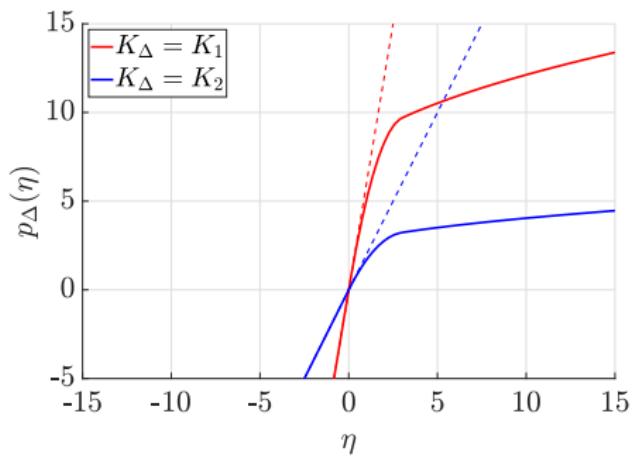
Decoding function: $p_{\Delta}(\eta) = \begin{cases} K_{\Delta} \left(\frac{4}{13} \sqrt{\eta + 1} + 1 \right), & \text{if } \eta \geq 3; \\ K_{\Delta} \left(-\frac{2}{13} \eta^2 + \eta \right), & \text{if } 0 \leq \eta < 3; \\ K_{\Delta} \eta, & \text{if } \eta < 0; \end{cases}$

Edges under attack: $\mathcal{E}_1 = \{(1, 2)\}, \quad \mathcal{E}_2 = \{(1, 2), (3, 5), (4, 6)\}$

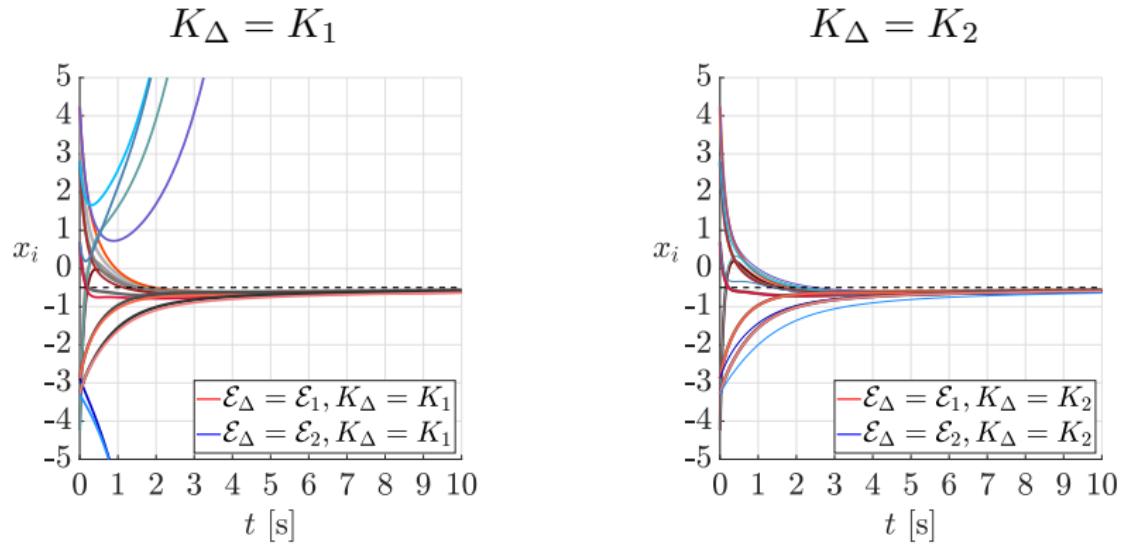
Couple of values for K_{Δ} : $K_1 = 2, \quad K_2 = 6$



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Numerical simulations (cont'd)



Semi-autonomous network dynamics:

$$\dot{\mathbf{x}} = (L_B(\mathcal{G}) \otimes I_D)\mathbf{x} + (B \otimes I_D)\mathbf{u},$$

where $L_B(\mathcal{G}) = L(\mathcal{G}) + \text{diag}(B\mathbf{1}_{|\mathcal{V}_l|})$ and $B \in \mathbb{R}^{n \times |\mathcal{V}_l|}$ such that $[B]_{i\ell} > 0$, if agent i belongs to the leader set $\mathcal{V}_l = \{1\}$; $[B]_{i\ell} = 0$, otherwise.

Conclusions

Final remarks

- the **secure-by-design consensus protocol** rests on novel methods (e.g. network manager, objective coding, information localization) to preserve integrity, synchronization and performance of networks
- the previously devised single-edge attack case has been broadened to a scenario with **multiple threats**
- **small-gain-theorem-based stability guarantees** based on the effective resistance are given, which depend on both network topology and encryption system employed
- **trade-off** between information hiding & robust stability is discussed
- the **conservatism** arising from a multiplicity of threats is addressed
- **future works:** extending this approach to nonlinear consensus and formation control protocols

**THANK YOU FOR YOUR
ATTENTION**

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