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Null is Not Always Empty:

Monitoring the Null Space for Field-Level Anomaly Detection in Industrial IoT Environments

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Agenda

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1. Introduction
2. Null Space Anomaly Detection
3. Use Case: Tennesse-Eastman
4. Results
5. Conclusions

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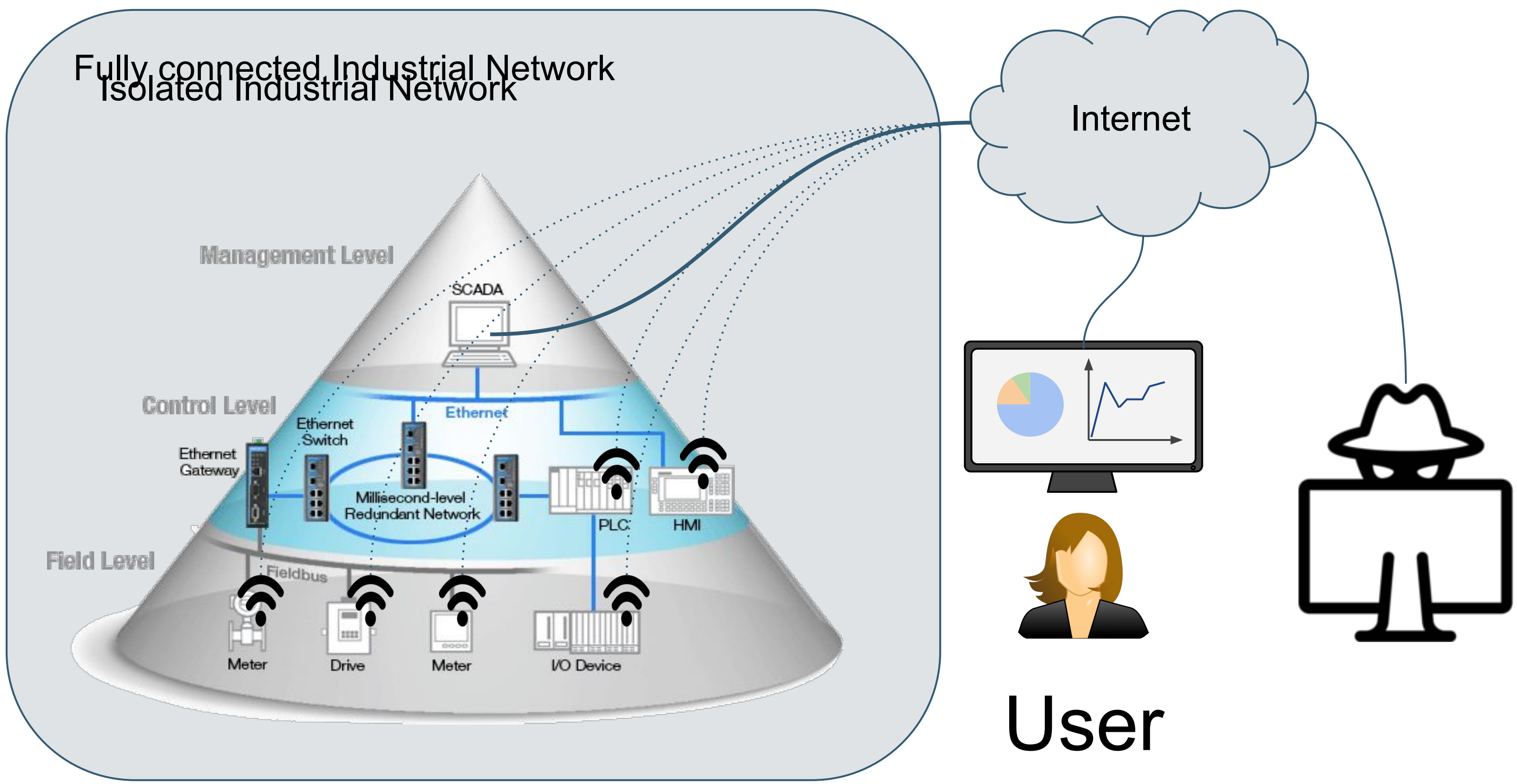
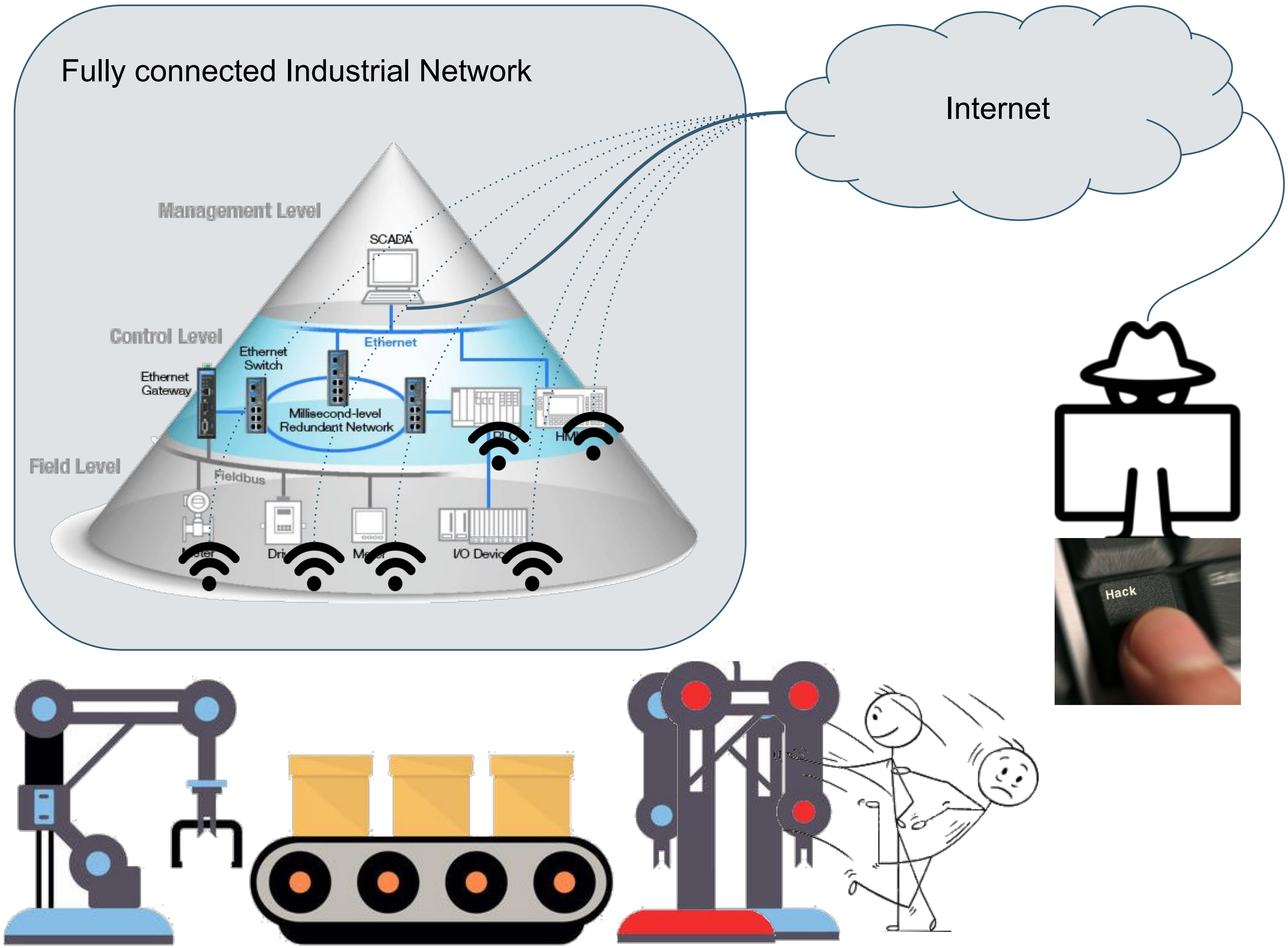
Introduction

Industrial Networks



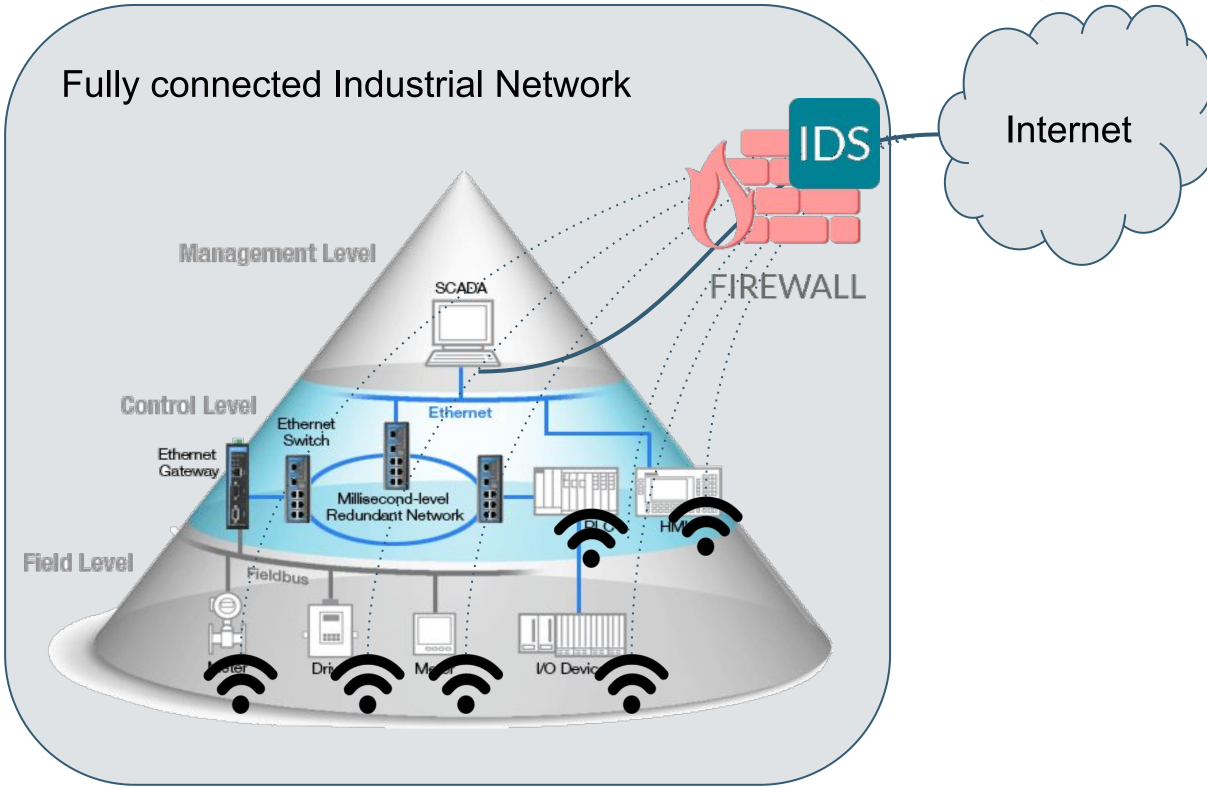
Process Control



Intrusion Detection System

1. Signature Based IDSs

2. Anomaly Detection Systems (ADS)



This work

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We present an **Anomaly Detection System that monitors physical quantities** of the process itself **to detect intrusions at field-level** that can lead to a unwanted activity within the monitored process

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Null Space Anomaly Detection

Null Space Anomaly Detection

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- Multivariate anomaly detection system
- Validated in fields like *Structural Health Monitoring*
- Based in Stochastic Subspace Identification[1]
- Uses time series measured in the process as input

$$\boldsymbol{Y} = [\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots, \boldsymbol{y}_m]$$

- Covariance Driven Hankel Matrix transform

$$\boldsymbol{H}_{p,q} = \begin{bmatrix} \boldsymbol{\Lambda}_1 & \boldsymbol{\Lambda}_2 & \boldsymbol{\Lambda}_2 & \dots & \boldsymbol{\Lambda}_q \\ \boldsymbol{\Lambda}_2 & \boldsymbol{\Lambda}_3 & \dots & \dots & \vdots \\ \boldsymbol{\Lambda}_3 & \dots & \dots & \dots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \boldsymbol{\Lambda}_{p+1} & \dots & \dots & \dots & \boldsymbol{\Lambda}_{p+q} \end{bmatrix}$$

$$\boldsymbol{\Lambda}_i = \left(\frac{1}{N-i-1}\right) \sum_{k=1}^{N-i} \boldsymbol{y}_{k+i} \boldsymbol{y}_k^t$$

[1] P. Van Overschee and B. De Moor, *Subspace identification for linear systems: Theory–Implementation–Applications.* Springer Science & Business Media, 1996.

Null Space Anomaly Detection

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- Hankel Matrix → System identification (*Control Theory)*
- For **ADS**, we do not need to identify the system
- We use **Singular Value Decomposition** on Hankel Matrix
- and find the **Null Space (U_{H0})**

SVD decomposition of H

$$H_{p,q} = U_H S_H V_H^t$$

U_{H0} property

$$U_{H0}^t H_{p,q} = 0$$

- Null hypothesis & Residual:

NullSpace Residual

The Residual Matrix is defined:

$$R_{i,j} = U_{H0}^t H_{i,j}$$

- $R_{i,j} = 0$, Healthy State
- $R_{i,j} \neq 0$, Abnormal State

Null Space Anomaly Detection

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- Algorithm
  - Learning phase: (NOC datasets)
    - extract Null Space
    - Calculate Residual values for NOC datasets
    - Threshold Calculation
  - Detection phase:
    - Calculate Residuals
    - check whether they are still under the threshold
- Residuals ≈ Anomaly Indicators (AI)[1]

[1] E. Zugasti, A. G. González, J. Anduaga, M. A. Arregui, and F. Martínez, "Nullspace and autoregressive damage detection:a comparative study," Smart Materials and Structures, vol. 21,no. 8, p. 085010, 2012.

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Use Case:
Tennessee Eastman

Tennessee Eastman Process

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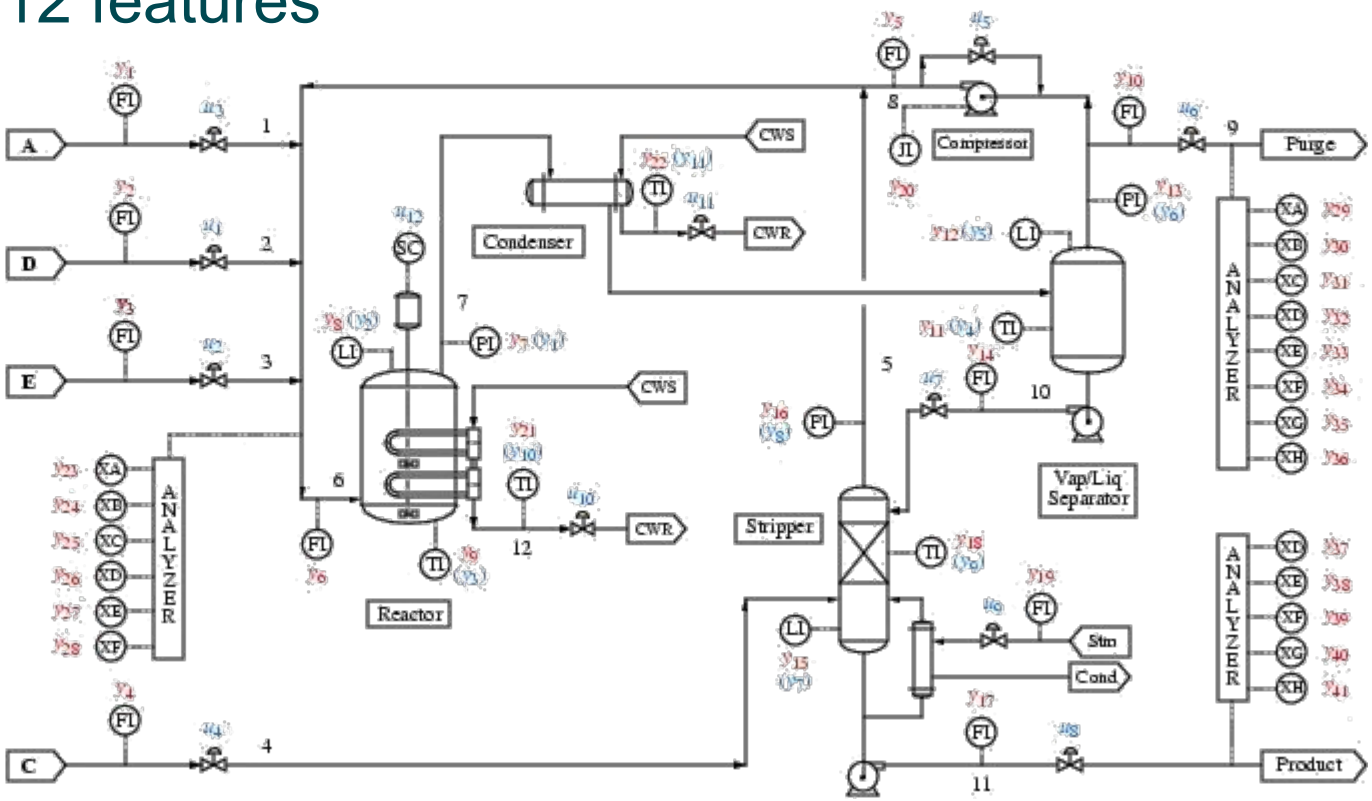
- Chemical Process[1]
- From 4 gaseous reactants → 2 liquid products
- 41 + 12 features



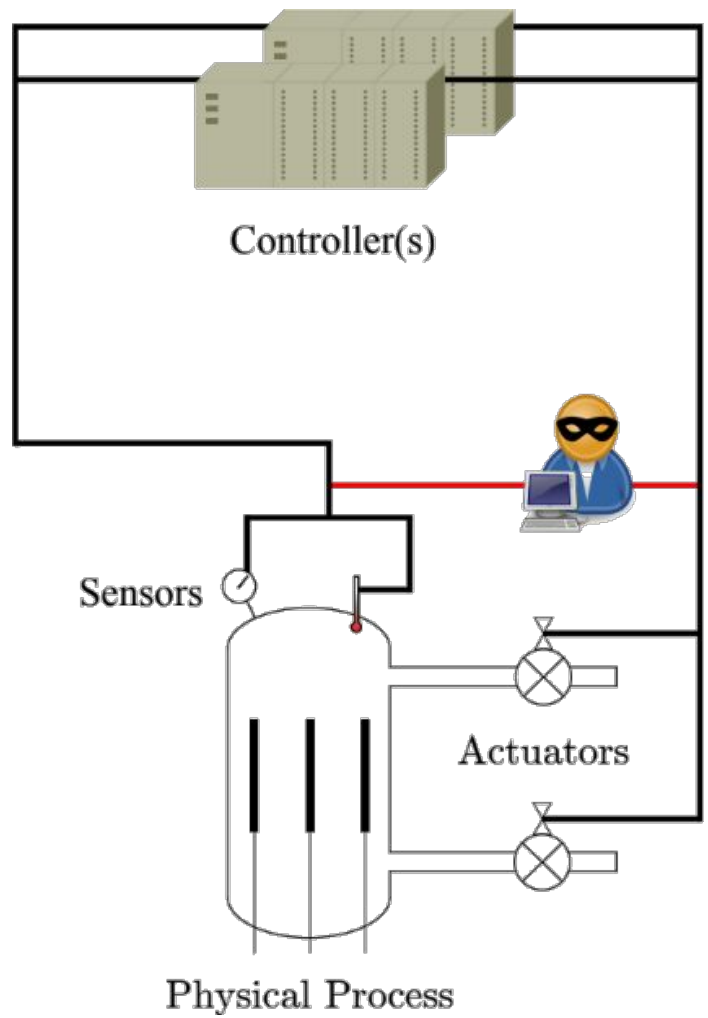
[1] J. J. Downs and E. F. Vogel, “A plant-wide industrial process control problem,” Computers & Chemical Engineering,vol. 17, no. 3, pp. 245–255, 1993.

Attack model

- Integrity attack:
  - time series injection
- DoS attack
  - Communication stop
- Performed attacks

Variable number	Variable name	Attack type
XMEAS1	A feed (stream 1)	Integrity
XMEAS8	Reactor level	Integrity
XMEAS9	Reactor temperature	Denial of Service
XMEAS14	Product Separator underflow (stream 10)	Denial of Service
XMEAS17	Stripper underflow (stream 11)	Integrity

- Simulation time: 72H
  - attack starts after 24H
- Fs=0.027 Hz



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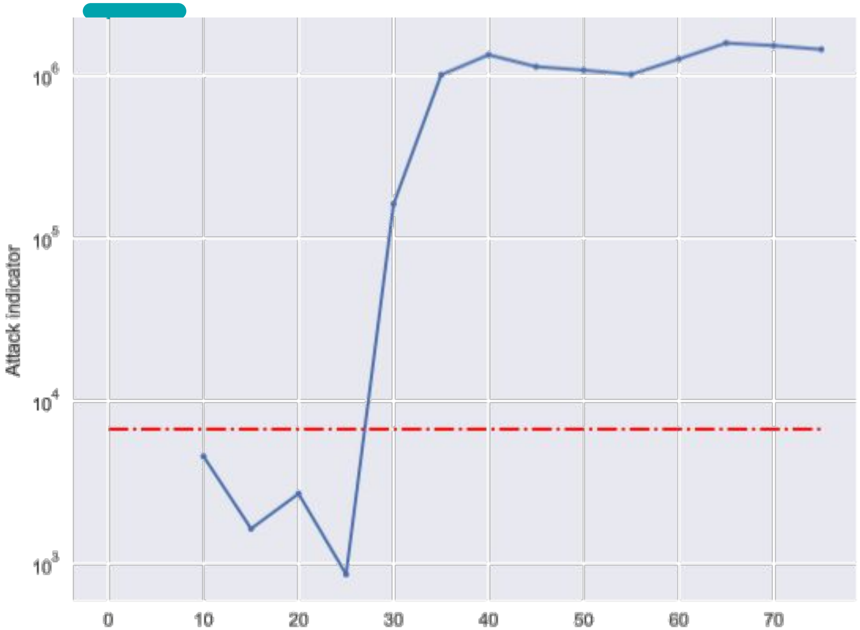
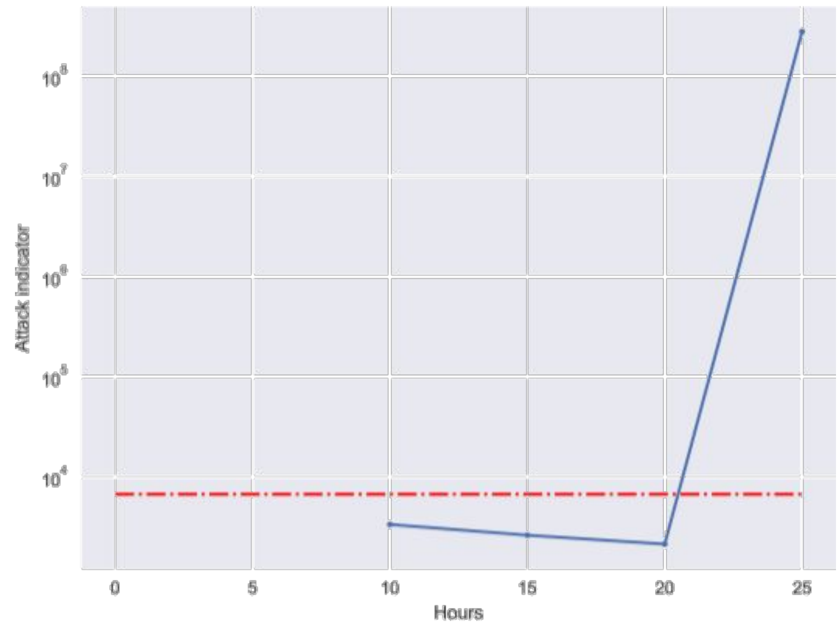
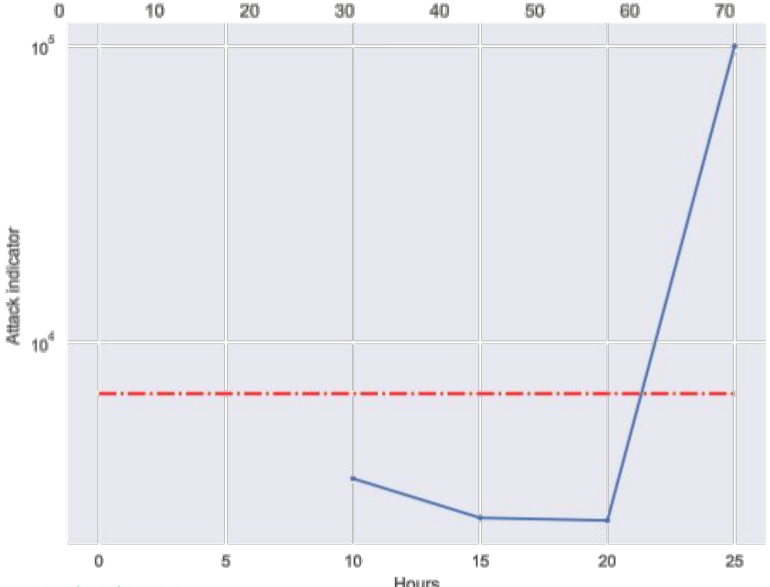
Results

Integrity attack results

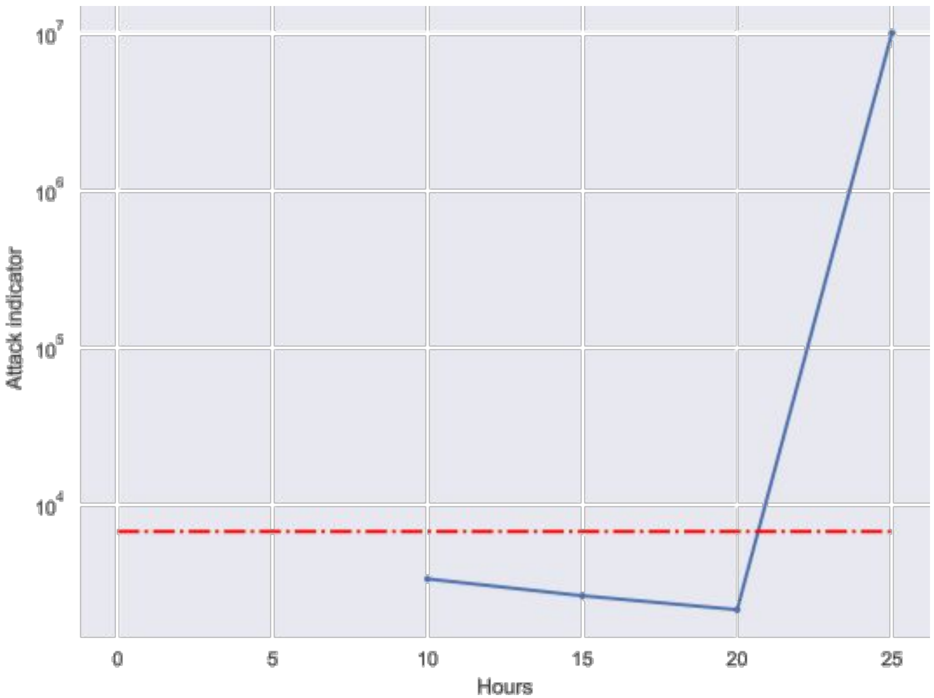


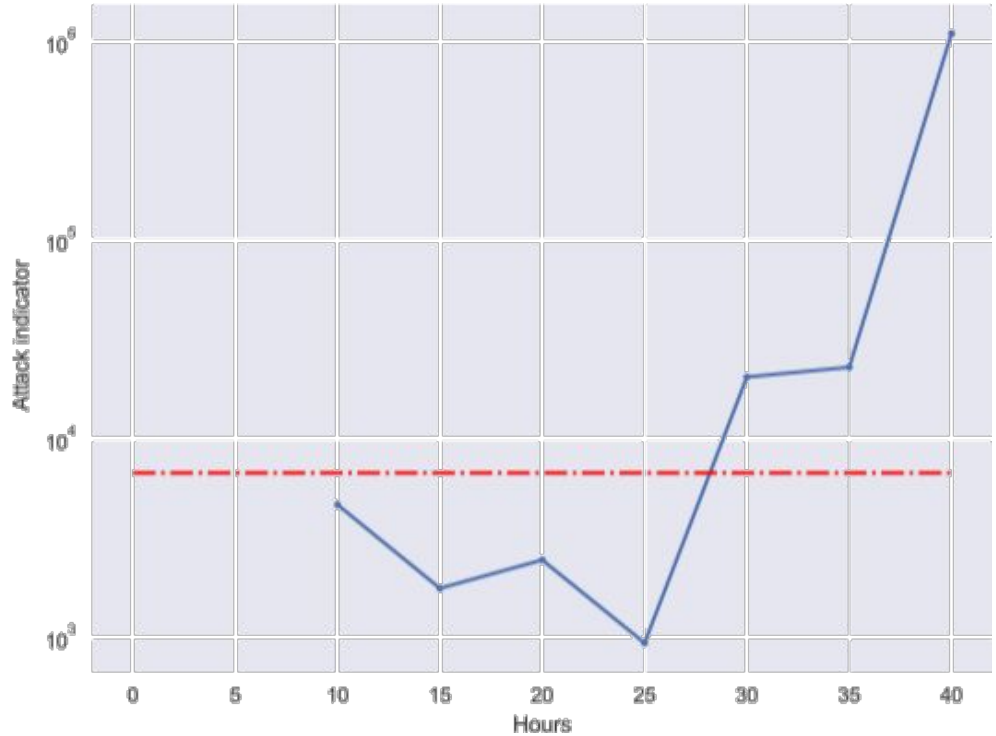




Variable number	Variable name
XMEAS1	A feed (stream 1)
XMEAS8	Reactor level
XMEAS17	Stripper underflow (stream 11)

DoS attack results





Variable number	Variable name
XMEAS9	Reactor temperature
XMEAS14	Product Separator underflow (stream 10)

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Conclusions

Conclusions

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- **Attack detection** in IIoT is still an **open challenge**
- We **present** an **ADS** that **detects field-level anomalies**
- The ADS computes an **Attack Indicator**
- **Approach validated** with Tennesee-Eastman process
  - Integrity attacks
  - DoS attacks

Future Work

- Preprocessing data to have a more sensitive method
  - Normalize the inputs
  - Feature transformation methods
- Sliding-window approach for a faster detection
- Add network-level variables to the ADS
- Use more validation scenarios

Acknowledments

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Eskerrik asko
Muchas gracias
Thank you

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