Cyber-physical systems can learn to be secure

CDC workshop on 'Data-Driven Control of Autonomous Systems with Provable Guarantees'.
9th December 2025.

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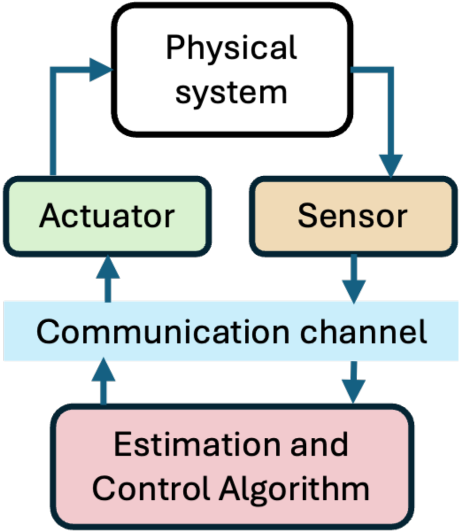
EINDHOVEN UNIVERSITY OF TECHNOLOGY

Cyber-Physical Systems are vulnerable



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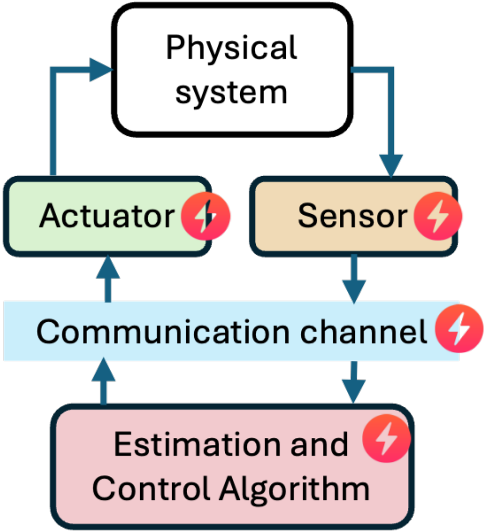

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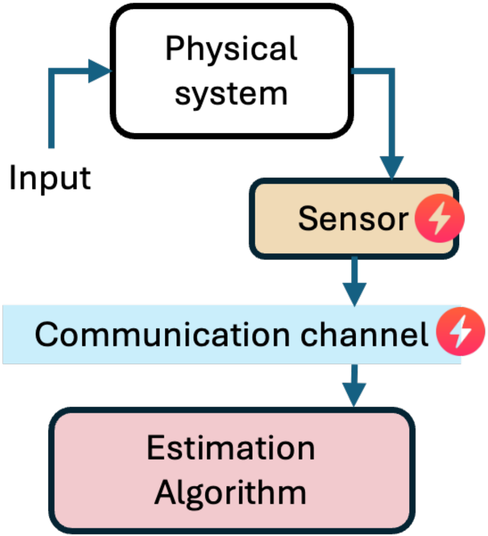
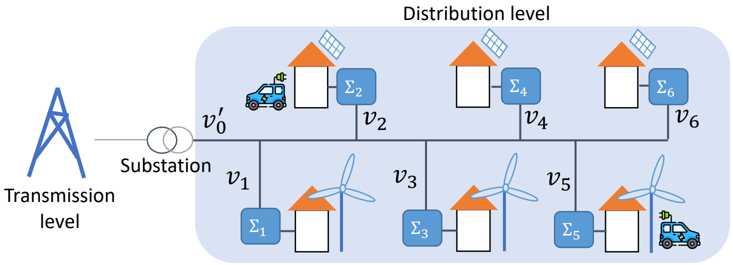


Sensor networks are vulnerable

Source: `toolsense.io`

Sensor networks in power grids are vulnerable



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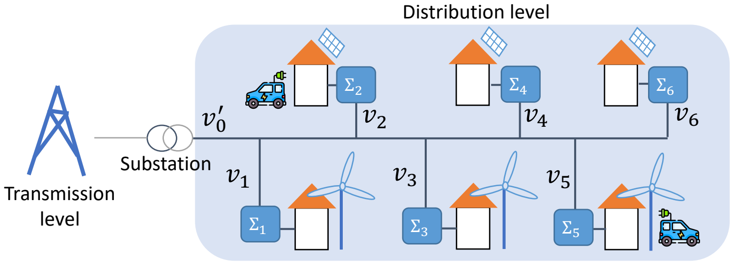
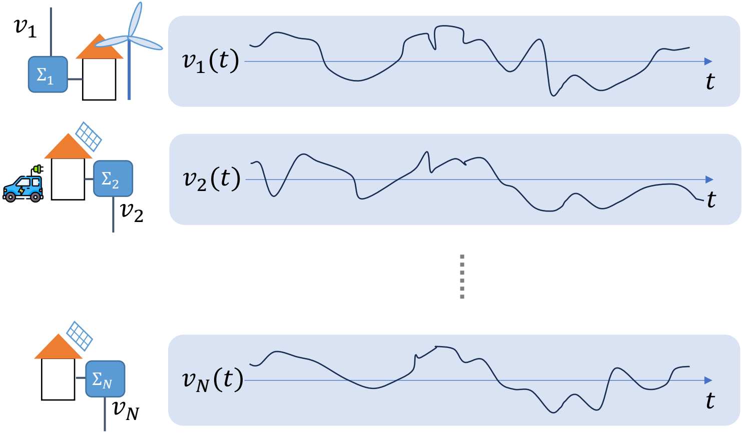


The health of the grid is monitored at the substation level.

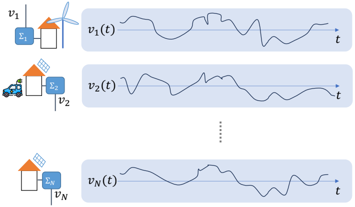
Data may be corrupted



The secure state estimation problem formulation

System with N sensors:

$$\mathrm{CT}: \begin{cases} \dot{x}(t) = f(x(t), u(t)), & t \in \mathbb{R}_{\geq 0}, \\ y_i(t) = h_i(x(t)) + a_i(t), & i \in [N]. \end{cases}$$



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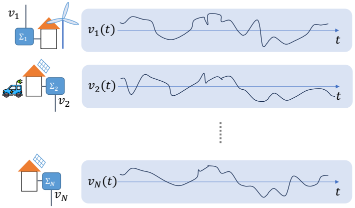

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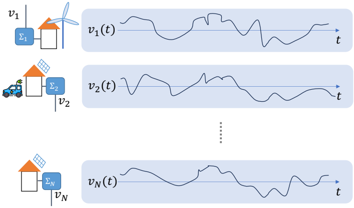

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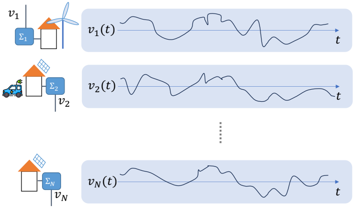

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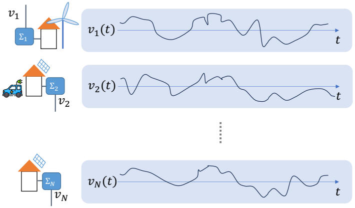

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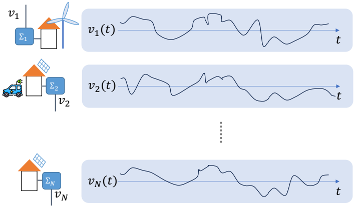

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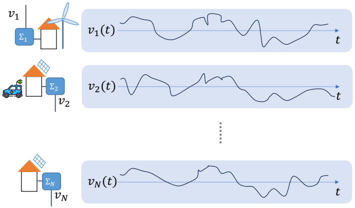

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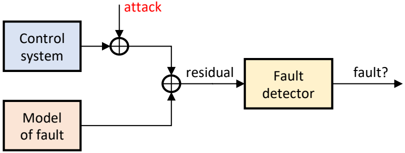
Why are traditional approaches not applicable for security?

Traditional approaches

1. Fault detection and isolation



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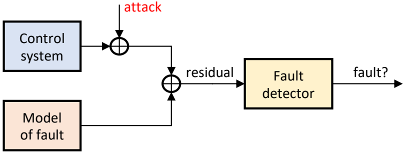

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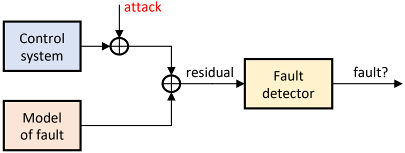

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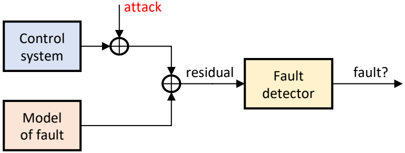

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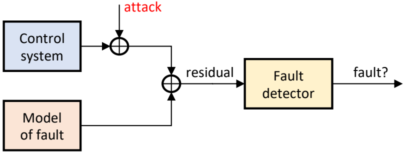

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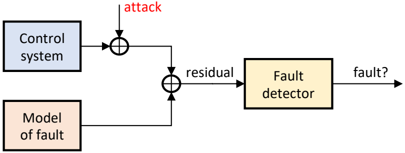

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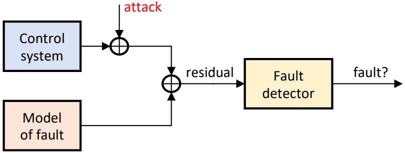

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Secure state estimation aims to achieve an estimation accuracy that is **independent of the attack**.

The intuition

Suppose there are 3 sensors measuring the same system. We know the *number* of sensors which have been corrupted, but not which ones.

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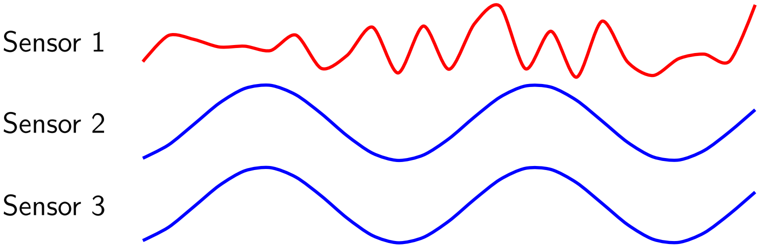

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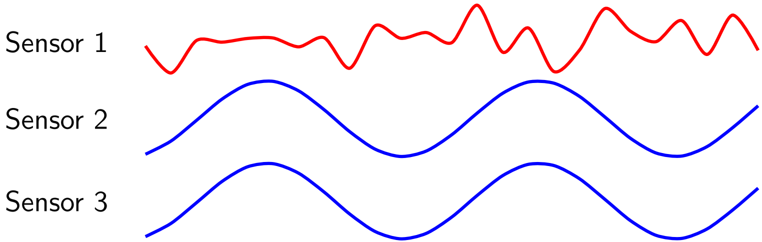

By inspection of the signals, easy to tell that Sensor 1 has been corrupted.

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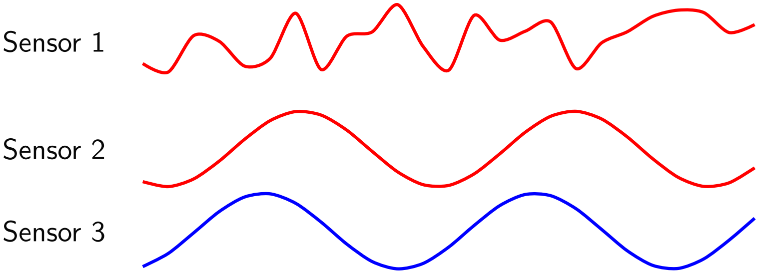

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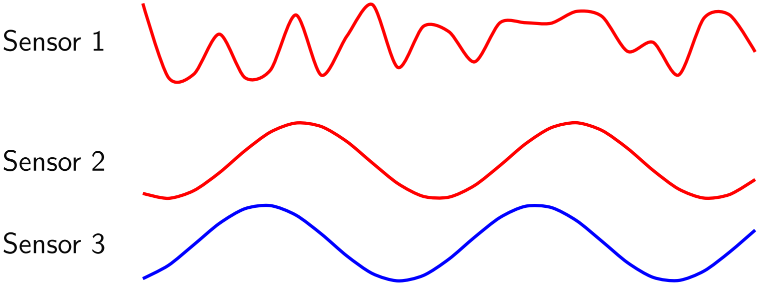

Difficult to tell by inspection of the signals. One might infer that Sensor 2 and 3 have been corrupted. Untrue!

Sensor redundancy is needed.

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$\downarrow$

M-attack observability

Theorem: M-attack observability

System with N sensors: $\begin{cases} x(k+1) = Ax(k) + Bu(k), \\ y_i(k) = C_i x(k) + a_i(k), \quad i \in [N], \end{cases} \quad k \in \mathbb{N}_{\geq 0}.$

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($\mathcal{A}_{\mathcal{I}}$ denotes the set of all vectors $(a_1, a_2, \ldots, a_N)$ where $a_j \equiv 0$, $j \in [N] \backslash \mathcal{I}$)

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$$y_i(t, x(0), u, a) = y_i(t, x'(0), u, a'), \forall t \in \{0, 1, \ldots, T\}, \forall i \in [N] \implies x(0) = x'(0).$$

Theorem

The system is ***M*-attack observable**, if and only if

1. $N > 2M$, where M is the number of compromised sensors,
2. the system is **observable** via every $y_{\mathcal{J}} := (y_i)_{i \in \mathcal{J}}$ sensors, where $\mathcal{J} \subset [N]$ with $N - 2M$ elements. (every $(A, C_{\mathcal{J}})$ pair is observable).

From M-attack observability to an algorithm

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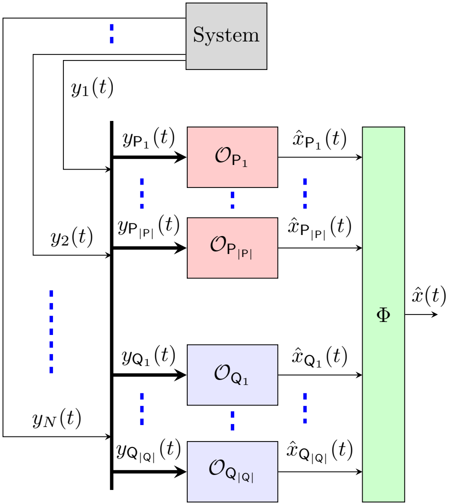
From theorem to a

model-based SSE algorithm

A model-based SSE algorithm

1. For each combination of $N - M$ ($\geq N - 2M$) sensors, construct an estimator $\mathcal{O}_{\mathsf{P}}$ based on those sensors, that is robust (input-to-state stable) w.r.t. attack a.



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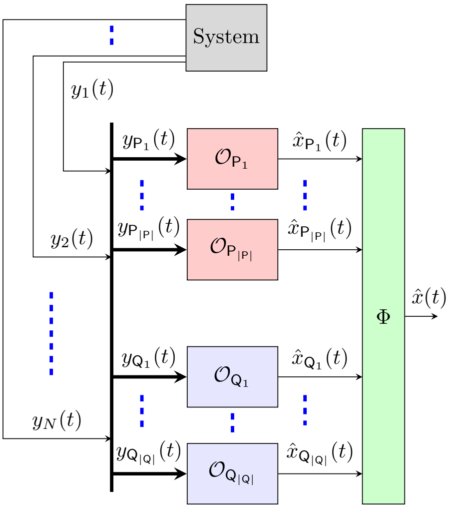

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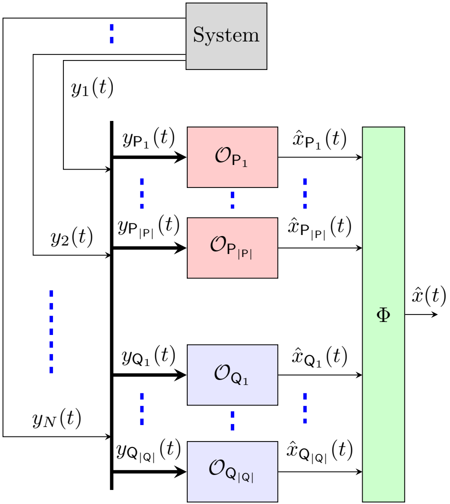

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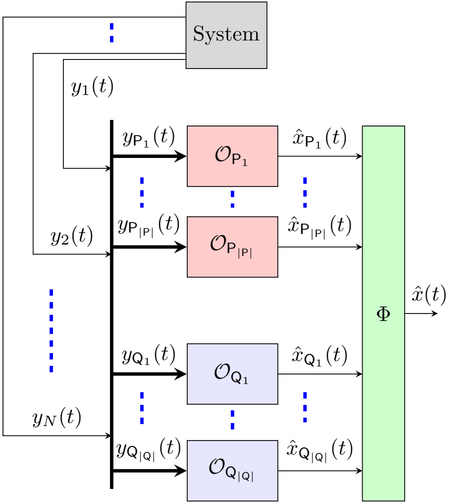
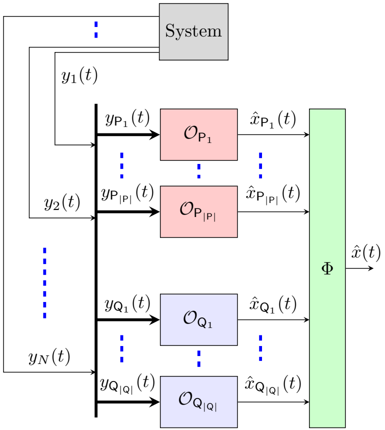


The consistency mapping Φ



Consistency mapping Φ to choose an estimate $\hat{x}$ from the multi-observer:

$$\pi_P(k) := \max_{Q \subset P, |Q| = N-2M} |\hat{x}_Q(k) - \hat{x}_P(k)|, k \geq 0.$$

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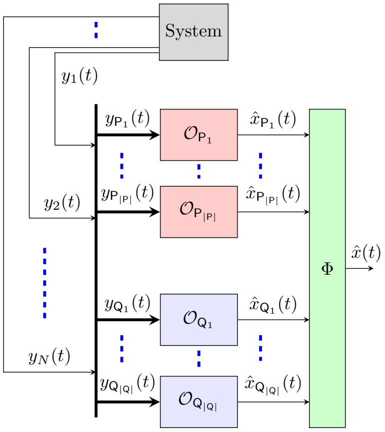

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Theorem

Suppose system is M-attack observable, then

$$|\hat{x}(k) - x(k)| \leq \underbrace{\beta(|\hat{x}(0) - x(0)|, k)}_{\text{independent of attack signals } a} \qquad k \geq 0,$$

where $\beta \in \mathcal{KL}$, for all $x(0)$, $\hat{x}_P(0)$, $\hat{x}_Q(0) \in \mathbb{R}^n$.

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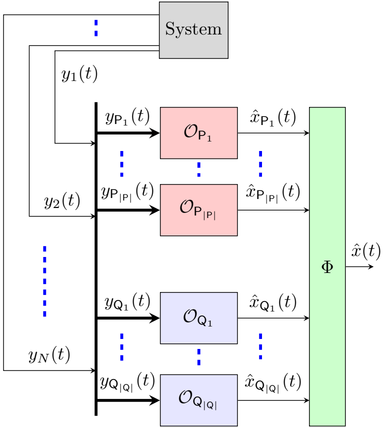

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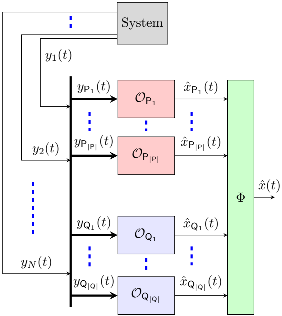
Corollary: As $t \to \infty$, $\sigma(t)$ chooses the attack-free set.

Takeaways: model-based SSE



When the model is known, we have

1. Necessary and sufficient conditions for **secure state estimation** of LTI systems.

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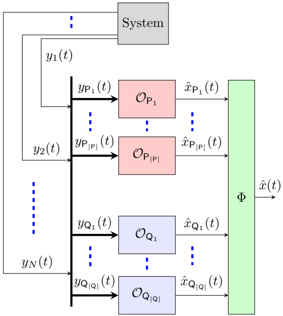

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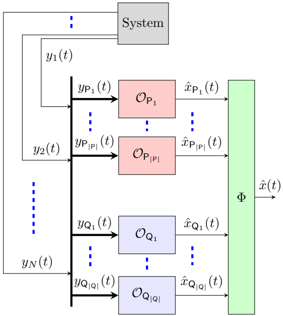

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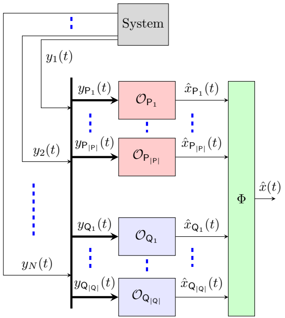

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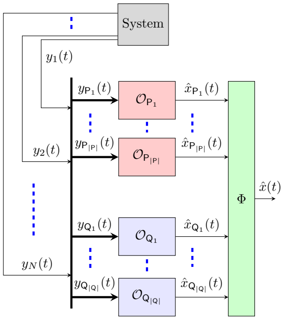

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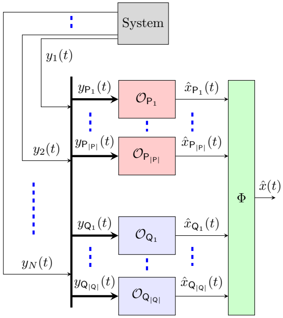

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- (Niazi, Alanwar, Chong, Johansson; 2023, 2025) on set-based SSE.

What if the model is unknown?

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Identify the attack-free set of sensors.

Our approach

Recall that we consider a LTI system with N sensors, where $M < N$ has been attacked:

$$x(k+1) = Ax(k) + Bu(k), \quad y_i(k) = C_i x(k) + a_i(k), \; i \in [N], \quad k \in \mathbb{N}_{\geq 0}.$$

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- For every $N - M$ set of sensors z_j, we have the following model:

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Since the model (A, B, C_i) are unknown, we will learn them from data!

Data-based representations for LTI systems

According to Willems et. al.'s Fundamental Lemma,

Model-based representation

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$U_{n,T}$, $\hat{X}_{j,n,T}$ and $\hat{X}_{j,n+1,T}$ are data matrices:

$$\begin{aligned} \hat{X}_{j,n,T} &= \begin{bmatrix} \mathcal{X}_j(n) & \dots & \mathcal{X}_j(n+T-1) \end{bmatrix}, \\ \hat{X}_{j,n+1,T} &= \begin{bmatrix} \mathcal{X}_j(n+1) & \dots & \mathcal{X}_j(n+T) \end{bmatrix}, \\ U_{n,T} &= \begin{bmatrix} u(n) & \dots & u(n+T-1) \end{bmatrix}, \end{aligned}$$

$$\mathcal{X}_j(k) := \begin{bmatrix} z_j(k-n) \\ \vdots \\ z_j(k-1) \\ \hdashline u(k-n) \\ \vdots \\ u(k-1) \end{bmatrix}$$

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Theorem

Recall $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$.

Model-based rep. = Data-based rep.

only if

$$\operatorname{rank} \begin{bmatrix} U_{n,T} \\ \hat{X}_{j,n,T} \end{bmatrix} = m(n+1) + (N-M)n \text{ with } T \geq (m+1)((m+N-M)n+1).$$

A data-based attack detection algorithm : the main idea

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Algorithm

1. **(Offline)** Construct Λ_j, $\forall j \in [n_J]$.
2. **(Offline)** Apply input u of length n, collect online measurements of length T until

$$\operatorname{rank} \begin{bmatrix} U_{n,T} \\ \hat{X}_{j,n,T} \end{bmatrix} = m(n+1) + (N-M)n \text{ with } T \geq (m+1)((m+N-M)n+1).$$

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Data-based representation

$$\text{For } j \in [n_\mathrm{J}], \quad \mathcal{X}_j(k+1) = \Lambda_j \begin{bmatrix} u(k) \\ \mathcal{X}_j(k) \end{bmatrix}, \qquad \Lambda_j := \hat{X}_{j,n+1,T} \begin{bmatrix} U_{n,T} \\ \hat{X}_{j,n,T} \end{bmatrix}^{\dagger}.$$

Algorithm

1. **(Offline)** Construct Λ_j, $\forall j \in [n_\mathrm{J}]$.
2. **(Offline)** Apply input u of length n, collect online measurements of length T until

$$\operatorname{rank} \begin{bmatrix} U_{n,T} \\ \hat{X}_{j,n,T} \end{bmatrix} = m(n+1) + (N-M)n \text{ with } T \geq (m+1)((m+N-M)n+1).$$

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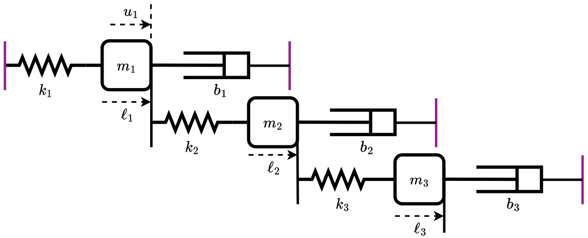
4. **(Online)** Compute set of attack-free sensors
$$j^*[k+1] \in \arg\min_{j \in [n_J]} \left\| \underline{\hat{X}}_{j,k+1,1} - \Lambda_j \begin{bmatrix} \underline{U}_{k,1} \\ \underline{\hat{X}}_{j,k,1} \end{bmatrix} \right\|_2 .$$

An example



$$\text{Let } x := \begin{bmatrix} l_1 \\ \dot{l}_1 \\ l_2 \\ \dot{l}_2 \\ l_3 \\ \dot{l}_3 \end{bmatrix}. \quad \dot{x} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ \frac{-k_1}{m_1} & \frac{-b_1}{m_1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ \frac{1}{m_2} & 0 & \frac{-k_2}{m_2} & \frac{-b_2}{m_2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & \frac{1}{m_3} & 0 & \frac{-k_3}{m_3} & \frac{-b_3}{m_3} \end{bmatrix} x + \begin{bmatrix} 0 \\ \frac{1}{m_1} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} u, \quad \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \left[\begin{array}{cc|cc|cc} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{array}\right] x$$

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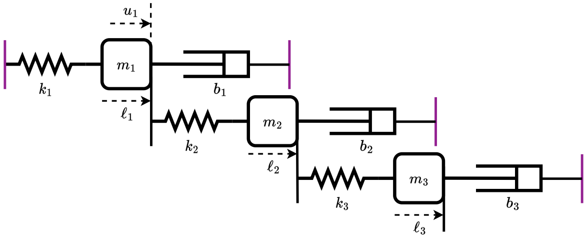

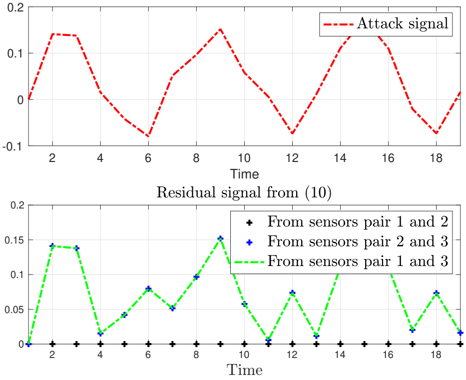

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- What about set-based approaches? Preliminary work presented at this CDC:

Z. Zhang, M. Niazi, M. Chong, K. Johansson, A. Alanwar
Data-driven Nonconvex Rechability Analysis using Exact Multiplication
`Thursday. C03. 1715-1730. Oceania III.`

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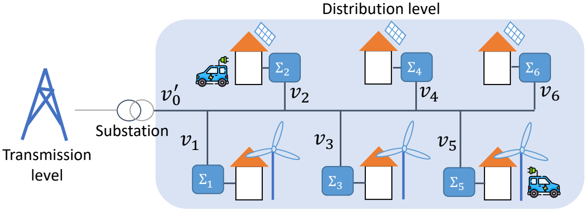
- Towards nonlinear and networked (hybrid) control systems!



Acknowledgments

RESli consortium,
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